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neural networks, machine learning, heuristic search, CAD/CAM

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SELECTION OF INPUT AND OUTPUT VARIABLES FOR ANN BASED MODELING OF CUTTING PROCESSES

Modeling of manufacturing operations is an important tool for production planning, optimization and control. Artificial neural networks (ANNs) can handle strong non-linearity, large number of parameters, missing information. Based on their inherent learning capabilities ANNs can adapt themselves to changes of the production environment and can be used also in the case if there is no exact knowledge about the relationships between various parameters of manufacturing.

Typical field of ANN based operation modeling is cutting. The relationships of the physical phenomena incorporated into the cutting operation are very complex. In the application of these models several tasks can be determined: e.g.

- in the planning phase the surface roughness is predefined and the model is expected to select the cutting parameters and to predict the cutting force, while
- during supervised production the cutting parameters are known and e.g. the cutting force is measured and the produced surface roughness is to be estimated.

In the above assignments, the operation parameters are the same but the operation model has other variables on the input and on the output sides.

In this paper a method is presented to build a general operation model with the requested accuracy. This method incorporates:

- determination of the number of output variables
- determination for every parameter to be input or output

The method is also useful in the case of strong nonlinear relationships. Experiments show the applicability of the approach.

1. MODELING OF PRODUCTION CHAINS – THE MAIN ASSIGNMENT

Modelling methods can be used in several fields of production e.g. in planning, optimisation or control. The production in our days incorporates several stages, the workpiece goes through a number of operations (Fig. 1.).

The output of one operation is the input of an 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

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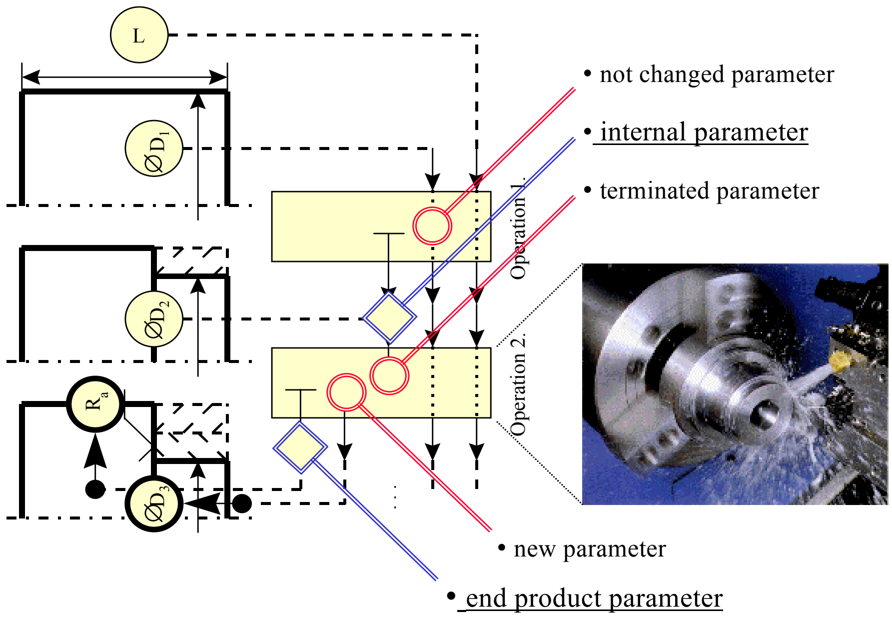

Fig. 1. Connections of the operations of the production chain through workpiece parameters. On the left side, the stages of material removal from an axle, the related operations in the middle, on the right side the related parameter stream of the workpiece along the production chain are presented [18].

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. Because operations are usually non-linear, the cumulation of errors is also non-linear. The error at the output side of the next model depends on the errors of the previous operation models and the model's own error. 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 (Fig. 2.) outlining the importance of models with prescribed estimation accuracy capabilities.

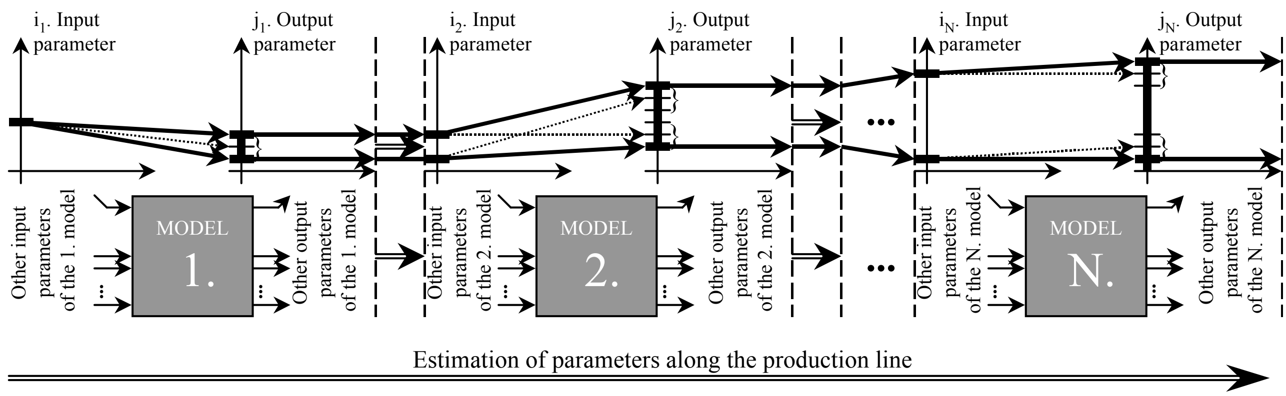

Fig. 2. Errors of parameter estimations along the whole production chain. The effect of the error of a model on the estimation of its own output parameter is indicated with "}".

2. ANN BASED APPROACHES OF TODAY: INPUT-OUPUT CONFIGURATION IS DETERMINED BY THE GIVEN ASSIGNMENT OF ENGINEERS

Several approaches can be found in the literature to represent the knowledge of manufacturing operations [11][12][13][14].

Artificial neural networks (ANNs) can be used as operation models because they can handle strong non-linearites, large number of parameters, missing information. Based on their inherent learning capabilities, ANNs can adapt themselves to changes in the production environment and can be used also in case there is no exact knowledge about the relationships among the various parameters of manufacturing.

The aim of this paragraph is to show the large variety of tasks and related input-output configurations of ANNs.

An interesting example was presented by Knapp & Wong [6] 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 [2]. The output of the ANN determines the number of resources for each workcenter.

Cutting tool selection is realised by Dini [4]. 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 [1].

The compensation of thermal distortion was the goal of Hatamura *et al.* [5]. 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 [8]. 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 [15]. Optimisation and search for input variables are presented in this paper, too.

Monostori described models to estimate and classify tool wear [10]. 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 [9], 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.

2.1. CUTTING: DIFFERENT ASSINGMENTS, DIFFERENT INPUT-OUTPUT CONFIGURATIONS OF RELATED ANN MODELS

In the following space, four cutting related assignments are presented. To solve each of the assignments the input-output configuration of related models are different although every model works on the same parameter set.

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 are outputs. Usually, the customer gives only an upper limit for the roughness, which means an interval of R_a is acceptable, in contrast to other parameters because other known parameters are given by their values.

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.

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 are outputs. The CNC controller has to select the appropriate cutting parameters to produce the requested surface.

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, v, 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 prescribed accuracy? The new concept can answer this question.

3. THE CONCEPT FOR SELECTING THE APPROPRIATE INPUT-OUTPUT CONFIGURATION OF AN ANN MODEL

Considering the input and output variables of a given assignment together as a set of parameters, the ANN model estimates a part of this parameter set based on the remaining part. This selection strongly influences the accuracy of the developed model especially if dependencies between parameters are non-invertable. In different stages of production (e.g. in planning, optimisation or control) tasks are different, consequently, the estimation capabilities of the related applied models are different even if the same set of parameters is used (e.g. in four cases of paragraph three).

The examples in the second paragraph show that a lot of effort has been made to apply ANNs for modelling manufacturing operations. 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. Consequently, the assignments determined the estimation capabilities of the related ANN models but this determination is in contrast with the message of the first paragraph that the main assignment of modelling is to develop operation models witch satisfies the accuracy requirements.

The concept of the new approach dissolves this contrast. The approach has regard only to the message of the first paragraph: *Because the input-output configuration of an ANN-based model influences its estimation capabilities the configuration has to be determined based on the required model accuracy not by the given assignment. By building an ANN-based model, this concept puts forward the physical, mathematical dependencies among parameters and puts down the given assignment.*

The main goal of the research to be reported here was to find a general model for a set of assignments, which can satisfy the accuracy requirements. To reach this goal a heuristics based algorithm was developed which is described in the next paragraph.

3.1. METHOD FOR SELECTION THE APPROPRIATE INPUT-OUTPUT CONFIGURATION

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 (No) from the available N parameters which can be estimated using the remaining Ni = N - No input parameters within the prescribed accuracy.
- Ordering of 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 first two steps can be formulated as follows. A search algorithm is needed to select all the possible outputs from the given set of parameter with regard to the accuracy demands. Usually, there is a large number of possible solutions 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. Based on previous experience, the ANN can learn some configurations quicker than others to achieve the requested accuracy. Experiments show that some complicated dependencies usually need a larger number of learning step then simple settings. 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. Based on a large number of experience, 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.

In the literature of ANNs one can find papers for determining

- the optimal adaptive learning rate during learning [16] or
- the geometrical property of the error function through the Lipschitz constant [17] or
- one theoretical supremum of the number of learning steps if the transformation functions of the nodes are linear, presented by D. Volper & Hampson [18] etc.,

but no papers could be found to predict the required number of backpropagation (BP) learning. Consequently for evaluating of the given configuration, the whole learning process has to be performed. The application of the sequential forward selection (SFS) [3] algorithm was the compromise taking into account the large search space and the time intensive ANN learning. The search works as follows (Fig. 3.): The user gives the learning data set in the form of N dimensional vectors. First, the SFS algorithm chooses only one parameter form 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

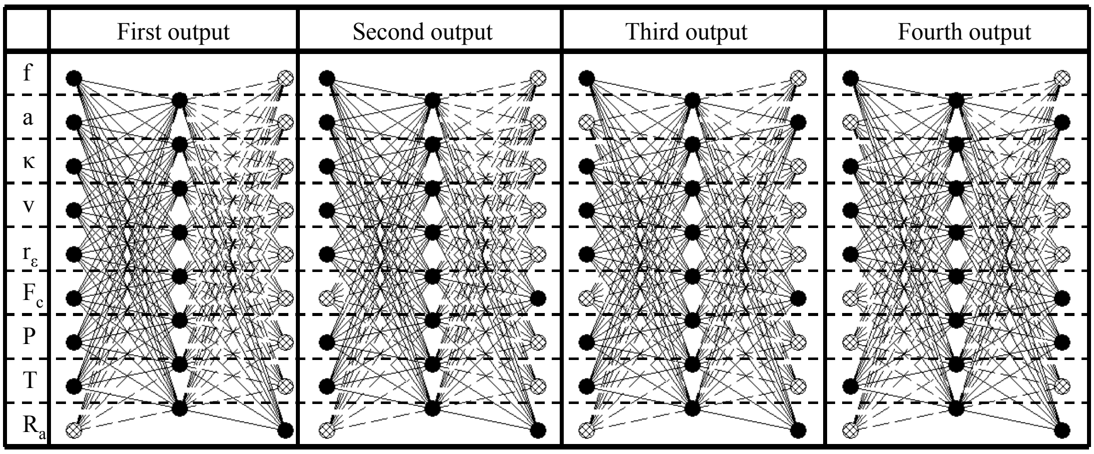

Fig. 3. The use of sequential forward selection algorithm to select all the possible output to build an ANN model with a given accuracy. In the picture ANNs use only the filled nodes and continuous weights.

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 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 shows 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.

In the developed method the estimation error is used to evaluate an ANN configuration. This error assures the user that all of the outputs can be estimated with equal or less than a given average error.

4. EXPERIMENTAL RESULTS

To test the behaviour of the developed algorithm non-invertable dependencies were tested first. One of the simplest cases is the square function. The developed method selected the independent variable to the input and the x^2 to the output side of the ANN model in all cases with varied network structures and differently initialised weights. Results were the same when higher dimensional dependencies were tested such as $x_3= x_1^2+ x_2^2$ and $x_4= x_1^2+ x_2^2+ x_3^2$, sin(x). These favourable results promised real world applicability, too.

In practical implementation sensors, machine controllers and computers would provide a part of parameters of an ANN operation model. For simulating the machining process 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 paper for engineering tasks above (force, power, tool life and roughness) (Equations 1.) [7].

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

, where the boundaries of the equations are as follows:

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

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 T and 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 only the variable χ is the exception, consequently, to get an accurate ANN model the variable χ has to be always input (Fig. 5.). 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. Several variations of input-output configurations were generated. The demanded estimation error was 0.0002 that is equal to the average error of an estimation of a value of ±2.5%. Fig. 6. shows the large variability of input-output configurations and their frequency after a hundred trials. The entire generated model has four outputs and which is equal to the number of equations from which the data was generated. This shows that the algorithm can find all of the dependencies among parameters. The variable χ is always on the input size of the ANN model as expected.

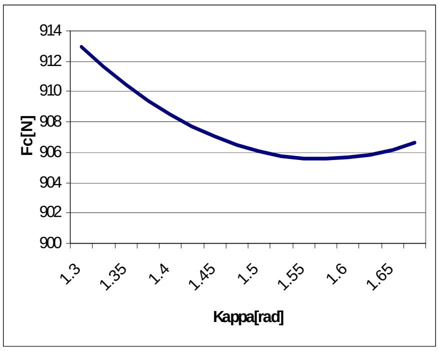

Fig. 5. Connection between F_c and χ in the given engineering task. (f=0.2, a=2)

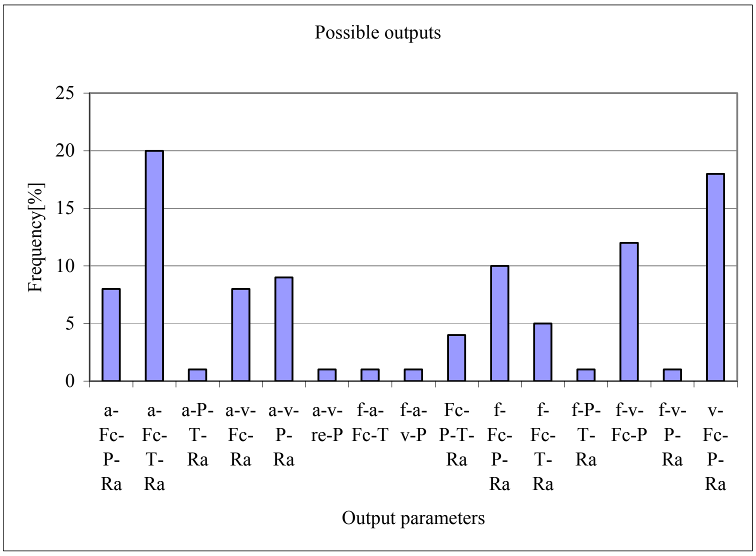

Fig. 6. On the horizontal axis resulted input-output configurations are listed represented by their output parameters. The vertical axis shows the resulted frequency of a given configuration after 100-repeated search.

For testing estimation capabilities (Fig. 7.)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

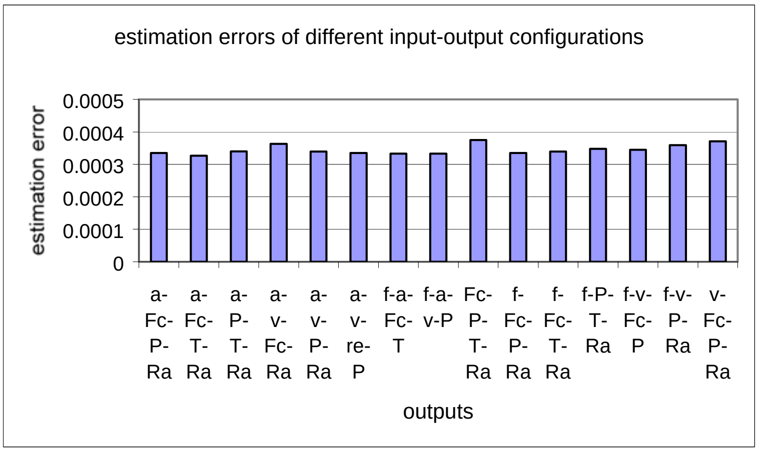

Fig. 7. Average of a hundred repeated training-testing procedures. The resulted input-output configurations are listed on the horizontal axis represented by their output parameters. No significant differences of estimation capabilities could be found among ANN configurations, which are results of the developed SFS search.

data vector were used and the average estimation errors were calculated. No significant difference could be found between input-output configurations if the dependencies among parameters are invertable.

For testing the developed algorithm the average of the demanded learning epoch were also calculated (Fig. 8.). Experiments show that the developed search algorithm needs smaller number of learning and model building time than some possible ANN configurations.

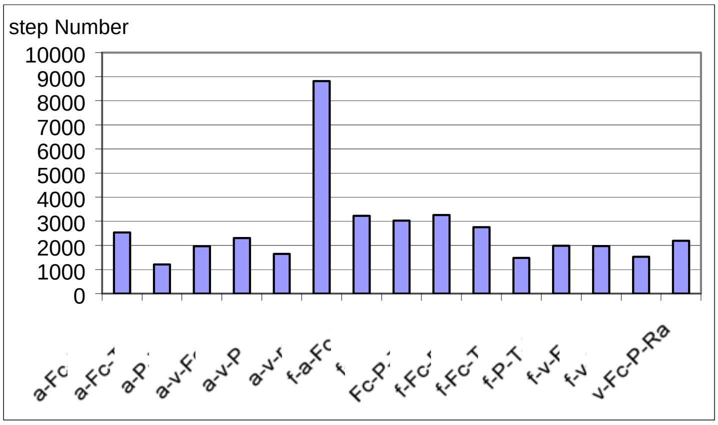

Fig. 8. On the horizontal axis resulted input-output configurations are listed represented by their output parameters. The vertical axis shows the average learning step after 100-repeated search.

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

5. CONCLUSION

Outlying the importance of accurate process models in the control of production chains, generation and application of ANN-based process models were addressed in the paper with special emphasis on the automatic input-output configuration of general process models which are expected to satisfy the accuracy requirements of a set of related modelling assignments. Combined use of sequential forward search, ANN learning were proposed. The applicability of the elaborated techniques was illustrated through results of experiments. The user usually knows some parameters of a process and the modelling has the task to determine the other parameters while satisfying some constraints. In the paragraph three a search method was introduced to select a general ANN model which is accurate enough and can be used for different assignments. Consequently, based on the given assignment, 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 of the modelling is to search for the remaining, unknown input and output parameters like in the engineering tasks presented before. This task can be satisfied by a search method which search for the appropriate unknown input parameters and after having this parameters the general ANN can estimate the unknown output parameters. This search method is now under development.

6. ACKNOWLEDGEMENT

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