Viharos, Zs. J.; Monostori, L.; Markos, S.; A framework for modelling, monitoring and optimisation of manufacturing processes and process chains by using machine learning and search algorithms, *9th IMEKO TC-10 International Conference on Technical Diagnostics* September 22-24, 1999, Wroclaw, Poland, pp. 249-254.

Key words:
Modelling and monitoring of technical processes,
Machine learning and search techniques

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A FRAMEWORK FOR MODELLING, MONITORING AND OPTIMISATION OF MANUFACTURING PROCESSES AND PROCESS CHAINS BY USING MACHINE LEARNING AND SEARCH ALGORITHMS

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.

1. INTRODUCTION

Reliable process models are extremely important in different fields of computer integrated manufacturing. 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, optimisation, control, monitoring and diagnostics, simulation of processes, and design of equipment [10].

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 offer especially viable solutions 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 on in the literature [2], [8], [4], [[1], [3], [5], [11].

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 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 ANN-based process models, i.e. models, which are expected to work with the required accuracy in different assignments, consists of the following steps [7]:

- Determining the (maximum) number of output parameters (No) from the available N parameters which can be estimated by using the remaining Ni = N - No input parameters within the prescribed accuracy.
- Ordering the available parameters into input and output parameter sets having Ni and No 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-invertable dependencies), using data derived from analytical descriptions for a set of engineering assignments (different levels of planning, optimisation and control), and by experimental machining [7].

3. OPTIMISATION OF MACHINING PROCESSES BY USING THE MULTIPURPOSE MODEL

Usually, some parameters are known, and using the multipurpose model generated according to the previous paragraph, the task is to determine the other parameters while satisfying some constraints. Because of the general nature of the multipurpose model, almost in every case, a part of the input and a part of the output variables of the model are known by the user and the unknown part of the inputs is to be determined by taking the above mentioned constraints into account.

Here, a *simulated annealing search* technique is proposed for the application phase of the multipurpose model. The search process is guided by the accuracy requirements of the estimation for the known output parameters while holding the unknown input and output parameter(s) within its (their) range of application boundaries. During the search process the unknown input parameters are to be determined and at the same time three conditions are to be satisfied:

1. *Condition regarding the known output parameters.* This condition assures that only that points of the search space can be accepted as result, which can adequately estimate the known output parameters by using forward calculation (*Error 1*, on Figure 1).

2. *Boundary conditions regarding the unknown input parameters.* This condition is determined by the validity of the ANN model. This validity is usually specified by the data set used for the training.
3. *Condition regarding the unknown output parameters.* The third condition relates also to the validity of the ANN. Values of the unknown input parameters are only acceptable if the estimated values of the unknown output parameters are within their allowed range (*Error 2*, on Figure 1).

The search algorithm is terminated if all of the three conditions above are met. An error value is ordered to all visited points of the search space. In the developed algorithm this value is the maximum of *Error1* and *Error2* presented above. The algorithm searches for the minimum error point.

As a result, this algorithm gives one solution for a given assignment of the user. To look for a larger number of solutions the search has to be repeated.

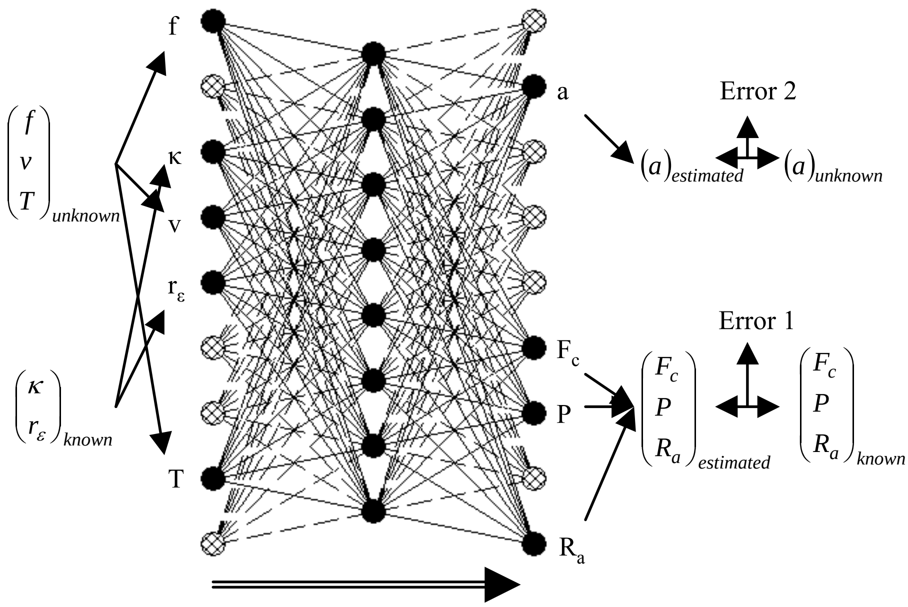

Figure 1: The generated ANN model and its application for the task presented in machining [7] (control of the cutting process with measured monitoring parameters)

There are different approaches to *optimise* a given process or process chain [9]. A block-oriented software was developed named *"ProcessManager"* to optimise operations and/or production chains form 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. Figure 2 and Figure 3 illustrate the application of *ProcessManager* for the threefold optimisation of the viewpoints of the customer (minimisation of the surface roughness), owner of the company (profit/productivity maximisation) and the employed engineer (maximisation of process stability through the 'a/f' ratio).

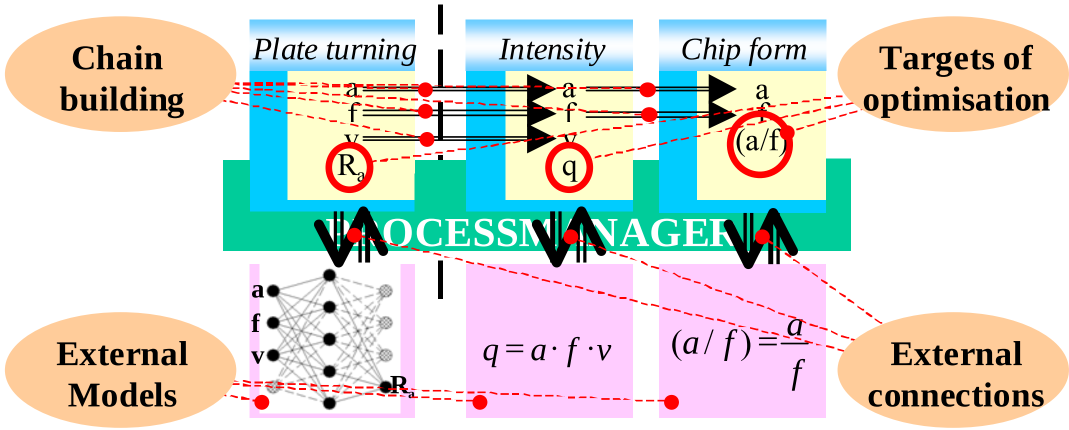

Figure 2: Chain model for optimisation of the plate turning operation with optimisation criteria

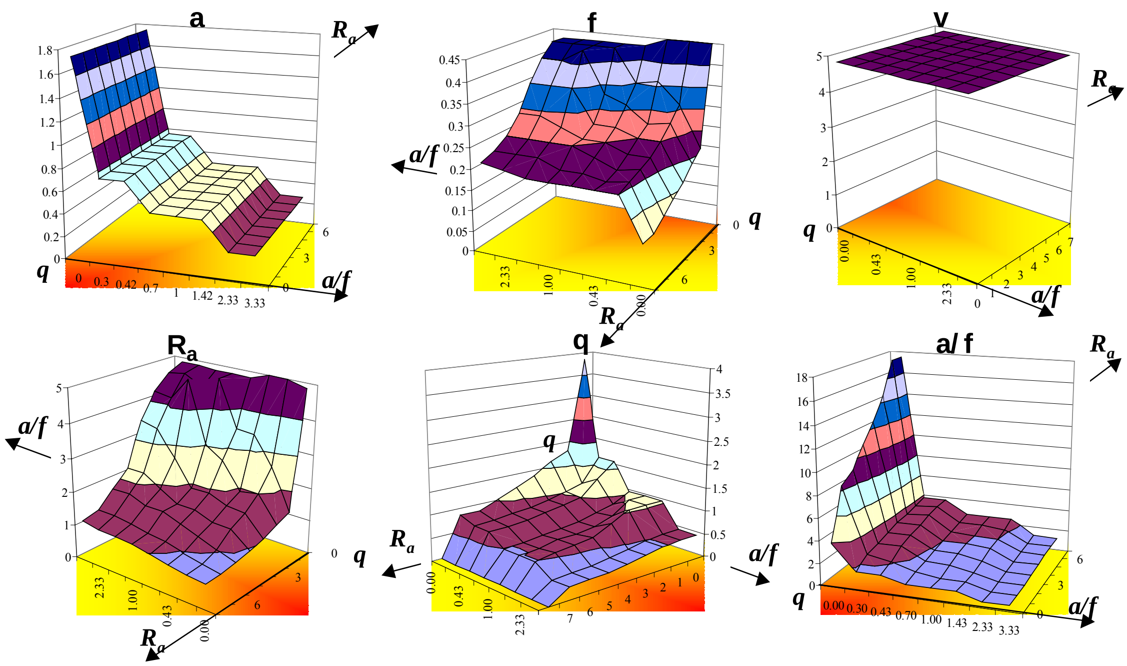

Figure 3: Parameters resulted by the threefold optimisation of the plate turning operation

Figure 2 shows the building up phase of *ProcessManager*, where the model of the plate turning is realised by an ANN and the other variables to be optimised, e.g. cutting intensity 'q' and 'a/f' for stability, are given by equations. Parameters resulted by the optimisation of the plate turning operation are illustrated by 3D-plots in Figure 3. Ratios of the weighting factors of the three variables to be optimised are represented along the axes. The "surfaces' are to be used together, i.e. the moving along the plane marked by 'R_a' and 'a/f' occurs on each of the diagrams at the same time. The corner marked by 'q' indicates the position, where the viewpoint of the company owner is the most important and by moving along the axes 'R_a' and 'a/f' represents that the viewpoints of the customer and the engineer become more and more important with respect to 'q'.

4. MODELLING AND OPTIMISATION OF PROCESS CHAINS

As it was pointed out in [12], 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.

The final part of the paper deals with the problem of modelling and optimisation of process chains through the extension of the modelling and search techniques introduced for single processes. The *ProcessManager* block-oriented framework for modelling, monitoring and optimisation of manufacturing processes and process chains referred above 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.

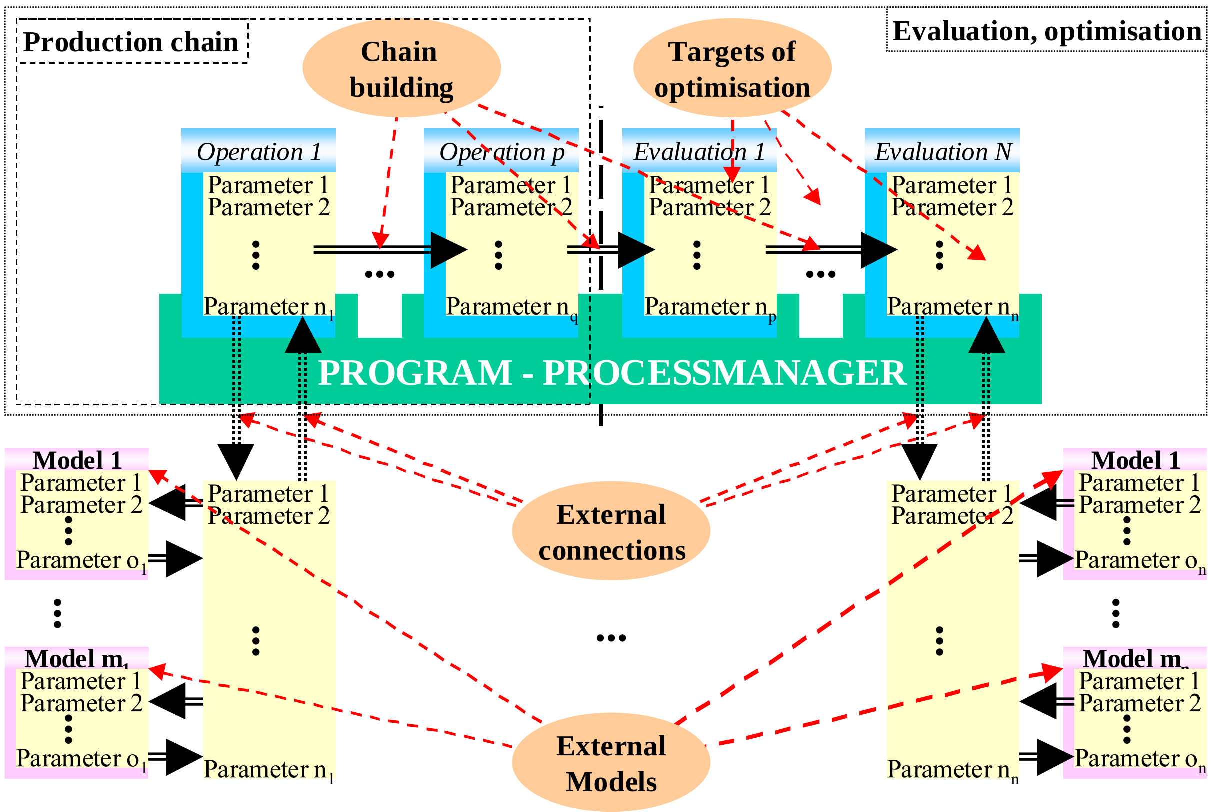

Figure 4: Errors of parameter estimations along the whole production chain

5. 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.

ACKNOWLEDGEMENTS

This work was partially supported by the *National Research Foundation, Hungary,* Grant Nos. F026326 and T026486. A part of the work was covered by the *Nat. Comm. for Techn. Dev., Hungary* Grants (EU-96-B4-025 and EU-97-A3-099) promoting Hungarian research activity related to the *ESPRIT LTR Working Groups* (IiMB 21108 and IMS 21995).

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