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Multipurpose modelling and optimisation of production processes and process chains by combining machine learning and search techniques

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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.

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 [17].

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 [12]. 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" [13].

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 [13].

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 [8]. Successful attempts were reported on in the literature [1, 6, 7, 8, 9, 10, 15]. 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.

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:

- 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 first two steps can be formulated as follows. A search algorithm is needed to select all the possible outputs from the given set of parameters with regard to the accuracy demands. The search space consists of all the conceivable possibilities. Usually, there is a large number of input-output configurations to select No parameters from N, moreover, No is unknown, indicating that the search space is quite large.

To evaluate whether a given configuration satisfies the accuracy demands, the appropriate learning process has to be also performed. Using a search method without heuristics would take too long time because of the size of the search space and of the slowness of evaluation. This is the reason why the developed search algorithm uses the properties of the learning stage of the ANN model as indicators for the evaluation.

The importance of the right input-output configuration is dominant in the case of non-invertable dependencies where the input-output ordering of the parameters is of fundamental importance. Experiments show that some complicated dependencies usually need a larger number of learning steps then simple settings. The basic assumption of the proposed search algorithm is – if enough runs are initiated – that the speed of the learning process can be used as indicator for the appropriateness of the chosen neural approach to realise the required mapping.

The application of the sequential forward selection (SFS) [2] algorithm was the compromise taking the large search space and the time intensive ANN learning into account. The search process is accomplished as follows. The learning data set is given by the user in the form of N dimensional vectors. To select the first output parameter, N ANNs are generated, each having one output and N-1 input parameters. After generating the ANNs, learning begins by all ANNs, concurrently. First, each ANN performs M learning steps. The ANN with the smallest estimation error is checked, whether it has reached the required estimation accuracy. If not, another learning phase is started with M epochs. If yes, then this means that an output was found which can be estimated with the given accuracy based on the remaining input parameters.

The next step of the algorithm is to order this variable to the output set of parameters and to select a further output parameter. This selection is realised by the same method as for the first output. For searching the second output, N-1 ANNs are generated because one output is already fixed, consequently, there are N-1 possibilities to add another output to the set of output parameters. The remaining N-2 parameters are used as inputs. After finding the second output, two outputs are fixed and a search starts to find a third output, etc.

Obviously, for adding a new output to the set of output parameters a successful learning step is required. Learning is regarded successful if an ANN configuration can learn the dependencies between input and output variables with the given accuracy. The algorithm terminates if after a large number of learning steps, none of the ANNs can achieve the given accuracy, i.e. it does not take the "natural" ordering of the available parameters into input and output sets into account.

During this search algorithm the largest number of outputs can be found, the accuracy demands are satisfied and the multipurpose ANN model is built up. It can be seen that this algorithm has regard only for the given accuracy requirement and not for the given assignment.

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.

2.1 Experimental results

To test the behaviour of the developed algorithm non-invertable dependencies were investigated first ($x_2=x_1^2$, $x_3= x_1^2+ x_2^2$, $x_4= x_1^2+ x_2^2+ x_3^2$, $\sin(x_1)$). Favourable results of these investigations promised real world applicability, too.

In the following space, results are presented with four engineering assignments where the required models work on the same parameter set but the feasible input-output configurations of these models are different.

1. The first task is planning. A surface has to be machined by turning to achieve roughness (parameter: R_a[mm]) demands of the customer. The engineer has to determine the tool (parameters: cutting edge angle: χ[rad], corner radius: r_ε[mm]), the cutting parameters (parameters: feed: f[mm/rev], depth of cut: a[mm], speed: v[m/min]) and predict phenomenon during cutting (parameters: force: F_c[N], power: P[kW] and tool life: T[min]) consequently a model is needed where R_a serves as input and other parameters as outputs. Usually, the customer gives only an upper limit for the roughness.
2. The second task is to satisfy the roughness demands of the customer but with a given tool. In this case the R_a, χ, r_ε are inputs and f, a, v, F_c, P, T are outputs.
3. The third task is to control the running cutting process with measured monitoring parameters such as force and power. Measured values of these parameters can be used as information about the current state of the cutting process. In this case R_a, χ, r_ε, F_c, P serve as input and f, a, v, T as outputs. The CNC controller has to select the appropriate cutting parameters to produce the requested surface.
4. The fourth task is the same as the third one but the CNC controller can change only the 'f 'and 'a' parameters because v is prescribed. This case needs a model with inputs R_a, χ, r_ε, F_c, P, v and with outputs f, a, T.

These assignments show several input-output configurations for modelling dependencies between the different elements of a parameter set. The question arises: which model describes the cutting process in the best way, i.e. with the highest accuracy? The heuristic search algorithm can answer this question.

In practical implementation sensors, machine controllers and computers would provide a part of parameters of an ANN operation model. For simulating the machining process in the investigations to be reported in this part of the paper, all information were generated via theoretical relations, which are functions of several input variables. It should be stressed that in a practical implementation these a priori relations are not necessary, the models are to be set up by using measured values. The validity of the equations is determined by the minimum and maximum boundaries of the parameters. Four equations (for force, power, tool life and roughness) are used in this paper for the above engineering tasks (1) [3],

$$
\begin{aligned}
&F_c = 1560 \cdot f^{0.76} \cdot a^{0.98} \cdot (\sin(\kappa))^{-0.22}, \qquad (1)\\
&P = 0.039 \cdot f^{0.79} \cdot a \cdot v,\\
&T = 1.85 \cdot 10^{10} \cdot f^{-0.7} \cdot a^{-0.7} \cdot v^{-3.85},\\
&R_a = 8.5 \cdot f^{1.8} \cdot a^{0.08} \cdot v^{-0.9} \cdot r_\varepsilon^{-0.5},
\end{aligned}
$$

where the boundaries of the equations are as follows (2):

$$
\begin{aligned}
&f : 0.1 \cdots 0.4[mm/rev], a : 1 \cdots 4[mm \qquad (2)\\
&\kappa : 1.3 \cdots 1.66[rad], v : 75 \cdots 200[m/\\
&r_\varepsilon : 0.4 \cdots 1.2[mm], T : 5 \cdots 60[\min],\\
&\text{consequently}, Fc \approx: 800 \cdots 3000[N],\\
&P \approx: 3.8 \cdots 13.5[kW],\\
&R_a \approx: 0.0015 \cdots 0.023[mm]
\end{aligned}
$$

With help of these strongly non-linear equations, values for tool life, force, power and roughness can be calculated based on the tool and machining parameters.

To create learning and testing parameter sets random values were determined in the allowed range of f, a, χ, v, r_ε considering also the boundaries of R_a, Fc, P, T while calculating their values using the above equations. The dependencies between parameters f, a, χ, v, r_ε, Fc, P, T, R_a were experienced as invertable in the given parameter range except the variable χ. Consequently, to get an accurate ANN model the variable χ has to be always input. A hundred data vectors were created as stated above. To test this type of problems the described input-output configuration and model building approach were repeated a hundred times. The allowed average estimation error was given as ±2.5%. Fifteen different ANN configurations were generated as results (Figure 1). The variable χ is always on the input size of the ANN model as expected. (Figure 1: On the horizontal axis the resulted input-output configurations are listed represented by their output parameters. The vertical axis shows the percentage a configuration has been selected in the hundred runs.)

For testing estimation capabilities of the resulted ANN based models all of the configurations were trained a hundred times but by each training the related physical parameters (f, a, χ, v, r_ε,) and the starting weights were generated randomly. The target average estimation error was ±0.0002 (±2.5%). To test, another set of a hundred randomly generated data vectors were used and the average estimation errors were calculated (Figure 2). No significant difference could be found between input-output configurations showing that most of the dependencies among parameters are invertable. (Figure 2: The resulted input-output configurations represented by their output parameters are listed on the horizontal axis.)

The results indicate that the developed technique is able to generate process models with the required accuracy, moreover, under given circumstances a result is a set of applicable models each guaranteeing the required accuracy performance.

As expected, the resulted input-output configurations can not be used directly to the given assignments. The solution for this problem is presented in the next paragraph.

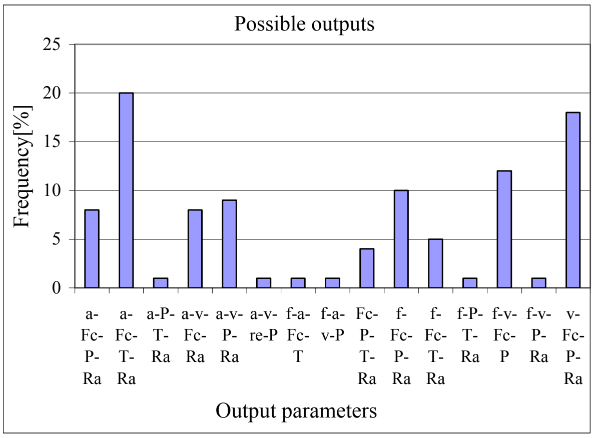

Figure 1: Resulted input-output configurations of the ANN models

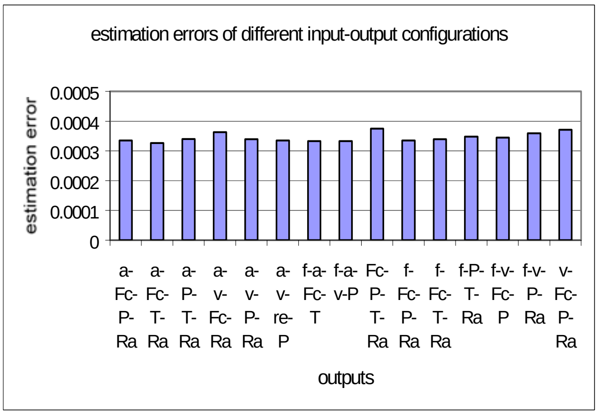

Figure 2: Average estimation errors of the models

3. Application of the multipurpose model for various assignments

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.

In the paper 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.

The search space consists of unknown input parameters. One point of the search space can be represented by one possible value set of the unknown input parameters. After placing these parameters together with the known input parameters to the input side of the given ANN an output vector can be calculated (forward propagation). 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. To measure the deviation between estimated and known output parameters an error can be calculated (*Error 1*, on Figure 3).
2. *Condition 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 [4]. Boundaries of the model can be handled by minimum and maximum values of the related parameters like in the engineering tasks presented above. (The search algorithm can take values for the unknown input parameters only from the related allowed intervals.)
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 3).

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.

The algorithm stops if no neighbour can be selected and the current error value is below the prescribed error limit. This simulated annealing algorithm works on the discrete points of the search space, therefore, the parameters of unknown part of the input vector consist of the discrete points of the related intervals. The distance between two points of an interval is chosen to satisfy the accuracy requirements of the estimation prescribed by the user.

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.

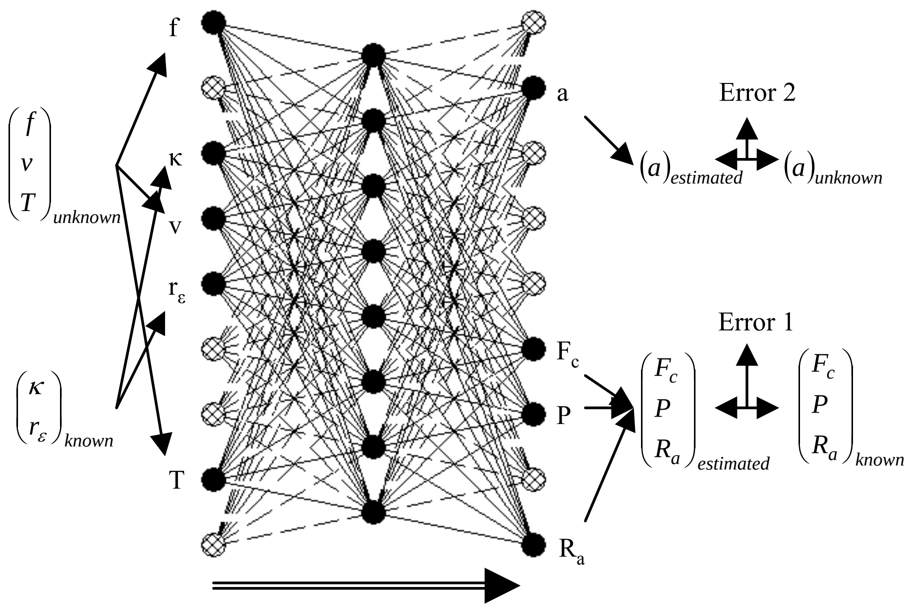

Figure 3: The generated ANN model and its application for the third task presented above (control of the cutting process with measured monitoring parameters)

3.1 Solution of the assignments

There are a large number of solutions for each of the enumerated assignments. To represent the whole interval of solutions for each parameter the search algorithm was repeated a hundred times at each assignment. 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 4. (The horizontal axis represents the number of the given tasks.) Results in this table show the descending intervals of acceptable parameters from the planning phase to the CNC control.

The requested value of parameter R_a is special because the user gives only upper limit for this parameter. In the assignments the allowed highest value for the roughness of the produced surface is 0.014 mm. The tool used for cutting is determined in the second task, values of related parameters are χ=1.549 rad, r_ε=0.7394 mm. In monitoring, measured values of force and power were Fc=2247N and P=8.69kW, respectively. In the fourth engineering task the prescribed speed value was v=161 m/min. In every case the task of the modelling was to satisfy the roughness demand of the user through choosing appropriate values of related parameters.

The diversity of solutions indicates the opportunity to incorporate optimisation into the decision making processes based on the generated multipurpose models.

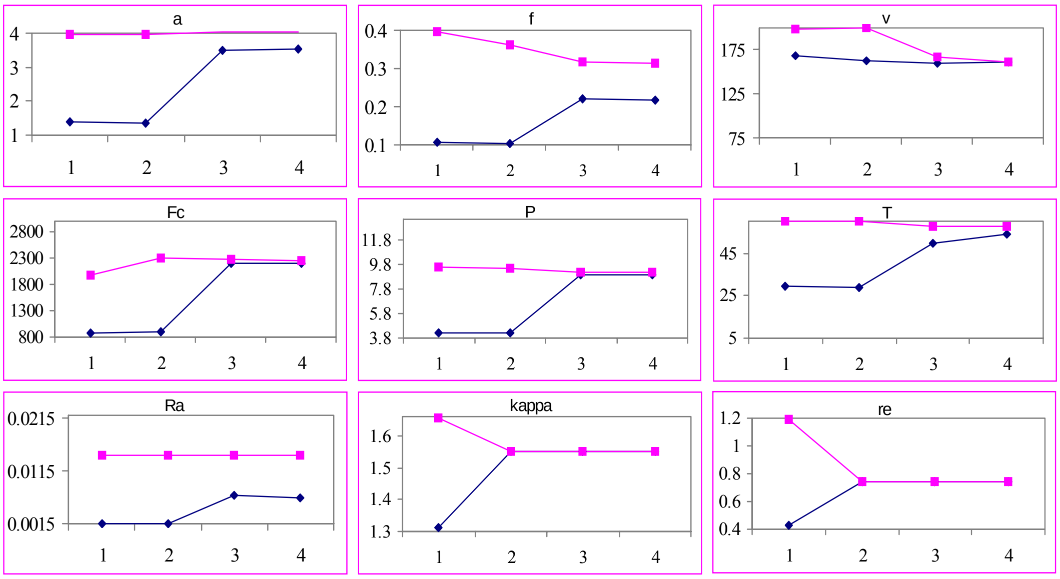

Figure 4: Descending intervals of allowed parameter fields in the four engineering tasks presented before

4. Optimisation of machining processes by using the multipurpose model

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 [11]. At the Computer and Automation Research Institute 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. Optimisations were performed from the twofold viewpoints of the customer (surface roughness minimisation), and the producer (minimisation of production time).

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

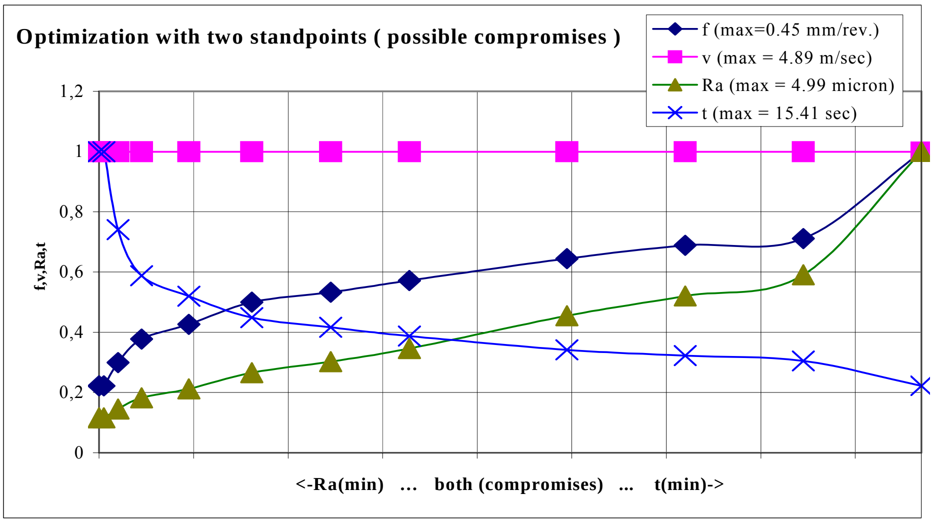

Figure 5: Parameters resulted by the optimisation of the plate turning operation. On the left side the viewpoint of the customer (R_a - min.) on the right side the viewpoint of the producer (t - min.) is satisfied. Curves show possible compromises between the two viewpoints.

Figure 6 and Figure 7 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 6 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 7. 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'.

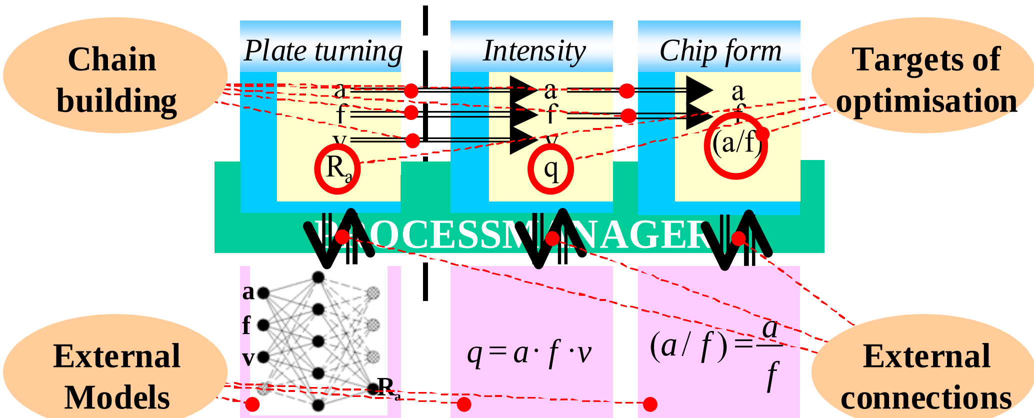

Figure 6: Chain model for optimisation of the plate turning operation with optimisation criteria

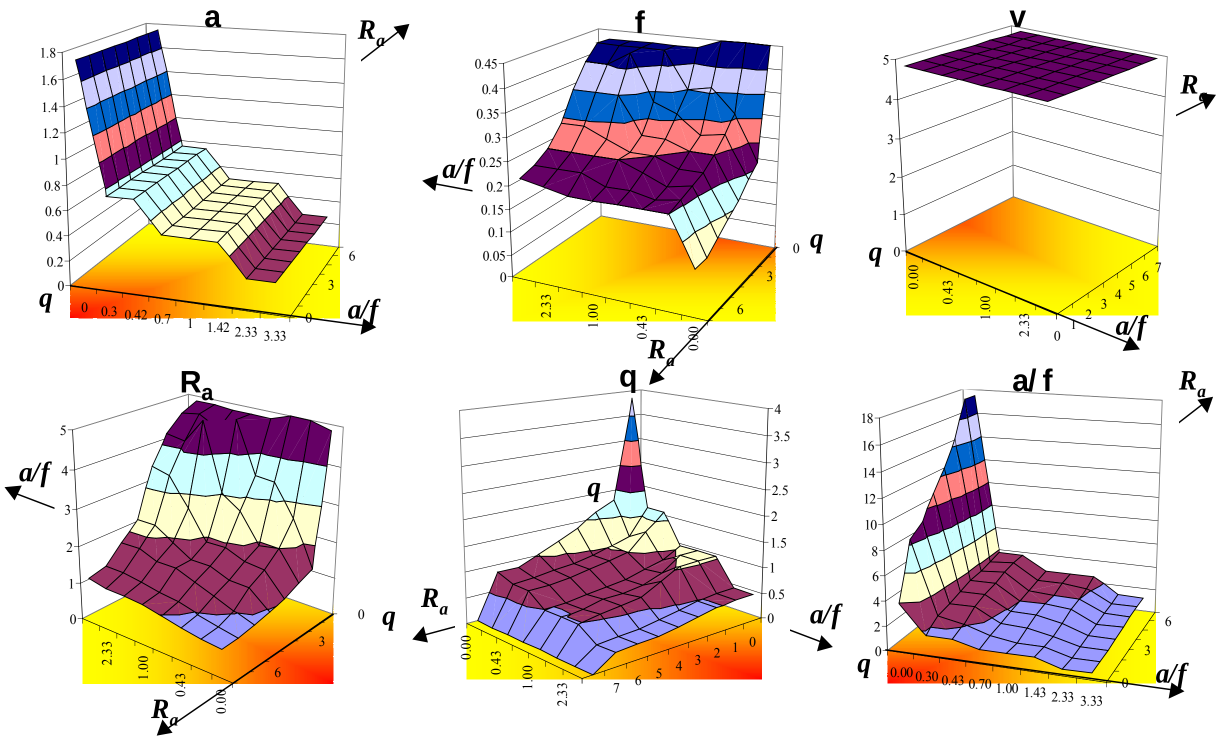

Figure 7: Parameters resulted by the threefold optimisation of the plate turning operation

5. Modelling and optimisation of process chains

As it was pointed out in [16], 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 [14]. To have process models with the required accuracy is especially important in the case of process chains where the errors can cumulate (Figure 8). (The effect of individual models on their output parameter is indicated with "}".)

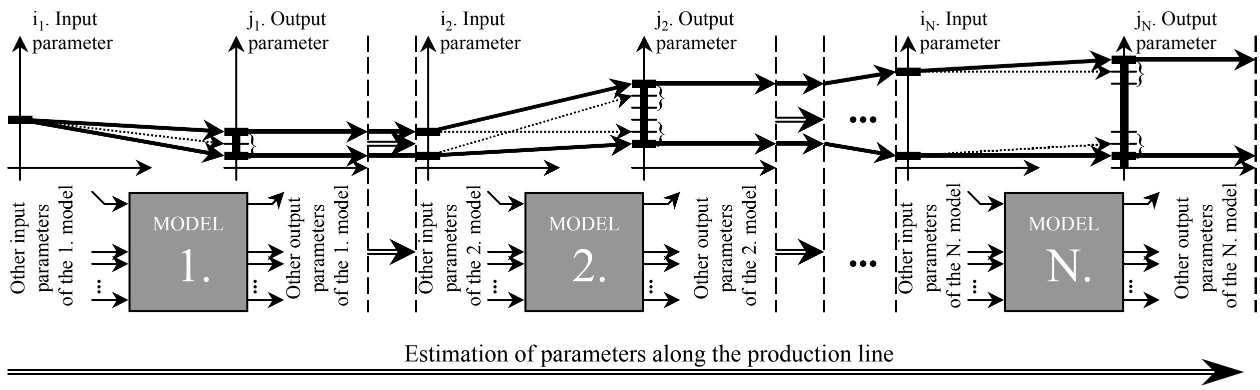

Figure 8: Errors of parameter estimations along the whole production chain

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 stochastic nature [16]

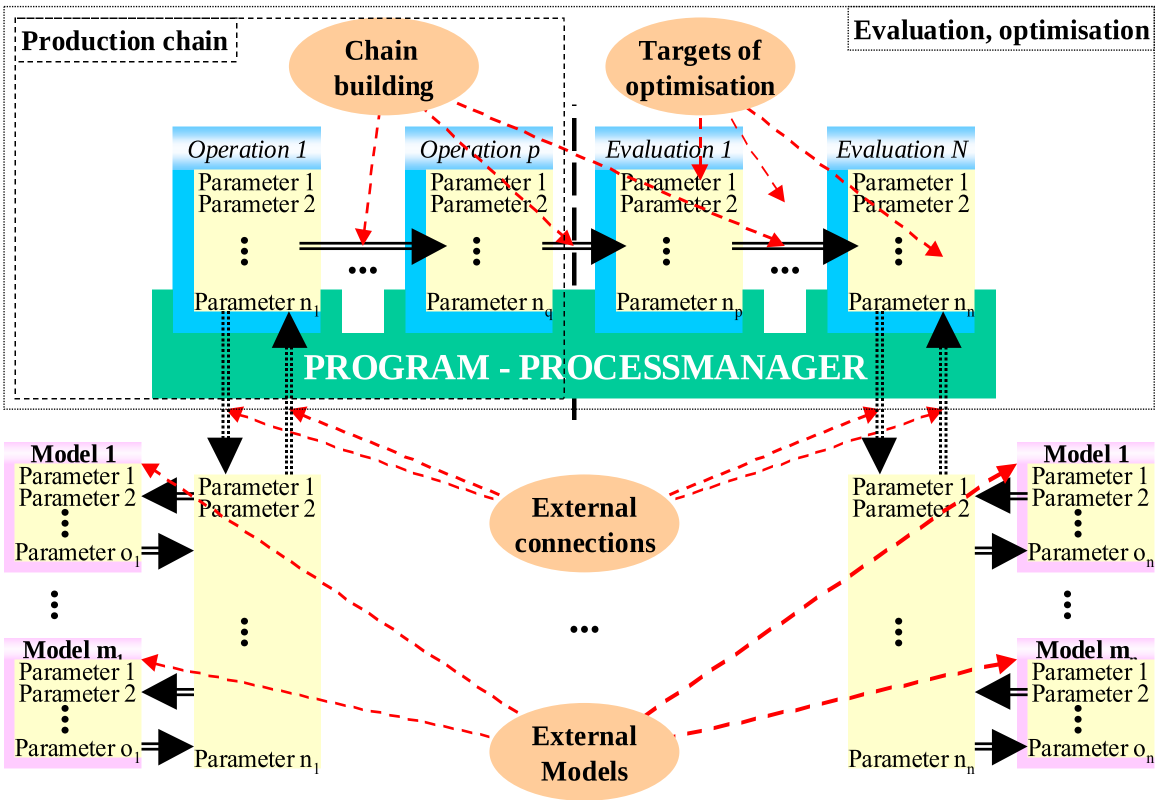

Figure 9: Errors of parameter estimations along the whole production chain

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 9):

- 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.

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.

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