

SATISFYING VARIOUS REQUIREMENTS IN DIFFERENT LEVELS AND STAGES OF MACHINING USING ONE GENERAL ANN-BASED PROCESS MODEL

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ABSTRACT

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.

Artificial neural networks (ANNs) can be used as process models because they can handle strong non-linearities, large number of parameters, missing information and can be used also in case where no exact knowledge is available about the relationships among the various parameters of manufacturing [12]. The input-output configuration of the used ANN strongly influences the accuracy of the developed model especially if dependencies between parameters are non-invertible. In various stages of production (e.g. in planning, optimisation or control) different tasks arise, consequently, the estimation capabilities of the related applied models are different even if the same set of parameters is used.

One of the main goals of the research to be reported here was to find a general model for a set of assignments, which can satisfy accuracy requirements. Research was also focused on how to apply the general model for various tasks.

KEYWORDS

Machining process model, Cutting, Neural network, Planning of production, Operation planning

INTRODUCTION

Several approaches can be found in the literature to represent the knowledge of manufacturing operations [14], [2], [13], [3].

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 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 [16].

Developments and trends in control and monitoring of machining processes shows the necessity of sensor integration, sophisticated models, multimodel systems, and learning ability [11].

A number of reasons back the required models: design of processes, optimisation of processes, control of processes, simulation of processes, and design of equipment [7].

ANN BASED APPROACHES TO MODELLING OF MACHINING PROCESSES

The aim of this paragraph is to show the large variety of machining assignments and input-output configurations of the related ANNs. It should be stressed that 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. The estimation capabilities of the applied ANN models are determined as results after the model building and testing stage.

An interesting example was presented by Knapp & Wang [10] who used an ANN in planning. The input vector of the ANN consists of parameters to identify the type of feature to be machined, the related geometrical parameters of the feature and parameters to identify the previous machining operations. The output of the ANN identifies the next operation. The goal of this research was to generate operation order.

In the ANN used for ordering of resources to workcenters, the performance measure values of operation policy of generated production plan act as network input [8]. The output of the ANN determines the number of resources for each workcenter.

Cutting tool selection is realised by Dini [1]. The inputs of the ANN are machining type, cutting conditions, clamping type, workpiece material, workpiece slenderness and outputs are five of parameters identifying the cutting tool.

To generate an optimum set of process parameters at the design state of injection molding, Choi *et al.* use an ANN model with inputs of filling time, melt

temperature, holding time, coolant temperature and packing pressure and with outputs of melt temperature difference, mold temperature difference, overpacked element, sink index and average and variance of linear shrinkage [9].

The compensation of thermal distortion was the goal of Hatamura *et al.* [19]. On the input side of the used ANN were parameters from deformation sensors and the outputs were used to decide if cooling, heating or no intervention are necessary.

For monitoring, features calculated from three signals (force, acceleration, power) are the inputs and five tool condition classes are the outputs of the developed model used by Li & Elbestawi [15]. The model is a fuzzy neural network. The target of their research was the monitoring of the tool condition. Outputs of the used ANN model were force, power and temperature for monitoring the cutting process and for estimation of workpiece roughness inputs were cutting parameters presented in the work by Rangwala & Dornfeld [17]. Optimisation and search for input variables are presented in this paper, too.

Monostori described models to estimate and classify tool wear [12]. The paper presents variable input-output configurations of ANN models according to variable tasks.

By building a model for creep feed grinding of aluminium with diamond wheels, presented by Liao & Chen [18], bond type, mesh size, concentration, work speed and depth of cut as the inputs and surface finish, normal grinding force per unit width and grinding power per unit width are used as the outputs of the ANN model. The paper also calls the attention to the problem that an ANN results the same values for output parameters when the input values were the same.

MODELLING OF PRODUCTION CHAINS

The production incorporates several stages, the workpiece goes through a number of operations (Fig. 1). 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. A chain of operations connected by their input-output parameters can model the sequence of production operations. Operations have several input- and output parameters and dependencies among them are usually non-linear, consequently, the related model has to handle multidimensionality and non-linearity. Some error is usually incorporated into modelling of real processes, the model estimates its output variables only with a limited accuracy. The error by the output side of an operation model in the production chain depends on its own error and the error incorporated into the input variables of the model. These input variables are usually output parameters from previous operations. Consequently, model errors can be summed up and, therefore, the

accuracy of the individual models is a crucial factor in the modelling of production chains.

VARIOUS ENGINEERING ASSIGNMENTS

To solve the ten assignments enumerated in this paragraph applied models have to realise mapping

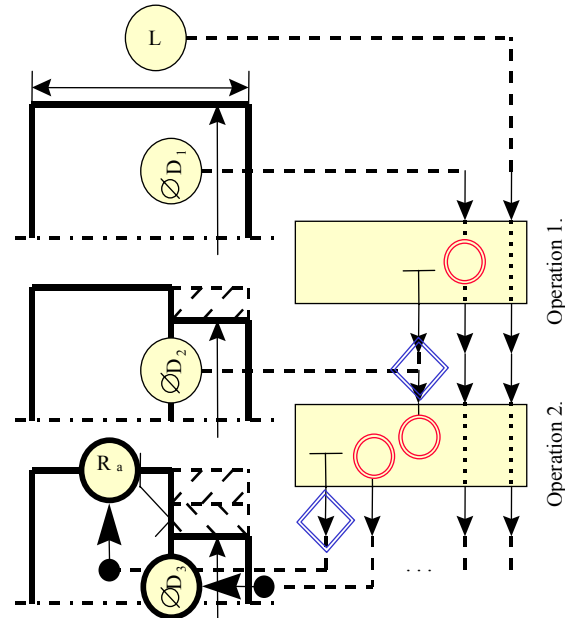


Figure 1. The stages of material removal from an axle and the related operations are represented on the left and right sides, respectively [6]

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 of the machine is handled through its three machining parameters:
 1. Depth of cut: a [mm]
 2. Feed: f [mm/rev]
 3. Speed: v [m/min]
- The tool is presented by three tool parameters:
 1. Cutting edge angle: χ [rad]
 2. Corner radius: r_c [mm]
 3. Tool life: T [min]
- Two monitoring parameters can be used for the turning operation:
 1. Force: F_c [N] (main force component)
 2. Power: P [kW]
- The customer demand is determined by the required roughness:
 1. R_a [mm]

These nine parameters build up the parameter set required to solve the ten engineering problems to be enumerated here. In brackets in the list of possible assignments the related configuration of known and unknown parameters are indicated. 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. ($R_a \Rightarrow \chi, r_e, f, a, v, F_c, P, T$)
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. ($\chi, r_e \Rightarrow f, a, v, F_c, P, T, R_a$)
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. ($R_a, \chi, r_e \Rightarrow f, a, v, F_c, P, T$)
4. The assignment is the same as the third one but the depth of cut is also prescribed. This is a finishing model. ($R_a, \chi, r_e, a \Rightarrow f, a, v, F_c, P, T$)
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. ($R_a, \chi, r_e, F_c, P \Rightarrow f, a, v, T$)
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 have 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. The question arises: Which model describes the cutting process in the best way, i.e. with the highest accuracy? The application of heuristic search

algorithm is proposed in this paper to answer this question.

BUILDING UP THE GENERAL PROCESS MODEL

A new search algorithm was developed which results in a general ANN model for handling dependencies among parameters of a given, usually non-linear parameter set. By building up of this general model the algorithm does not have any regard to the given assignment of engineers its target is to satisfy accuracy requirements.

The automatic generation of the general process model, i.e. model, which is 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 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 N_o parameters from N , moreover, N_o 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. Based on previous experience, the ANN can learn some configurations quicker than others to achieve the requested accuracy.

The importance of the right input-output configuration is dominant in the case of non-invertible 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 than simple settings. The basic assumption of the proposed search algorithm is – if we initiate enough runs – 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) [21] algorithm was the compromise taking the large search space and the time intensive ANN learning into account. The search works as follows: The user gives the learning data set in the form of N dimensional vectors. First, the SFS algorithm chooses only one parameter from the N parameters to be output of the model. 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 step. The evaluation follows for checking whether the ANN with the smallest estimation error had reached the required estimation accuracy. If not, another learning phase is started with M epoch. 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 algorithms 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 previous output(s). 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. This indicates that for adding a new output to the set of output parameters successful learning is required.

Learning is successful if an ANN configuration can learn the dependencies between input and output variables with a given accuracy. The algorithm stops if after a large number of learning steps, none of the ANNs, being in their learning stages can achieve the given accuracy. During this search algorithm the largest number of outputs can be found, the accuracy demands are satisfied and the 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 method, how to solve a given assignment with the resulted general ANN model, will be described in the paper below.

General turning models

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 here all information were generated via theoretical models, which are functions of several input variables. It should be stressed that in a practical implementation theoretical models are not necessary. They are used in the present case only to provide simulated samples for training and testing purposes. The validity of the equations is determined by the minimum and

maximum boundaries of the parameters. Four equations are used in this to create data vectors Eq. (1) [5], [20],

$$F_c = 1560 \cdot f^{0.76} \cdot a^{0.98} \cdot (\sin(\kappa))^{-0.22}, \quad (1)$$

$$P = 0.039 \cdot f^{0.79} \cdot a \cdot v,$$

$$T = 1.85 \cdot 10^{10} \cdot f^{-0.7} \cdot a^{-0.7} \cdot v^{-3.85},$$

$$R_a = 8.5 \cdot f^{1.8} \cdot a^{0.08} \cdot v^{-0.9} \cdot r_\epsilon^{-0.5},$$

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

$$f : 0.1 \dots 0.4 [mm/rev], a : 1 \dots 4 [mm], \quad (2)$$

$$\kappa : 1.3 \dots 1.66 [rad], v : 75 \dots 200 [m/min],$$

$$r_\epsilon : 0.4 \dots 1.2 [mm], T : 5 \dots 60 [min],$$

$$\text{consequently, } F_c \approx 800 \dots 3000 [N],$$

$$P \approx 3.8 \dots 13.5 [kW],$$

$$R_a \approx 0.0015 \dots 0.023 [mm]$$

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

To create parameter sets for learning and testing random values were determined in the allowed range of f , a , χ , v , r_ϵ considering also the boundaries of T and R_a , F_c , P , T . Dependencies between parameters f , a , χ , v , r_ϵ , F_c , P , T , R_a were experienced as invertable in the given parameter range only the variable χ is the exception, 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 average of the acceptable estimation error was $\pm 2.5\%$. Several variations of input-output configurations were resulted. Figure 2 shows the large variability of input-output configurations and their frequency after the hundred trials. As expected, the variable χ is always on the input size of the ANN model.

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. To test, another set of a hundred randomly generated data vector were used and the average estimation errors were calculated. In this respect, no significant difference could be found among the resulted input-output configuration [5].

The results 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.

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.

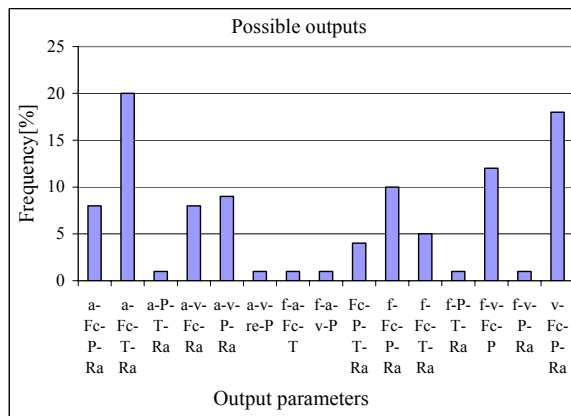


Figure 2. On the horizontal axis the resulted input-output configurations are listed represented by their output parameters. The vertical axis shows the percentage a configuration has been selected in the hundred runs.

SATISFYING VARIOUS ASSIGNMENTS WITH THE GENERAL MODEL

Generally, the user knows some parameters of a process and the modelling has the task to determine the other parameters while satisfying some constraints. In the paragraph above a search method was introduced to select a general ANN model with the required accuracy which can be used for different assignments. Consequently, in almost every case a part of input and a part of output variables of the general model are known by the user and the task is to search for the remaining, unknown input and output parameters like in the engineering assignments presented before. A search method can solve this problem. The search space consists of unknown input parameters. The task for the search method can be formulated as follows: It has to find values for the unknown input parameters but at the same time it has to satisfy three conditions:

1. 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 by the ANN estimation (forward calculation). This first condition has to assure that only that points of the search space can be accepted as result, which can adequately estimate the known output parameters by using the forward calculation. To measure the deviation between estimated and known output parameters an error can be calculated. To minimise this deviation the user can prescribe upper limit for this error.
2. Boundaries of the model can be handled by minimum and maximum values of the related parameters. The second condition for the

unknown input parameters is determined by the validity of the ANN model. This validity is usually determined by the data set used for the training [4]. This means that the search algorithm can take values for the unknown input parameters only from their allowed intervals.

3. The third condition relates also to the validity of the ANN. These boundaries come forward by that part of the estimated output vector, which is unknown by the user. Because of the limited validity of the ANN model there are also boundaries for parameters of this part of the estimated output vector. Values of the unknown input parameters are only acceptable if the estimated values of the unknown output parameters are within their allowed range. To measure this condition an error can be calculated for those unknown output parameters that are out of their boundaries. For the search algorithm the user can prescribe an upper limit also for this type of error.

The search algorithm is terminated if all of these three conditions are met. Simulated annealing has been selected as search method [22]. In the simulated annealing search an error value is ordered to all points of the search space. In the developed algorithm this value is the maximum of the two errors presented above. The algorithm searches for the minimum error point.

The simulated annealing method has a special parameter, the temperature, which decreases during the search algorithm. The algorithm discovers the search space by repeated change from the current point into a neighbour point. A probability value is used to evaluate a neighbour incorporating information about the error difference between the neighbour and the current point and about the current temperature. 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. To realise this, the parameters of unknown part of the input vector consist of the discrete points of their allowed intervals. The distance between two points of an interval is chosen to satisfy the accuracy requirements of the estimation.

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.

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 (Fig. 3-11). 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. On the horizontal axis the number of assignments is indicated according to the list presented before. The vertical axes show the values of the related parameter. Minimum and maximum values on the vertical axes represent the model boundaries.

In cases where the roughness is known its value is

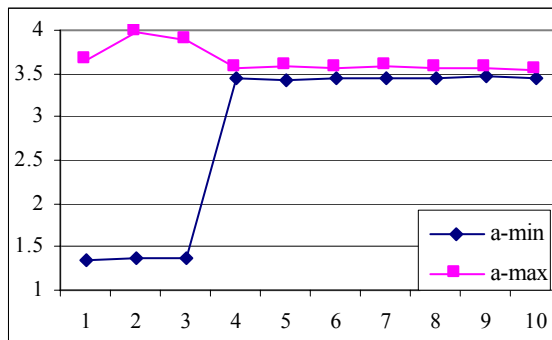


Figure 3.

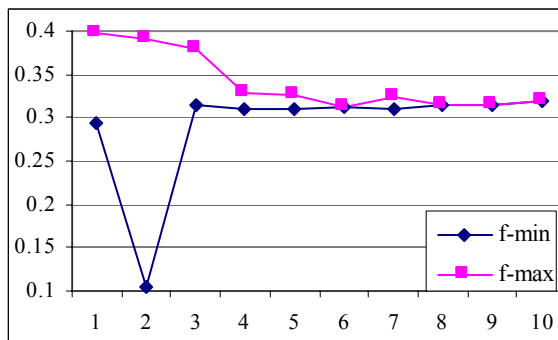


Figure 4.

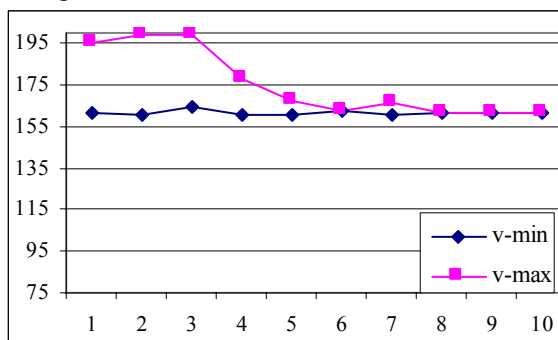


Figure 5.

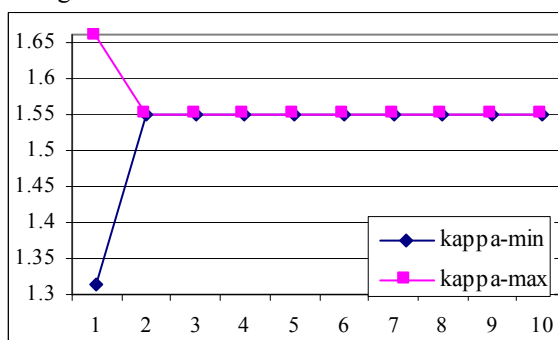


Figure 6.

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 (Fig. 12) with the same input-output configuration and using the developed simulated annealing search method, indicating the acceptability of the techniques

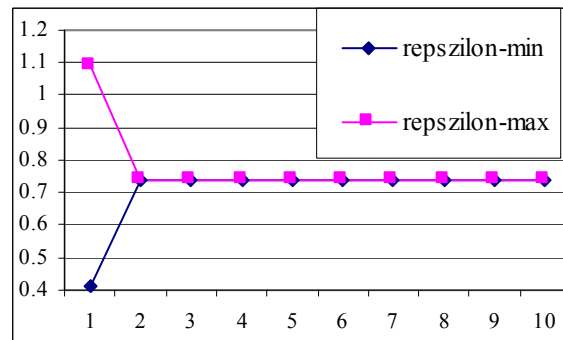


Figure 7.

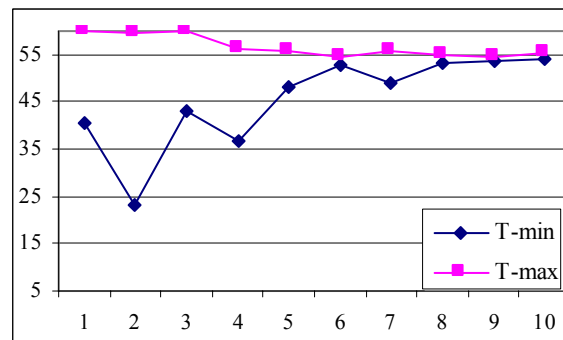


Figure 8.

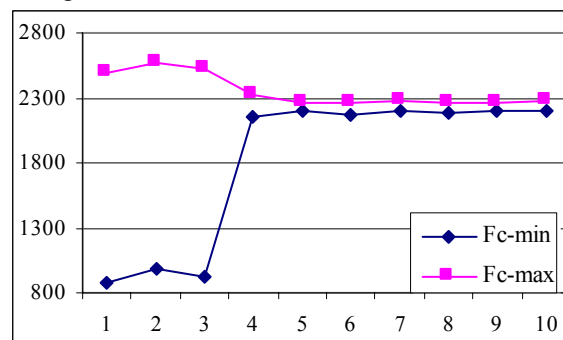


Figure 9.

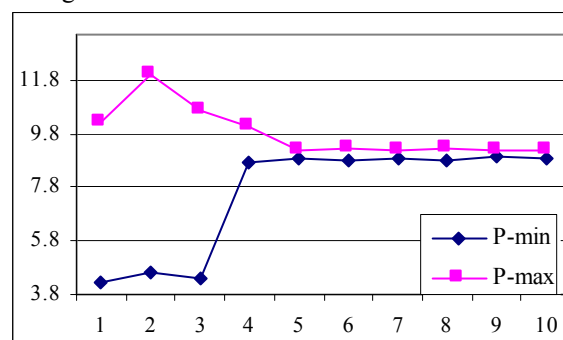


Figure 10.

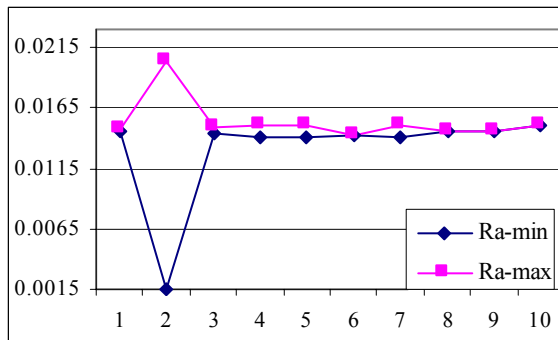


Figure 11.

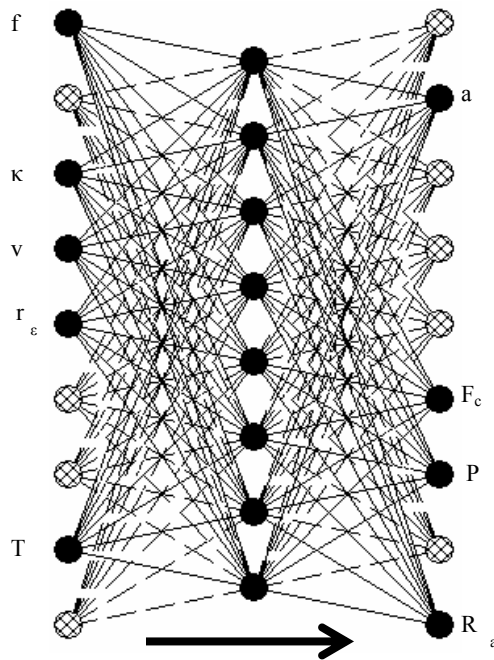


Figure 12. The used general ANN model for the turning operation resulted by the SFS search

presented.

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

ACKNOWLEDGEMENT

This work was partially supported by *National Research Foundation*, Hungary, Grant No. F026326 and T026486.

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BIOGRAPHY

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manufacturing, modelling of machining processes for planning, optimisation and control.

CONCLUSIONS

This paper presents a new approach with novel techniques by using ANNs for modelling machining operations. A new search algorithm has been developed which results a general ANN model for handling dependencies among parameters of a given, usually non-linear parameter set. By building up of this general model the algorithm does not have any regard to the given assignment of engineers its target is to satisfy accuracy requirements. This technique also eliminates the problem of mapping non-invertible dependencies. Another new search algorithm was developed to solve a large amount of engineering assignments using this general ANN model. The applicability of this new approach is presented through the determination of practicable fields of unknown parameters of various assignments concerning the turning operation. Several steps of the new approach are to be improved further. Some of them are:

- By searching the appropriate input-output configuration a method could be useful which prunes the variables which are not important for output estimations.
- By searching the unknown variables an optimisation should be included in this method like in the paper of Rangwala & Dornfeld [17]. E.g. cost minimisation, manufacturing time minimisation etc. This is important only if there are more solutions for the given task.

The above improvements will be subject of future publications.