Viharos, Zs. J.; Monostori, L.; Intelligent, quality-oriented supervisory control of manufacturing processes and process chains; *DYCOMANS Workshop,* Bled-Slovenia, 12-14 May, 1999, Slovenia, pp. 129-134.

INTELLIGENT, QUALITY-ORIENTED SUPERVISORY CONTROL OF MANUFACTURING PROCESSES AND PROCESS CHAINS

Zs. J. Viharos, L. Monostori

Computer and Automation Research Institute, Hungarian Academy of Sciences, Hungary
Kende u. 13-17,H-1111 Budapest, Hungary, Tel.: (36 1) 4665-644, Fax: (36 1) 4667-503, viharos@sztaki.hu

Keywords: machine learning, artificial neural networks, process modelling, optimisation, compromises among viewpoints

1. Abstract

The paper presents a novel approach for generating multipurpose models of machining operations combining machine learning and search techniques. These models are intended to be applicable at different engineering and management assignments. Simulated annealing search is used for finding the unknown parameters of the models in given situations. It is expected that the developed block-oriented framework will be a valuable tool for modelling, monitoring and optimisation of manufacturing processes and process chains. The applicability of the proposed solution is illustrated by the results of experimental runs.

2. Introduction

Reliable process models are extremely important in different fields of computer integrated manufacturing. They are required e.g. for selecting optimal parameters during process planning, for designing and implementing adaptive control systems or model based monitoring algorithms.

A way is to implement *fundamental models* developed from the principles of machining science on computer. However, in spite of progress being made in fundamental process modelling, accurate models are not yet available for many manufacturing processes. *Heuristic models* are usually based on the rules of thumb gained from experience, and used for qualitative evaluation of decisions. *Empirical models* derived from experimental data still play a major role in manufacturing process modelling (Warnecke and Kluge, 1997).

In the CIRP survey on developments and trends in control and monitoring of machining processes, the necessity of sensor integration, sophisticated models, multimodel systems, and learning ability was outlined (Tönshoff et al.,1988). Attaching further importance to the issue, in 1995 the *CIRP Working Group on Modelling of Machining Operations* was established “to promote the development of models of chip removal operations by defined cutting edges with the aim to quantitatively predict the performance of such operations, and to promote the use of such models in industry” (Van Luttervelt et al., 1998).

Difficulties in modelling manufacturing processes are manifold: the great number of different machining operations, multidimensional, non-linear, stochastic nature of machining, partially understood relations between parameters, lack of reliable data, etc.

A number of reasons back the required models: design of processes, optimisation of processes, control of processes, simulation of processes, and design of equipment (Van Luttervelt et al., 1998).

Artificial neural networks (*ANNs*), *neuro-fuzzy* (*NF*) systems are general, multivariable, non-linear estimators, therefore, offer a very effective process modelling approach. Such soft computing techniques seem to be a viable solution for the lower level of intelligent, hierarchical control and monitoring systems where abilities for *real-time functioning, uncertainty handling, sensor integration*, and *learning* are essential features (Monostori and Barschdorff, 1992). Successful attempts were reported on in the literature (Chryssolouris et al.; Monostori, 1993; Monostori and Barschdorff, 1992; Monostori et al., 1996; Rangawala and Dornfeld, 1989; Warnecke and Kluge, 1997). The assignments to be performed determined the input-output configurations of the models, i.e. the parameters to be considered as inputs and the ones as outputs.

Different assignments, however, require different model settings, i.e. different input-output model configurations. Considering the input-output variables of a given task together as a set of parameters, the ANN model estimates a part of this parameter set based on the remaining part. The selection of input-output parameters strongly influences the accuracy of the developed model, especially if dependencies between parameters are non-invertable. At different stages of production (e.g. in planning, optimisation or control) tasks are different, consequently, the estimation capabilities of the related applied models vary, even if the same set of parameters is used.

The paper summarises the first results of the research activity aiming at finding a *multipurpose model* for a set of assignments, which can satisfy the various accuracy requirements. A method for automatic generation of ANN-based process models by back propagation and heuristic search is described. The application phase of the process models is also detailed. A novel technique based on simulated annealing search is introduced to find the unknown parameters of the model in given situations. The applicability of the proposed solution is illustrated by the results of experimental runs. The extension of the approach to modelling and optimisation of process chains is also addressed.

3. ANN based approaches to modelling of machining processes

The aim of this paragraph is to shortly overview the large variety of machining assignments and input-output configurations of the related ANNs. ANN applications in machining (e.g. in planning, in setting of tool and machine parameters, in monitoring and control) are presented in the paper of Viharos *et al.* (Viharos et al., 1999). It should be stressed that following the classical approach, in every application the input-output configuration of the applied ANN model is determined by the given assignment, namely known parameters serve as inputs and unknown parameters as outputs. The estimation capabilities of the applied ANN models are determined as results of the model building and testing stage.

A model building for creep feed grinding of aluminum with diamond wheels is presented by Liao & Chen (Liao and Chen, 1994). The paper also calls the attention to the problem that the measurement could not been satisfactory handled by the chosen ANN model realising one to one mapping between input and output parameters.

4. ANN applications for modelling the plate turning

Surface roughness is one of the mostly used requirements of customers buying steel parts. The roughness requirement is expressed through prescribed value of the 'R_a' parameter of the surface of the part, consequently, among others the producer has to select the machining parameters appropriately. This paper addresses the problem of appropriate selection of feed, depth of cut and speed in plate turning using an ANN based cutting model.

To build up an ANN model for plate turning, a hundred and fifty experiments were performed to produce data for learning and testing. All of the machining parameters were varied and the roughness of the produced surface was measured while performing these cutting experiments. Circumstances of cuttings were:

- Material: 42CrMo4.
- Machine: NC, Voest-Alpine, Nr. 085064, Type: WNC500S/1,
- Tool: CNMG12040843, cp 3, 1820091, p15, k20, radius: 0.8 mm,
- With cooling.

The speed was varied form 2.12 to 4.89 m/s, the depth of cut form 0.25 to 1.75 mm and the feed from 0.1 to 0.45 mm/revolution. Measured roughness values were between 0.4 and 4.95 micrometer. A hundred randomly chosen data were used to build up the ANN model and the remainder fifty data were used for testing. Several examples of ANN models in machining were presented in the previous paragraph. In every application the input-output configuration of the applied ANN model is determined by the given assignment, namely known parameters serves as inputs and unknown parameters serves as outputs. Using this classical concept for the problem of plate turning the prescribed R_a parameter acts as input and machining parameters as outputs.

The experiments show that estimation accuracies are different for various machining parameters and conclude that estimations of depth of cut ('a') and speed ('v') are poor but estimations of feed ('f') are quite good. Based on the classical approach the averages of estimation errors can be reported as results without further investigations as in the papers presented above.

5. Selection of the appropriate input-output configuration of the ANN based plate turning model

Outlying the multidimensional and non-linear nature of the machining operations and the fact that closely related assignments require different model settings, Viharos *et al.* (Viharos et al., 1999) addresses the problem of automatic input-output configuration and generation of ANN-based process models with special emphasis on modelling of production chains. In this paper an algorithm is presented to build up a general ANN model through automatic selection of its input-output configuration. The algorithm does not have any regard to the given assignment of engineers its target is to satisfy the accuracy requirements. The following three tasks are solved with help of the developed algorithm:

1. Determination of the (maximum) number of output parameters (No) from the available N parameters which can be estimated using the remaining Ni = N - No input parameters within the prescribed accuracy.
2. Ordering of the available parameters into input and output parameter sets having Ni and No elements, respectively.
3. Training the network whose input-output configuration has been determined in the preceding steps.

This algorithm was used to determine the appropriate input-output configuration of the ANN based plate turning model. The allowed maximum estimation error was ±5%. This algorithm resulted a general ANN based turning model with parameters of 'f', 'a' and 'v' on the input and 'R_a' on the output side. The same were the results by repeating the algorithm with various numbers of hidden nodes, consequently, dependencies between these four parameters are non-invertable. This fact explains the existence of multiple solutions for the given assignment introduced above. Figure 1 illustrates an example of the local dependencies among these parameters learned by the general ANN model taking feed rate at a constant value.

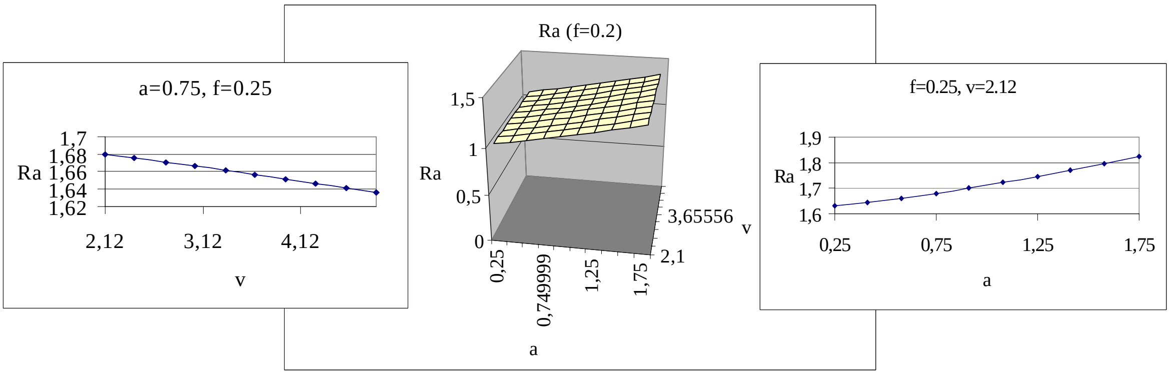

Fig. 1. Learned dependencies among parameters.

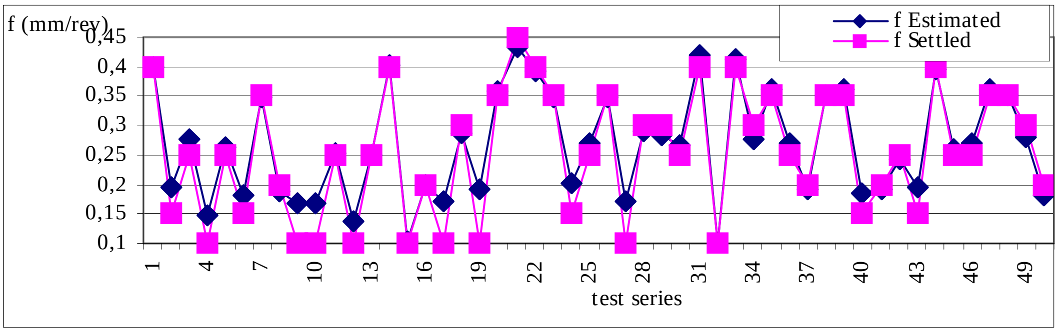

Fig. 2. Good estimation of the feed rate ('f') using the introduced new method

6. Estimations of machining parameters

Monostori&Viharos presented a method for solving different assignments of various levels and stages of machining with the general ANN model resulted by the above-referred method (Viharos and Monostori, 1999; Monostori and Viharos, 1999). This algorithm searches for the unknown parameters of the general ANN model without having any regard to the input-output positions of them. To solve the assignment presented above the unknown 'a', 'f' and 'v' parameters can be determined based of the known value of the 'R_a', however the 'R_a' is on the output and the other ones on the input side of the ANN model. To show the capabilities of the ANN model the estimation errors of the parameter 'f' were determined using the fifty test data. Figure 2. shows estimated and real values of 'f' and concludes that the 'f' can be estimated quite accurate using the introduced methods. It indicates that there is no significant difference between the new approach and the classical approach by estimation of the parameter 'f', consequently, using any of the methods the feed rate can be determined quite accurate.

Results are different in cases of parameters of 'a' and 'v'. These parameters can't be estimated with the required accuracy based on the classical approach. This can have two reasons:

1. There are no dependencies between these parameters and the roughness, or
2. in the classical approach the input-output configuration of the applied ANN model was not appropriate.

Experiences show that there are dependencies between these parameters and the roughness, consequently, inadequate ANN models can be built up following the classical approach. Also the different input-output configurations resulted by the classical and by the new approach indicate this conclusion.

7. Multiple solutions for the given assignment

Results show that dependencies between 'a', 'f', 'v' and 'R_a' are non-invertable, consequently, there are several solutions for the given assignment presented above. To present a field of possible solutions the search for the unknown machining parameters were repeated a thousand times for one prescribed 'R_a' value. Solutions are presented in the figure 3.

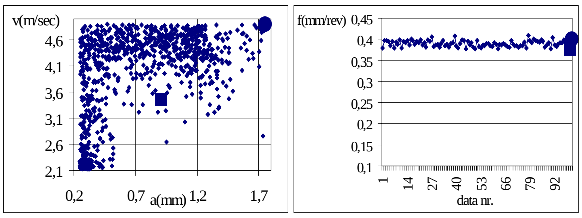

Fig. 3. A thousand of possible machine settings are presented as small rhombuses in the pictures to produce the surface with the given roughness. Circles in the pictures represent the original machine setting. Large squares represent estimation of the classical method.

It concludes that the allowed interval of 'f' is quite small but there are a large number of solutions for choosing the appropriate 'a' and 'v' values to produce a surface with the prescribed roughness, consequently, optimisation of parameter setting can be performed as described in the next paragraph.

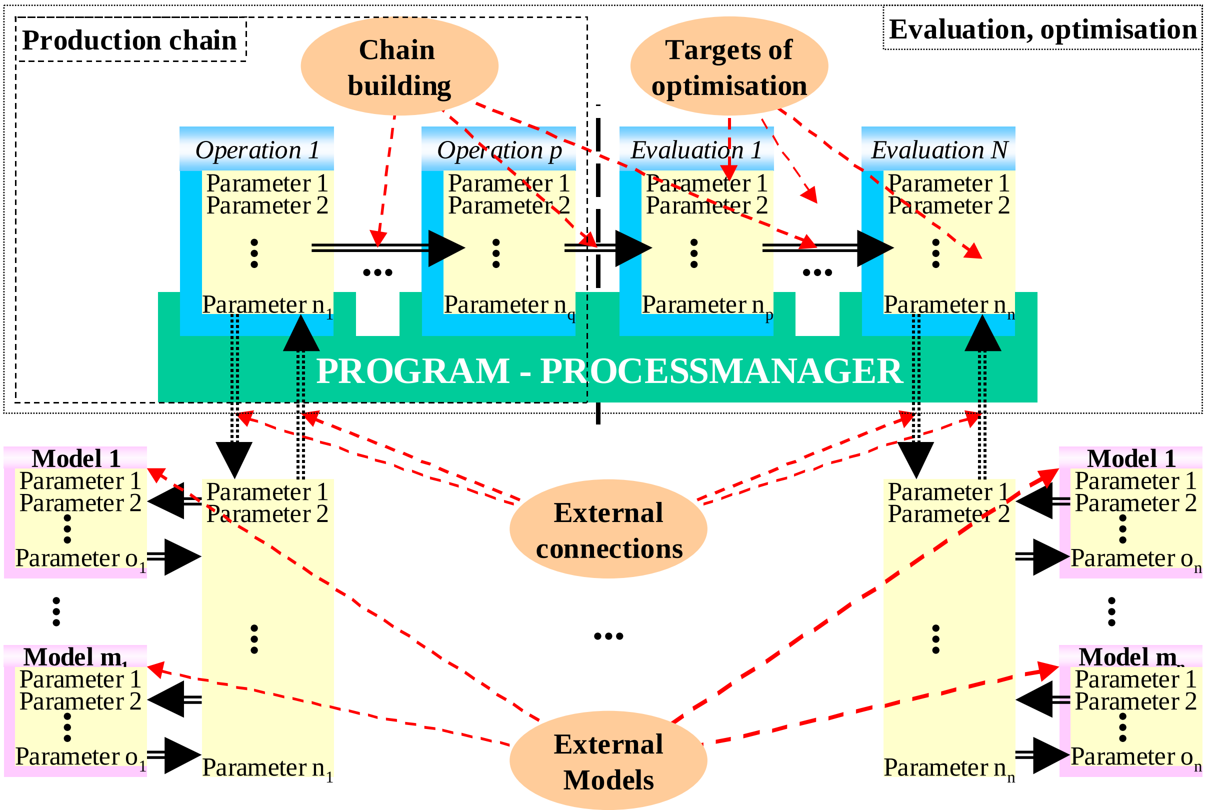

Figure 4. The program – PROCESSMANAGER

8. Optimisations of machining processes from various points of views

Optimisations can be realised to satisfy some constrains or goals where there are several solutions of a given assignment. There are different approaches to optimise a given process or process chain (Tóth and Erdélyi, 1995). Block-oriented software was developed by Monostori&Viharos (Monostori and Viharos, 1999) under the name "ProcessManager" to optimise operations and/or production chains from various points of view in the same time.

The *ProcessManager* block-oriented framework for modelling, monitoring and optimisation of manufacturing processes and process chains incorporates (Figure 4.):

- definition of the elements of the chain,
- determination of the process models by integrating analytical equations, expert knowledge and example-based learning,
- connecting the single models into a process chain by coupling input-output model parameters not limited to models of successive processes in the chain,
- definition of eligible intervals or limits for the process parameters and monitoring indices,
- definition of a cost function to be optimised, etc.

Multiple of objectives can be handled by the usual weighting technique.

This software tool determines the capabilities of the given operation(s) through possible values of parameters belongs to different optimisation viewpoints and gives also the related machining circumstances.

This program was used to optimise the plate turning assignment. Optimisations were performed:

1. From the point of view of the producer: The production time has to be minimised.
2. From the point of view of the customer: The roughness has to be minimised.

To realise optimisations from both of these viewpoints weighting factors were varied to result in different compromises. Figure 5 shows possible compromises through values of the related parameters belonging together. The diagram can be used in the following way:

1. The representatives of the different viewpoints have to make compromises. This means, they have to select that point on the horizontal axis, which corresponds to acceptable values for both of them, for the producer (t) and also for the customer (R_a).
2. Using also this diagram, having selected the point of the compromise, the related machining parameters can be determined resulting in the acceptable compromise. The values of these parameters correspond to the same horizontal position as the point of the compromise.

These results can be also used directly to support business decisions and compromises.

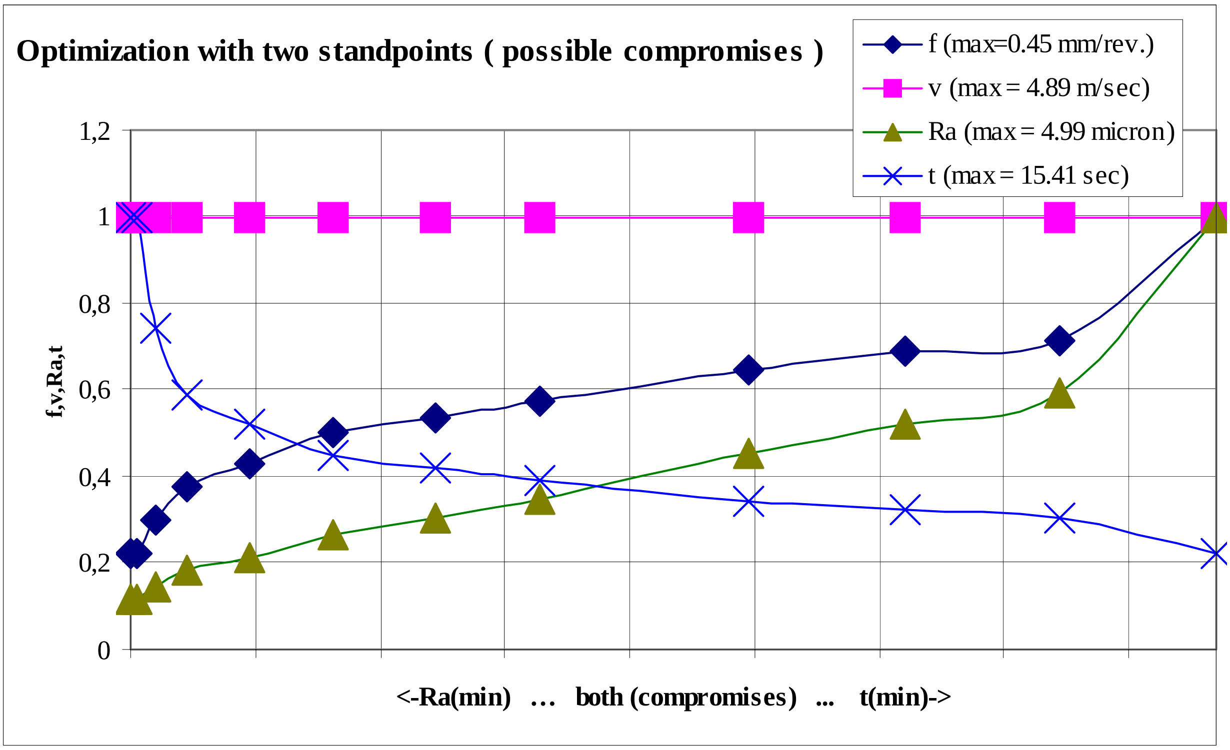

Figure 5. Parameters resulted by the optimisation of the plate turning operation. On the left side the viewpoint of the customer (R_a - min.) on the right side the viewpoint of the producer (t - min.) is satisfied. Curves show possible compromises between the two viewpoints.

9. Conclusions

The paper presented a novel approach for generating multipurpose models of machining operations, which combines machine learning and search techniques. Simulated annealing search was used for finding the unknown parameters of the multipurpose model in given situations. It is expected that the developed *ProcessManager* will be a valuable tool for modelling, monitoring and optimisation of manufacturing processes and process chains. Taking the globalisation issues and the increasing role of virtual enterprises into account, the distributed version of the system will show up further benefits.

10. Acknowledgements

This work which is related to the DYCOMANS activities was partially supported by the *National Research Foundation, Hungary*, Grant Nos. F026326 and T026486.

References

Chryssolouris G., Guillot M., Domroese M., *An approach to intelligent machining*, Proc. of the 1987 American Control Conf., Minneapolis, MN, June 10-12, pp. 152-160. (1987)

Liao, T.W.; Chen, L.J., A neural network approach for grinding processes: modeling and optimization, Int. J. Mach. Tools Manufacturing, 1994, Vol. 34, No. 7, pp. 919-937.

Monostori L., *A step towards intelligent manufacturing: Modelling and monitoring of manufacturing processes through artificial neural networks*, CIRP Annals, 42, No. 1, pp. 485-488. (1993)

Monostori L., Barschdorff D., *Artificial neural networks in intelligent manufacturing*, Robotics and Computer-Integrated Manufacturing, Vol. 9, No. 6, Pergamon Press, pp. 421-437. (1992)

Monostori L., *Hybrid AI approaches for supervision and control of manufacturing processes*, Key-note paper, Proc. of the AC'95, IV Int. Conf. on Monitoring and Automation Supervision in Manufacturing, Miedzeszyn, Poland, Aug. 28-29, pp. 37-47. (1995)

Monostori L., Márkus A., Van Brussel H., Westkämper E., *Machine learning approaches to manufacturing*, CIRP Annals, Vol. 45, No. 2, pp. 675-712. (1996)

Monostori L.; Viharos Zs. J., Multipurpose modelling and optimisation of production processes and process chains by combining machine learning and search techniques, The 32nd CIRP International Seminar on Manufacturing Systems, New Supporting Tools for Designing Products and Production Systems, 1999, Leuven, Belgium (accepted paper)

Monostori L.; Viharos Zs. J., Satisfying various requirements in different levels and stages of machining using one general ANN-based process model; 15th International Conference on Computer-Aided Production Engineering; CAPE'99, 1999, Durham, U.K., pp. 477-484

Rangwala S.S., Dornfeld D.A., *Learning and optimisation of machining operations using computing abilities of neural networks*, IEEE Trans. on SMC, Vol. 19, No. 2, March/April, pp. 299-314. (1989)

Tóth T., Erdélyi F., The inner structure of computer aided process planning having regard to concurrent engineering, 2nd International Workshop in Intelligent Manufacturing Systems, Hungary, 1995, pp. 142-167.

Tönshoff H.K., Wulsberg J.P., Kals H.J.J., König W., Van Luttervelt C.A., *Developments and trends in monitoring and control of machining processes*, CIRP Annals, Vol. 37, No. 2, pp. 611-622. (1988)

Van Luttervelt C.A., Childs T.H.C., Jawahir I.S., Klocke F., Venuvinod P.K., *Present situation and future trends in modelling of machining operations*, CIRP Annals, Vol. 47, No. 2, (1998)

Viharos Zs. J., Monostori L., Automatic input-output configuration and generation of ANN-based process models and its application in machining, Proceedings of the XII. International Conference on Industrial & Engineering Applications of Artificial Intelligence & Expert Systems IEA/AIE-99, Kairo, Egypt, 1999, accepted paper

Viharos Zs. J.; Monostori L.; Markos S; Selection of input and output variables of ANN based modeling of cutting processes, Proceedings of the X. Workshop on Supervising and Diagnostics of Machining Systems of CIRP, Poland, 1999, pp. 121-131.

Warnecke G., Kluge R., *Control of tolerances in turning by predictive control with neural networks*, Proceedings of The Second World Congress on Intelligent Manufacturing Processes & Systems, June 10-13, 1997, Budapest, pp. 1-7. and Journal of Intelligent Manufacturing, Vol. 9, No. 4, August 1998, Special Issue on Soft Computing Approaches to Manufacturing, Chapman & Hall, pp. 281-287.

Yerramareddy S., Lu S.C.-Y., Arnold K.F., *Developing empirical models from observational data using artificial neural networks*, Journal of Intelligent Manufacturing, Vol. 4, pp. 33-41. (1993)