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A COMPROMISE ORIENTED OPTIMIZATION TOOL FOR SUPPORTING DECISION MAKING IN MACHINING

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

Because of their model free estimation, uncertainty handling and learning abilities, artificial neural networks (ANNs) are frequently used for modelling of machining processes. Successful attempts were reported on in the literature [3][11][12][14][17][21]. 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.

Outlying the multidimensional and non-linear nature of the problem and the fact that closely related assignments require different model settings, the paper addresses the problem of automatic input-output configuration and generation of ANN-based process models with special emphasis on modelling of production chains. Combined use of sequential forward search, back propagation (BP) ANN learning and simulated annealing are proposed for determination and application of general process models which are expected to comply with the accuracy requirements of different modelling assignments. The applicability of the elaborated techniques is illustrated through results of experiments.

2. ANN based approaches to modelling and monitoring of machining processes

Several approaches can be found in the literature to represent the knowledge of manufacturing operations [11][12][12][16]. 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 [7] 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 [3]. The output of the ANN determines the number of resources for each workcenter. Cutting tool selection is realised by Dini [5]. 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 [6]., on the input side of the used ANN parameters from deformation sensors were 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 act as outputs of the developed model used by Li & Elbestawi [9]. 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 while inputs were cutting parameters presented in the work by Rangwala & Dornfeld [18]. Optimisation and search for input variables are presented in this paper, too. Monostori described models to estimate and classify tool wear [11]. 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 [10], 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 in the same values for output parameters when the input values were the same.

3. ANN applications for modelling the plate turning

Surface roughness is one of the mostly demanded requirements of customers buying steel parts. It is expressed through prescribed value of the ‘Ra’ parameter of the surface of the part, which is to be achieved through the machining parameters selected by the producer. This paper addresses the daily problem of appropriate selection of feed, depth of cut and cutting speed in plate turning by using an ANN based cutting model.

For the plate turning operation there are no general, analytical models available about the relations among the machining parameters of the plate turning operation and the resulted surface roughness. Some relations among the above quantities are however experienced, consequently, there is a free scope for building up ANN based process models. To build up an ANN model for plate turning, a hundred and fifty experiments were performed to produce data for learning and testing. All of the machining parameters were varied and the roughness of the produced surface was measured while performing these cutting experiments. Circumstances of cuttings were: Material: 42CrMo4, Machine: NC, Voest-Alpine, Nr. 085064, Type: WNC500S/1, Tool: CNMG12040843, cp 3, 1820091, p15, k20, radius: 0.8 mm, With cooling. The cutting speed was varied form 2.12 to 4.89 m/s, the depth of cut form 0.25 to 1.75 mm and the feed from 0.1 to 0.45 mm/revolution. Measured roughness values were between 0.4 and 4.95 micrometer. A hundred randomly chosen data were used to build up the ANN model and the remainder fifty data were used for testing. Several examples of ANN models in machining were presented in the previous paragraph. In every application the input-output configuration of the applied ANN model was determined by the given assignment, namely known parameters serve as inputs and unknown parameters serve as outputs. Using this classical concept for the problem of plate turning the prescribed Ra parameter acts as input and machining parameters as outputs (Figure 1).

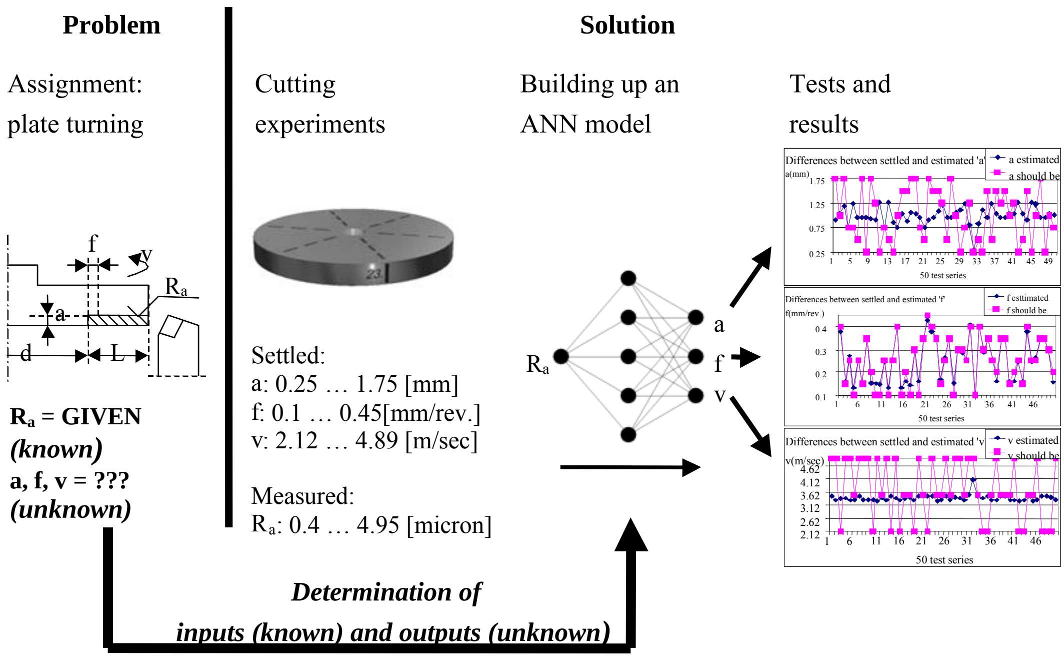


Figure 1 The classical way of ANN application

Based on the classical approach the averages of estimation errors were reported as results as in the papers referred above. The next paragraphs show a basically new concept for using ANNs as process models and improve the ANN based solutions of the given plate turning assignment.

4. Two insufficiencies of the classical ANN approach

This paragraph outlines the two main insufficiencies of the classical ANN approach. The first problem is that different assignments 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 of the applied ANN model strongly influences the accuracy of the developed model. 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 following four assignments give an example for this fact:

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 the other parameters as 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 known parameters, which are given by their values.

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 are 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 examples show that it is unknown, which input-output configuration describes the cutting process in the best way.

The second problem of the classical approach relates to the dependencies among the parameters. Naturally, BP ANN networks cannot realise multivalued functions. This model building problem however can be usually avoided by the appropriate selection of its input-output parameters. In practice, ANNs are used as process models if neither the dependencies nor the type of the dependencies among parameters are known. Consequently, in the ANN model building stage it is unknown whether a model realising a one to one mapping and built up according to the given assignment is appropriate or not. This information comes to light only in the model-testing phase where it turns out, whether the given problem can or can not be solved using ANN models.

Studying the problems of the ANN modelling technique it was found that the main problem of the classical approach is that the input-output configuration of the used ANN model corresponds to the given assignment, not to the dependencies among parameters. This indicates that a method is needed which finds the appropriate configuration of the ANN model automatically. Not the given assignment but only the accuracy requirements regarding to the resulted model have to be taken into account during the model building stage, which is the basic idea of the presented new approach. The proposed method results in a general ANN model, which is applicable for the different assignments, consequently, also an additional method has to be developed, which can solve different assignments using the same general ANN model.

This paper presents these two generally new methods and shows some promising applications. A new tool was also developed for optimisation of different processes and process chains. It is able to discover the possible field of compromises among different optimisation viewpoints using also the same corn idea.

5. Automatic generation of ANN-based process models

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

1. 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.
2. Ordering of the available parameters into input and output parameter sets having Ni and No elements, respectively.
3. 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. 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. Application of 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 utilises 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 steps 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. No papers could be found in the literature to predict the required number of steps in the 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) [4] 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 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. The opposite 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 shows that for adding a new output to the set of output parameters a successful learning phase is required. The learning process is regarded as 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.

5.1 Experiments based on machining database

The mathematical tests were successful and 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, 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 well known empirical equations of the cutting practice and their boundaries were used to create data vectors. With the 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, v, r_ε, F_c, P, T, R_a were experienced as invertable in the given parameter range, only the variable χ was 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 ±2.5%. Several variations of input-output configurations were resulted. As expected, the variable χ is always on the input part 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.

5.2 Experiments based on measurements

This automatic input-output configuration of ANNs was used to build up the general process model for the above introduced plate turning assignment. It resulted in an ANN having the three machining parameters as inputs and the surface roughness as output (Figure 4) 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.

6. Satisfying various assignments with the general model

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 previous paragraph a search method was introduced to select a general ANN model which is accurate enough and 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 of the modelling is to search for the remaining, unknown input and output parameters like in the engineering tasks presented before (Figure 2.). A search method can solve this task. The search space consists of unknown input parameters. The task for the search method can be formulated as follows: It has to find the unknown input parameters but at the same time three conditions are to be satisfied (Figure 2):

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 2

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 [1]. 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 2).

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. E.g. this picture shows the third engineering task presented above.

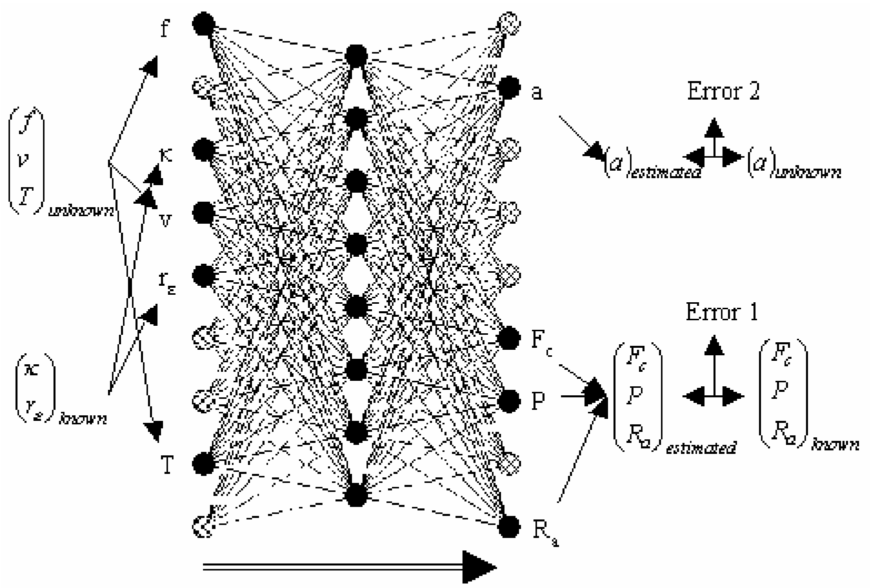


Figure 2 The method to solve various assignments with the general ANN model

The applied search algorithm - *simulated annealing* - has a special parameter, the temperature, which decreases during the search algorithm. The algorithm discovers the search space by repeated changes 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 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.

6.1. Results of the simulated annealing search

To test the developed simulated annealing search first the $x_3 = x_1^2 + x_2^2$ problem was used. One hundred random values of x_1 and x_2 were generated and values for x_3 were calculated based on the given equation. The ANN model was generated automatically, x_1 and x_2 were selected as input and output. In the forward estimation the ANN model works like ordinary ANN models. To test how the simulated annealing search works, two values of x_3 were given and the simulated annealing search was repeated thirty times at each value of x_3. Points resulted by the developed algorithms are near to the theoretical solution circle, consequently, the algorithms can solve also the inverse problem.

More interesting were the results of the four engineering assignments presented in before. 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 3.

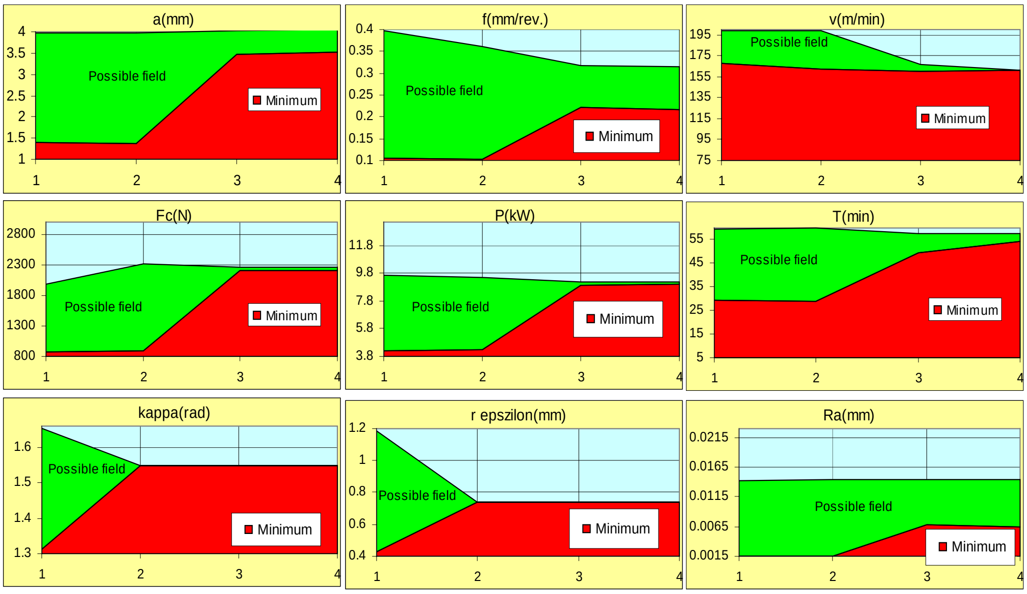


Figure 3 Descending intervals of allowed parameter fields in cutting in the four engineering tasks presented above. The horizontal axis represents the number of the given tasks. By every case from planning to CNC control one or more new parameter(s) becomes to be restricted to one value.

Results in this table show the descending interval of acceptable parameters from the planning phase to the CNC control. The requested value of parameter Ra 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, rε=0.7394 mm. By the control with monitoring, measured value of force was Fc=2247N and of power P=8.69kW. 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. By every case from planning to CNC control one or more new parameter(s) becomes to be restricted to one value.

Results show that by the first planning task a large field of parameters can be chosen to satisfy the user demands. Using the given tool in the second task, the possible fields of intervals are only a bit smaller. The intervals in the third task, in monitoring, the cutting process with measured monitoring parameters is much smaller. In the fourth task when the speed is prescribed, the allowed intervals become much smaller. It should be stressed that these results were received with only one ANN model with the same input-output configuration and using the developed simulated annealing search method, indicating the acceptability of the techniques presented here. The developed sequential forward selection algorithm determined the appropriate input-output configuration automatically.

Interesting are also the results of the above presented plate turning example. After building up the general ANN model for this type of machining the original assignment was solved: determination of the machining parameters to produce a prescribed surface roughness. A thousand of possible solutions of machine parameters are presented in the Figure 4 to produce a surface roughness with the prescribed 4.26 micron.

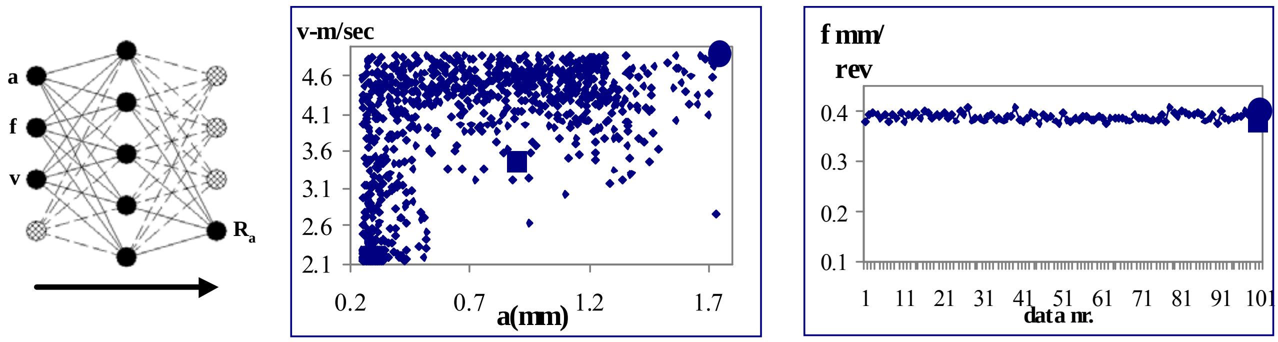


Figure 4 On the diagrams a thousand of possible machine settings to produce the surface with the given roughness are presented as small rhombuses in the pictures. A circle in the pictures indicates a real machine setting, while large squares represent the estimation of the classical method.

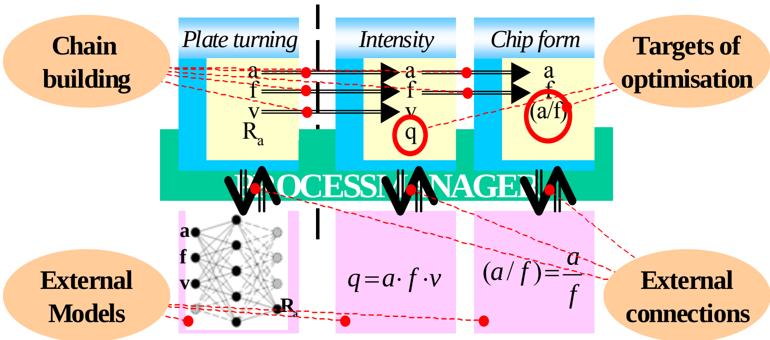
7. Compromise oriented optimisation of processes and production chains

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. 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 plate turning optimisation. The above introduced, general ANN model of the plate turning is used as process model and the necessary evaluation parameters are calculated based on equations. The blocks in Figure 5 are separated programs and they communicate with the *"ProcessManager"* using a developed protocol.

Optimisations were performed from the twofold viewpoints of the company owner (productivity maximisation through the maximisation of the parameter 'q', which is equal to the product of the three machining parameters), and the engineer (maximisation of the cutting stability through minimisation of the 'a/f' ratio).

To realise optimisations from both of these viewpoints weighting factors of the viewpoints were varied to result in different compromises. Figure 5 shows possible compromises through values of the related parameters belonging together. Curves represent possible compromises between the two viewpoints. This diagram shows the possible fields of compromises through attainable values of 'q' and 'a/f'. The representatives of the two viewpoints have to find that points on the horizontal axis, which belongs to those values of 'q' and 'a/f' which, are acceptable for both of them. After having this point the diagram shows also the corresponding machining parameters as the way to the compromise.



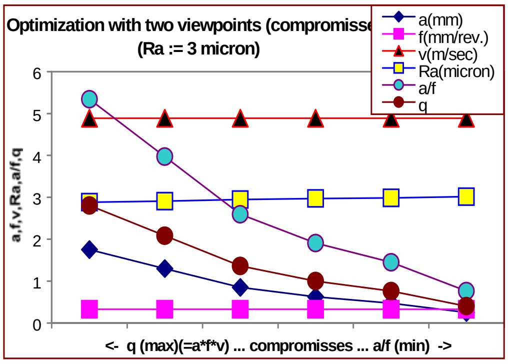


Figure 5 The block oriented model with the *"ProcessManager"* for the twofold optimisation of the plate turning assignment (left). Parameters resulted by the optimisation of the plate turning operation. On the left side of the digram the viewpoint of the company owner (q - max.) on the right side the viewpoint of the engineer, process stability (a/f - min.) is satisfied (right).

8. Conclusions

A new approach was presented in the paper for modelling of machining processes. The corn idea of this modelling technique is that the model building stage has not any regard on the given assignment(s), the task of modelling is to find all the dependencies among parameters while satisfying accuracy requirement(s). This main idea was used in the presented SFS search algorithm, which avoids the problem of modelling of non-invertable dependencies and determines the input-output configuration of the used ANN automatically, resulting in the general process model. A search algorithm based on simulated annealing was also introduced to solve possible various assignments using the general ANN model through finding values for the unknown parameters based on the known parameters without regard to its input or output position. Using the corn idea and the simulated annealing search algorithm, 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. The applicability of these ideas and algorithms are presented through tests of basic mathematical problems and equation based cutting examples. Solutions of different real assignments for plate turning and its optimisation from different viewpoints resulting in possible compromises proof the applicability of this new concept.

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