

## QUALITY-ORIENTED MODELLING AND OPTIMISATION OF PRODUCTION PROCESSES AND PROCESS CHAINS

**L. Monostori, Zs. J. Viharos**

Computer and Automation Research Institute, Hungarian Academy of Sciences  
Kende u. 13-17, H-1111, Budapest, Hungary

*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.*

*Keywords: Quality management, expert systems in decision making, technical diagnostics*

### 1. 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.

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 [1].

*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 [4]. Successful attempts were reported in the literature [2][3][4][5][6]. 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-invertible. 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 is described which are expected to be applicable in different assignments. The application phase of the multipurpose process model 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.

## 2. AUTOMATIC INPUT-OUTPUT CONFIGURATION AND GENERATION OF MULTIPURPOSE ANN-BASED PROCESS MODELS

The automatic generation of appropriate process models, i.e. models, which are expected to work accurately enough in different assignments, consists of the following steps:

- Determination of the (maximum) number of output parameters ( $N_o$ ) from the available  $N$  parameters which can be estimated using the remaining  $N_i = N - N_o$  input parameters within the prescribed accuracy.
- Ordering of the available parameters into input and output parameter sets having  $N_i$  and  $N_o$  elements, respectively.
- Training the network whose input-output configuration has been determined in the preceding steps.

The above steps are performed parallel, using the speed of the learning process as an indicator for the appropriateness of the given ANN architecture to realise the required mapping. In order to accelerate the search for the ANN configuration, which complies with the accuracy requirements with the minimum number of input parameters, *sequential forward search (SFS)* algorithm is used.

The applicability of the approach was tested by artificial data (e.g. for handling non-invertible dependencies) and using data derived from analytical descriptions for a set of engineering assignments (different levels of planning, optimisation and control). The results to be described in the paper indicate that the developed technique is able to generate process models with the required accuracy, moreover, under given circumstances, the result is a set of applicable models each guaranteeing the required accuracy performance.

A heuristic based search method was developed by the authors to solve these tasks, which results in the general model of the given operation. The search method is detailed in [10].

## 3. APPLICATION OF THE MULTIPURPOSE MODEL FOR DIFFERENT ASSIGNMENTS

### 3.1. Various engineering assignments

To solve the ten assignments enumerated in this paragraph applied models have to realise mapping among parameters of the same parameter set but in different assignments the known part of this parameter set is different.

All of the assignments are concerned to the turning process described by the following parameters:

- Setting is handled through the three machining parameters: depth of cut:  $a$  [mm]; feed:  $f$  [mm/rev]; speed:  $v$  [m/min].
- The tool is presented by three tool parameters: cutting edge angle:  $\chi$  [rad]; corner radius:  $r_\epsilon$  [mm]; tool life:  $T$  [min].
- Two monitoring parameters can be used for the turning operation: force:  $F_c$  [N] (main force component); power:  $P$  [kW].
- The customer demand is determined by the required roughness:  $R_a$  [mm].

These nine parameters build up the parameter set required to solve the ten engineering problems to be enumerated here. In the list of possible assignments the related configuration of known and unknown parameters are indicated in brackets. Known parameters are on the left and unknown on the right side of the mark "⇒". The assignments are:

1. The first assignment is to satisfy customer requirements: The customer determines the demanded roughness and possible fields of tool and machining parameters have to be selected, force, power and tool life are to be estimated. This is a typical design assignment. ( $R_a \Rightarrow \chi, r_\epsilon, f, a, v, F_c, P, T$ )
2. Determination of possible cutting circumstances of a given tool means that the two geometrical tool parameters are known and others are unknown. The results of this assignment show the achievable field of surface roughness and the related turning circumstances for a given tool. E.g. for a producer and customer of the tool. ( $\chi, r_\epsilon \Rightarrow f, a, v, F_c, P, T, R_a$ )
3. Determination of the attainable fields of machine parameters and prediction of monitoring parameters and tool life if the tool is selected and the roughness is prescribed. ( $R_a, \chi, r_\epsilon \Rightarrow f, a, v, F_c, P, T$ )
4. The assignment is the same as the third one but the depth of cut is also prescribed. This is a finishing model. ( $R_a, \chi, r_\epsilon, a \Rightarrow f, v, F_c, P, T$ )
5. Adaptive control of roughing can be realised if the roughness is prescribed, the tool is selected and monitoring parameters are measured. The assignment is to determine machine parameters and estimate the tool life. ( $R_a, \chi, r_\epsilon, F_c, P \Rightarrow f, a, v, T$ )

6. For simulation the turning process the assignment is the estimation of cutting conditions when the tool and machining parameters are selected. The produced roughness, monitoring parameters and tool life has to be estimated. ( $\chi, r_e, f, a, v \Rightarrow F_c, P, T, R_a$ )
7. This control assignment is the same as the fifth one but the depth of cut is also prescribed. This is the adaptive control of finishing. ( $R_a, \chi, r_e, a, F_c, P \Rightarrow f, v, T$ )
8. The task is to simulate the turning if the roughness is prescribed through determination of monitoring parameters and tool life if the tool is selected, roughness is prescribed and machining parameters are settled. ( $R_a, \chi, r_e, f, a, v \Rightarrow F_c, P, T$ )
9. Monitoring through estimation of tool life and roughness with a given tool, machining parameters and with help of measured monitoring parameters. ( $\chi, r_e, f, a, v, F_c, P \Rightarrow T, R_a$ )
10. Monitoring when the roughness is known. The assignment is the same as the previous but the customer prescribes the roughness. ( $R_a, \chi, r_e, f, a, v, F_c, P \Rightarrow T$ )

These assignments show several input-output configurations for modelling dependencies between the different elements of a parameter set. They require the same information about the parameters of the cutting process but the mathematical model describing them has to be applied in different directions. The question arises: Is it possible to build up a model once and to apply this model for solving the enumerated assignments?

### 3.2. SOLUTIONS OF THE ASSIGNMENTS

The ten engineering assignments were used for testing the developed simulated annealing search. To get a simple view about the possible solution field, the maximum and minimum values of the results were selected for all parameters, for each task. These parameter fields are listed in Figure 1-9. There are a large number of solutions for each of the enumerated assignments. These intervals were created from a hundred repeated searches at each assignment. Results in the figures show various intervals of acceptable unknown parameters for various assignments.

In cases where the roughness is known its value is 0.014 mm. Values for selected tool were  $\chi=1.549$  rad,  $r_e=0.7394$  mm. In monitoring, measured values of force was  $F_c=2247$  N and of power  $P=8.69$  kW. Known machining parameters were  $v=161$  m/min,  $f=0.32$  mm/revolution and  $a=3.5$  mm.

It should be stressed that these results were received with only one ANN model here (Figure 10.) with the same input-output configuration and using the developed simulated annealing search method, indicating the acceptability of the techniques presented.

Results show that the realisation of the new concept works adequately.

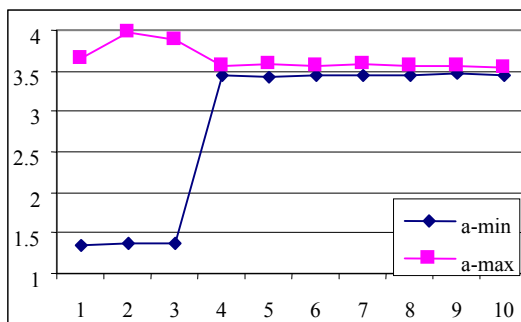


Figure 1.

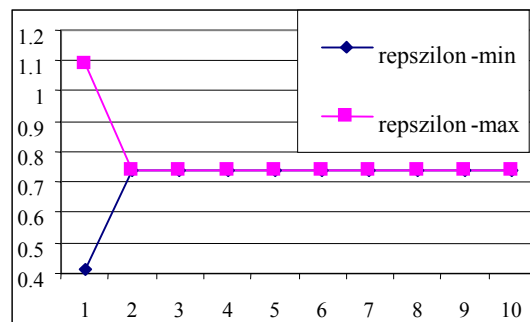


Figure 2.

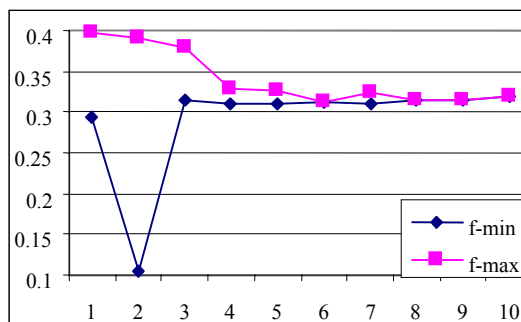


Figure 3.

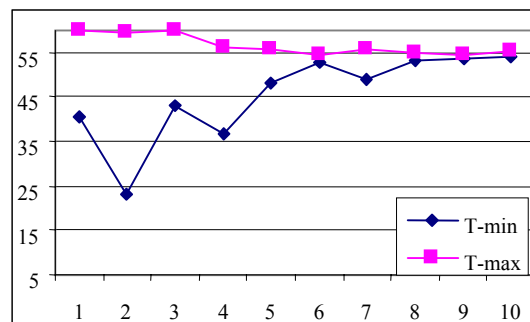


Figure 4.

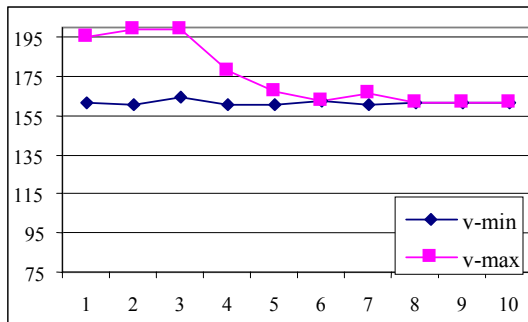


Figure 5.

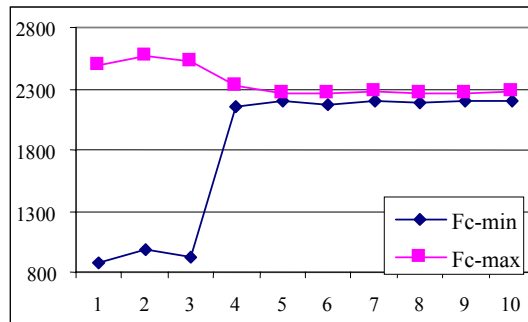


Figure 6.

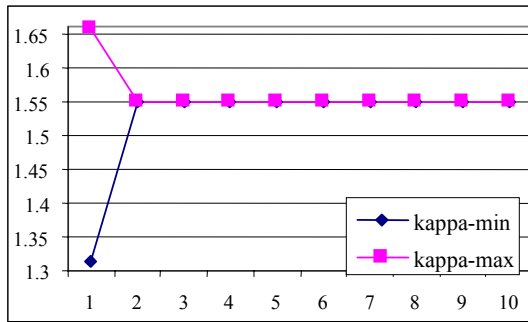


Figure 7.

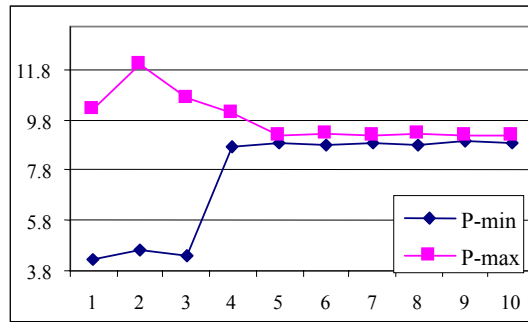


Figure 8.

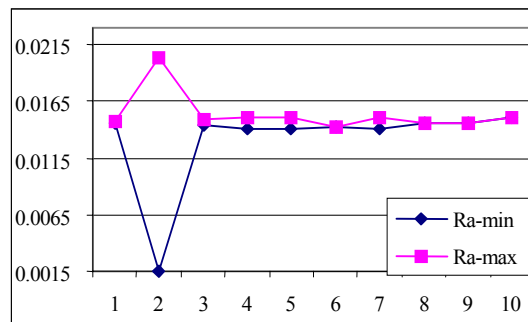


Figure 9.

Figures 1-9. The figures show the results of the above-enumerated assignments. On the horizontal axis the number of the assignment is indicated according to the list presented before. The vertical axes show the values of the related parameter. The solutions of an assignment are between the maximum and minimum values.

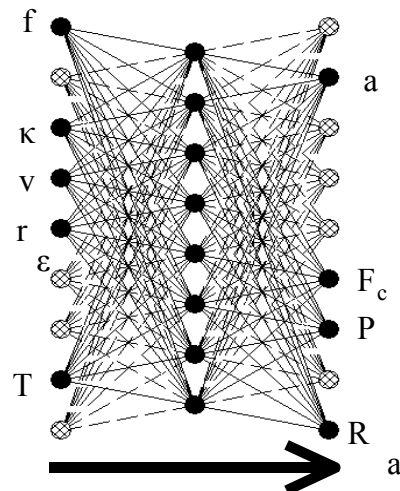


Figure 10. The general ANN model of the plate turning operation. This general model was used to solve all of the ten, above-enumerated engineering assignments.

#### 4. MODELLING AND OPTIMISATION OF PROCESS CHAINS

As it was pointed out in [9], it is not enough to concentrate on the final tolerances usually defined by design. The final tolerances are determined not only by the finishing operations, but are the results of the initial tolerances of the workpieces and the intermediate tolerances reached by the elements of the *process chain* resulting in the finished part. The output of one operation is the input of another one or it is a feature of the end product. To build a model for a production chain, models have to be ordered to every stage of production. The sequence of production operations can be modelled by a chain of operations connected by their input-output parameters [7][8][10]. To have process models with the required accuracy is especially important in the case of process chains where the errors can cumulate.

The *tolerance channel* through which the manufacturing process is to be led is influenced by a number of parameters: material properties, nominal and actual machine parameters, cutting conditions, tool state, etc. The *non-deterministic nature* of manufacturing processes is the fundamental

barrier that prevents us from determining this channel and mapping it to NC programs before machining. *Systematic* and *accidental non-conformities* can be enumerated that contribute to this stochasticity [9].

At the Computer and Automation Research Institute a block-oriented software was developed named "*ProcessManager*" to optimise operations and/or production chains from various points of view at the same time. Multiple of objectives can be handled by the usual weighting technique.

The applicability of the program system is illustrated here through the optimisation of the plate turning assignment. Optimisations were performed from the twofold viewpoints of the company owner (productivity maximisation through the maximisation of the parameter 'q', which is equal to the product of the three machining parameters), and the engineer (maximisation of the cutting stability through minimisation of the 'a/f' ratio). During the optimisations the customer prescribed the required roughness value. The dependencies among the machining parameters (speed, depth of cut and feed) and the surface roughness are modelled by an artificial neural network, built up using a series of cutting measurements of a real, plate turning operation. The parameter 'q' and the 'a/f' ratio is to be calculated by a simple, function based model what can be easy connected with the program "*ProcessManager*". Several optimisations were performed using various weightings of the optimisation viewpoints and so the importances of them are different in the resulted optimum points. The determination of the possible compromises between these two viewpoints is the results (Figure 11.).

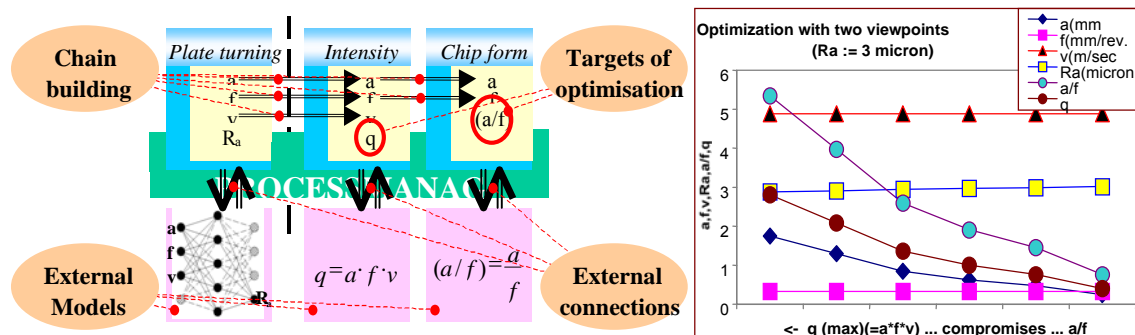


Figure 11. The block oriented model with the "*ProcessManager*" for the twofold optimisation of the plate turning assignment (left). Parameters resulted by the optimisation of the plate turning operation. On the left side of the digram the viewpoint of the company owner (q - max.) on the right side the viewpoint of the engineer, process stability (a/f - min.) is satisfied (right).

## 5. CONCLUSIONS AND FUTURE WORK

A new approach was presented in the paper for modelling machining processes. The corn idea of this modelling technique is that the model building stage has no regard on the given assignment(s), the task of modelling is to find all the dependencies among parameters while satisfying accuracy requirement(s). This major idea was used in the presented SFS search algorithm which avoids the problem of modelling non-invertible dependencies and automatically determines the input-output configuration of the used ANN, resulting in the general process model. A search algorithm based on simulated annealing was also introduced to solve various possible assignments using the general ANN model through finding values for the unknown parameters based on the known parameters without regard to their input or output position. Using the corn idea and the simulated annealing search algorithm a block-oriented software was developed, named "*ProcessManager*", to optimise operations and/or production chains from various points of view, at the same time. The applicability of these ideas and algorithms is presented through testing basic mathematical problems and equations based on cutting samples. Solutions of different real assignments for plate turning and their optimisation from different viewpoint result in possible compromises proving the applicability of this new concept.

The presented concept for optimising manufacturing processes from different aspects is based on application-independent general models of different operations. The general models incorporate all the dependencies among the parameters concerning the individual production steps. The optimisation searches for the appropriate values of all parameters of every operation. This is manifested in a really hard mathematical and informatic problem in almost every case. Practical assignments prove that the optimisation does not require the search for each parameter of the whole process chain. It is enough to determine the parameters only, which basically influence the parameters of the optimisation viewpoints. There are already methods in our hands to determine these most important parameters [1]. Considering only these ones as parameters of the optimisation much less informatic resources are

required than the optimisation is performed on all of the operation parameters. But also for this easier problem the dependencies among the most important parameters must be known and modelled, consequently, a part of the original general models of the individual operations have to be used. Unfortunately, different optimisation problems require different parts of the general models of the individual operations, which stresses that model builders have to divide their general models in to as small sub-models as possible. The sub-model determination makes it possible to select the sub-models before optimisation which incorporate the most important operation parameters. This requirement indicates our research directions, namely to develop a method for dividing the general, application independent models of the different machining operations in as small sub-models as possible. The first steps are already made indicating successful realisations serving as the basics of further publications.

## 6. ACKNOWLEDGEMENT

This work was partially supported by the National Research Foundation, Hungary, Grant Nos. F026326 and T026486. The authors express their thanks to Dr. Sándor Markos, TU Budapest, for his valuable comments.

- [1] Van Luttervelt, C.A.; Childs, T.H.C.; Jawahir, I.S.; Klocke, F.; Venuvinod, P.K., 1999, Present situation and future trends in modelling of machining operations, *CIRP Annals*, Vol. 47, No. 2, (in print)
- [2] Chryssolouris, G.; Guillot, M.; Domroese, M., 1987, An approach to intelligent machining, Proc. of the *1987 American Control Conf.*, Minneapolis, MN, June 10-12, pp. 152-160.
- [3] Monostori, L., 1993, A step towards intelligent manufacturing: Modelling and monitoring of manufacturing processes through artificial neural networks, *CIRP Annals*, 42, No. 1, pp. 485-488.
- [4] Monostori, L., 1995, 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.
- [5] Monostori, L., Barschdorff, D., 1992, Artificial neural networks in intelligent manufacturing, *Robotics and Computer-Integrated Manufacturing*, Vol. 9, No. 6, Pergamon Press, pp. 421-437.
- [6] Monostori, L., Márkus, A., Van Brussel, H., Westkämper, E., 1996, Machine learning approaches to manufacturing, *CIRP Annals*, Vol. 45, No. 2, pp. 675-712.
- [7] VIHAROS, ZS. J.; MONOSTORI, L.; *Optimization of process chains by artificial neural networks and genetic algorithms using quality control charts*. Proc. of Danube - Adria Association for Automation and Metrology, Dubrovnik, 1997. pp. 353-354. ISBN3901509046
- [8] S. Markos, Zs. J. Viharos, L. Monostori, Quality-oriented, comprehensive modelling of machining processes, in: *Proceedings of 6<sup>th</sup> ISMQC IMEKO Symposium on Metrology for Quality Control in Production*, Vienna, Austria pp. 67-74, 1998
- [9] Westkämper, E., 1995, Supervision of quality in process chains by means of learning process models, Proc. of the *Second Int. Workshop on Learning in IMSs*, Budapest, Hungary, April 20-21, pp. 566-590.
- [10] Viharos, Zs. J.; Monostori, L.; Markos, S., 1999, Selection of input and output variables of ANN-based modelling of cutting processes, *Innovative and Integrated Manufacturing, X. International Workshop on Supervising and Diagnostics of Machining Systems*, Karpacz, Poland, March 21-26, pp. 121-131
- [11] 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, pp. 659-668.

**AUTHORS:** Prof. Dr. Laszlo MONOSTORI, Zsolt Janos VIHAROS, Computer and Automation Research Institute, Hungarian Academy of Sciences, Kende u. 13-17, H-1111, Budapest, Hungary  
Phone: (36 1) 2096-990, Fax: (36 1) 4667-503, e-mail: [laszlo.monostori@sztaki.hu](mailto:laszlo.monostori@sztaki.hu), [viharos@sztaki.hu](mailto:viharos@sztaki.hu)