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Optimisation of process chains and production plants using hybrid, AI- and simulation based general process models

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Abstract

The paper describes a novel approach for generating multipurpose models of machining operations, combining machine learning and search techniques. A block-oriented framework for modelling and optimisation of process chains is introduced and its applicability is shown by the results of the optimisation of cutting processes. The paper illustrates how the framework can support the simulation-based optimisation of whole production plants. The benefits of substituting the time-consuming simulation by ANN models are also outlined. The applicability of the proposed solution is demonstrated by the results of an industrial project where the task was to optimise the size spectrum of the ordered raw material at a plant producing one- and multi-layered printed wires.

Keywords: Manufacturing Systems, Artificial Intelligence, Optimisation

1 INTRODUCTION

Reliable process models are extremely important in different fields of computer integrated manufacturing [5]. On the base of the applied knowledge, fundamental, heuristic and empirical models can be distinguished.

Model-based simulation is usually an efficient technique to make difficult problems more tractable. It can contribute to elaborating new algorithms, supporting decision makers, decreasing the risk in investments, and running the systems exposed to changes and disturbances more efficiently.

From simulation point of view, one can distinguish knowledge-based hybrid systems (KBHSs) if simulation and some kind of intelligent techniques, e.g. expert systems (ESs), artificial neural networks (ANNs), fuzzy systems or their combination are used together [8],[9].

Learning denotes changes in the system that is adaptive in the sense that learning techniques enable the system to do the same or similar task more effectively next time [3],[7]. Obviously, machine learning (ML) techniques can enhance the performance of any KBHS architecture, i.e. embedded, parallel, co-operative, intelligent front-end [8],[9]. From another point of view, simulation can be used for generating training examples for learning.

The paper illustrates the benefits of combining AI, ML and simulation techniques in the optimisation of:

- manufacturing processes,
- process chains, and
- production plants.

2 MULTIPURPOSE MODELLING OF MANUFACTURING PROCESSES

Difficulties in modelling manufacturing processes are manifold: the great number of different machining operations, multidimensional, nonlinear, stochastic nature of machining, partially understood relations between parameters, lack of reliable data, etc. A number of reasons back the required models: the design, optimisation, control and simulation of processes and the design of equipment [1],[4],[12].

Artificial neural networks (ANNs) are general, multivariable, nonlinear estimators. This soft computing technique can offer viable solutions especially for problems where abilities for real-time functioning, uncertainty handling, sensor integration, and learning are essential features [7]. Successful applications in manufacturing were reported on in the literature [6],[10],[14]. The assignments to be performed determined the I/O configurations of the models, i.e. which parameters are to be considered as inputs and which ones as outputs. This predetermination, however, results in models, which do not necessarily realise the best mapping between the considered quantities.

2.1 Generation of multipurpose ANN-based process models with automatic I/O configuration

In the following space an approach based on back propagation ANN-learning and heuristic search for generating multipurpose models is described, which are expected to work with the required accuracy in different assignments. It consists of the following phases:

- Determining the (maximum) number of output parameters (N_o) from the available N parameters which can be estimated by using the remaining $N_i = N - N_o$ input parameters within the prescribed accuracy.
- Ordering 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 above phases are performed parallel, using the speed of the learning process as an indicator for the appropriateness of the ANN architecture in question 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, the sequential forward search (SFS) technique [2] is used. A more detailed description of the algorithm can be found in [13]. The selection of the right I/O configuration is especially important in the case of noninvertible dependencies.

2.2 Application of the multipurpose models in various assignments

Because of the general nature of the multipurpose models, almost in every application only some of the input parameters are known and the task is to determine the unknown parameters while satisfying some constraints.

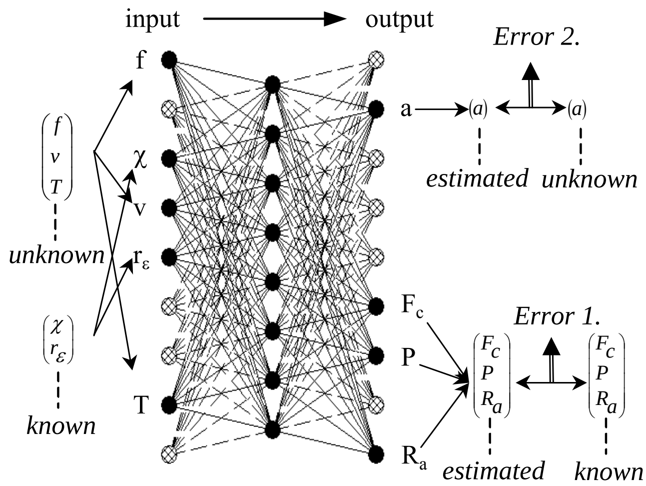

Figure 1: The generated ANN model and its application for the adaptive control of the plate turning

Figure 1, e.g., relates to the adaptive control of the plate turning operation using an ANN-based multipurpose model generated by the algorithm described in Sect. 2.1. In this model feed rate (f[mm/rev]), speed (v[m/min]), tool life (T[min]), cutting edge angle (χ[rad]), and corner radius (r_ε[mm]) of the tool serve as inputs, and the depth of cut (a[mm]), force (F_c[N]), power (P[kW]), and surface roughness (R_a[mm]) as outputs. Obviously, this setting does not fit to the given adaptive control task where R_a, χ, r_ε, F_c, P are known and f, a, v, T are unknown.

In order to resolve the above contradiction, a simulated annealing search technique was developed. The search process for finding the unknown input parameters is guided by three conditions to be satisfied:

- The condition related to the known output parameters ensures that only the points of the search space are acceptable which can adequately estimate the known output parameters. (Error 1, in Figure 1).
- The condition for the unknown input parameters is determined by the validity of the ANN model specified by the data set used for the training [13].
- The condition related to the unknown output parameters also relates to the validity of the ANN. The unknown input parameters are only acceptable if the estimated values of the unknown output parameters are within their allowed range (Error 2, in Figure 1).

The search algorithm is terminated if all of the three conditions above are met. As a result, this algorithm gives one solution for a given assignment of the user. To generate a larger number of solutions the search has to be repeated [13].

3. 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 [4][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 2 shows possible compromises through values of the related parameters belonging together. These results can be also used directly to support business decisions and compromises.

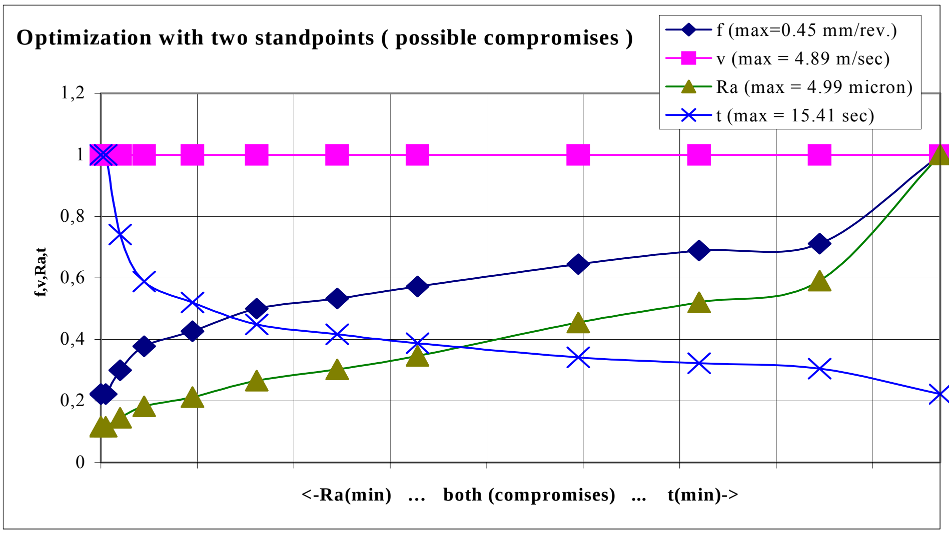

Figure 2: Parameters resulted by the optimisation of the plate turning operation. On the left side the viewpoint of the customer (R_a - min.) on the right side the viewpoint of the producer (t - min.) is satisfied. Curves show possible compromises between the two viewpoints.

Figure 3 and Figure 4 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 3 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 4. 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'.

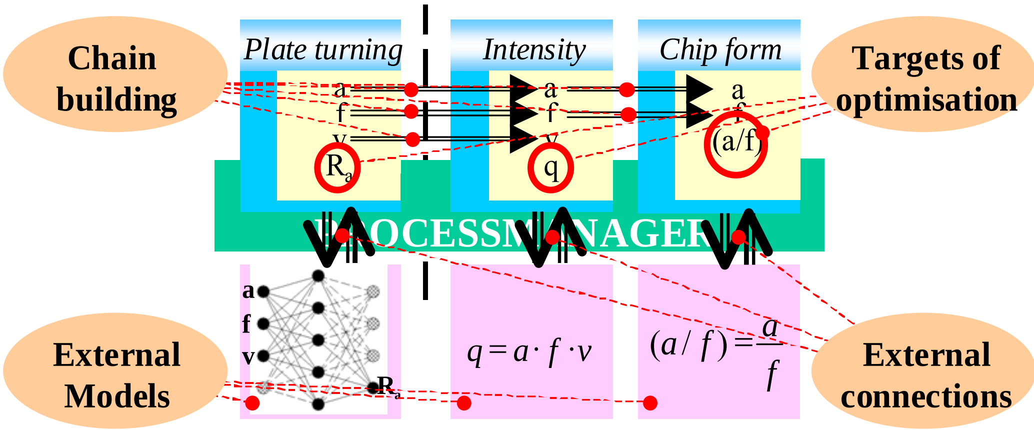

Figure 3: Chain model for optimisation of the plate turning operation with optimisation criteria

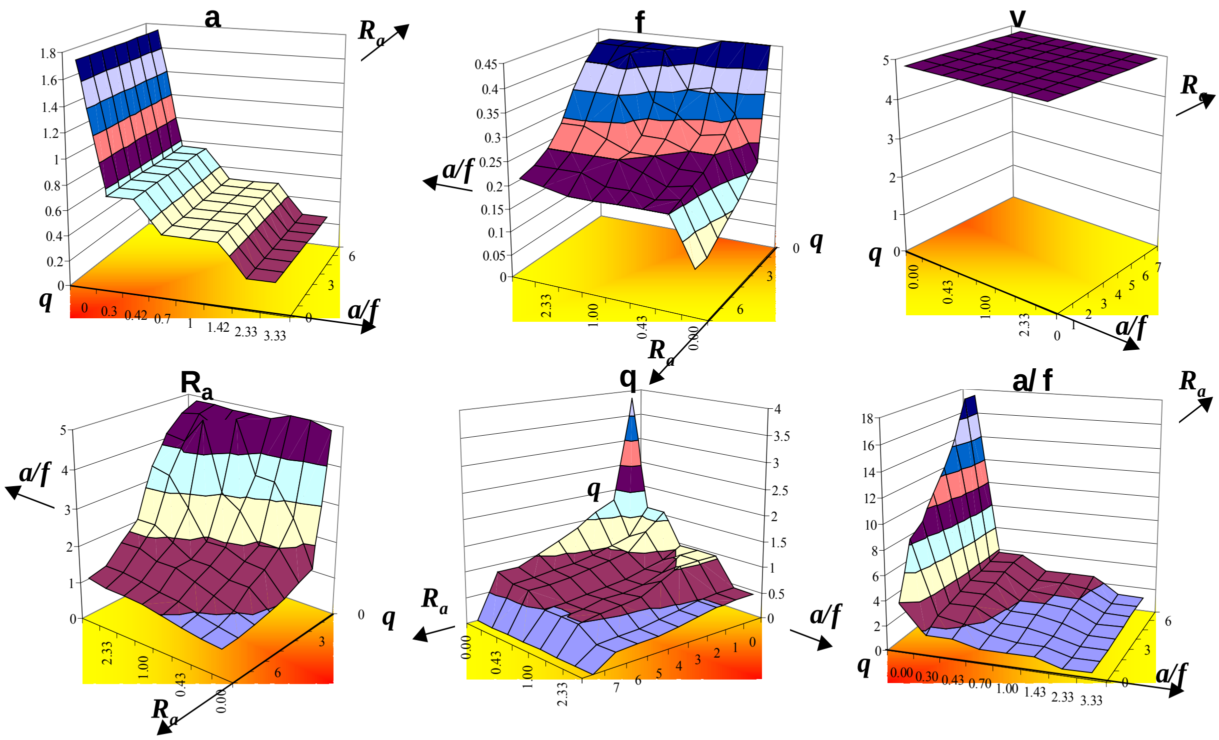

Figure 4: Parameters resulted by the threefold optimisation of the plate turning operation

4. Modelling and optimisation of process chains

As it was pointed out in [15], 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 [16]. To have process models with the required accuracy is especially important in the case of process chains where the errors can cumulate (Figure 5). (The effect of individual models on their output parameter is indicated with "}".)

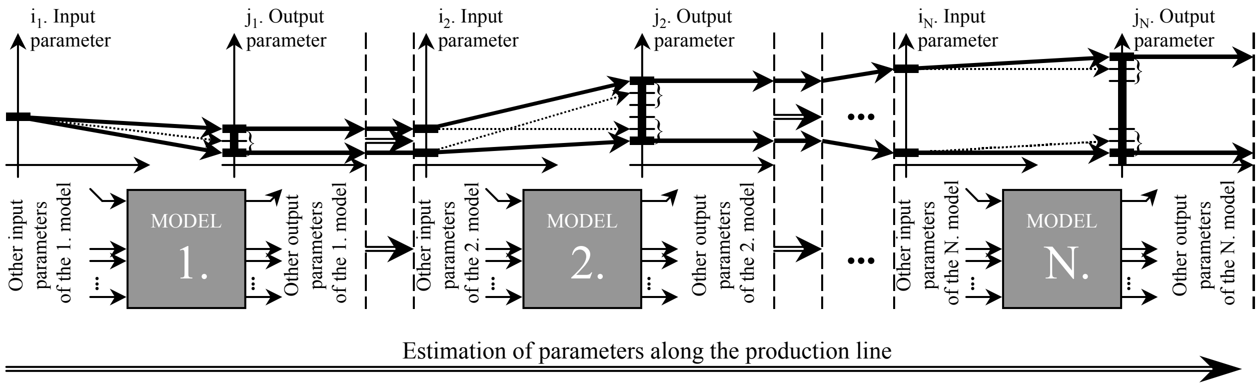

Figure 5: Errors of parameter estimations along the whole production chain

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 [15].

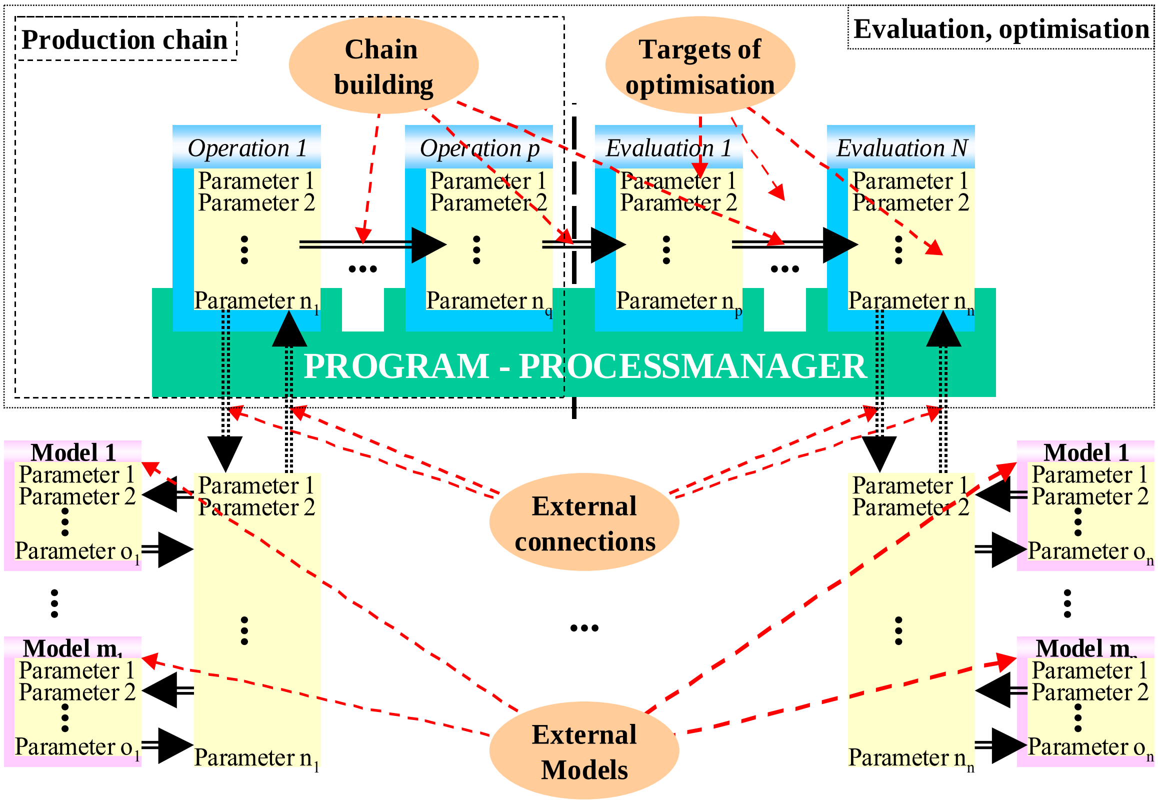

Figure 6: Errors of parameter estimations along the whole production chain

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 6):

- 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.

5 HYBRID, AI-, ML- AND SIMULATION-SUPPORTED OPTIMISATION OF PRODUCTION PLANTS

Simulation techniques can be advantageously used in the design of new production plants. However, their application is usually extremely time-consuming. Some preliminary results of an iterative procedure for the design of manufacturing systems (resource requirements) employing ANNs in conjunction with simulation were presented in [1]. The aim of the ANN was to learn the inverse of the simulation function. Given desired performance measure levels (e.g. mean job tardiness, mean job flowtime, mean resource utilisation and the completion time of all tasks), the network should output appropriate values for the system parameters (e.g. the number of resources for each work centre of a job shop). The approach was regarded as a valuable tool for the manufacturing system design problem, guiding the highly iterative design process and hence reducing the required number of simulations by a simple and automatic training procedure.

Now, it will be shown how the modelling and optimisation approach and the developed framework described in the previous sections can be used for the optimisation of whole production plants where the simulation function cannot be inverted, therefore, a search process is required. The concept is illustrated in Figure 7.

According to this concept, the production plant is represented as a chain of processes where the most important part (parts) is (are) simulated by appropriate (in most cases discrete event) simulation packages. In the case of plant optimisation, most of the parameters are fixed and - satisfying some constraints - the values of other parameters are to be determined in order to reach some performance measures. Naturally, some constraints have to be satisfied at the same time.

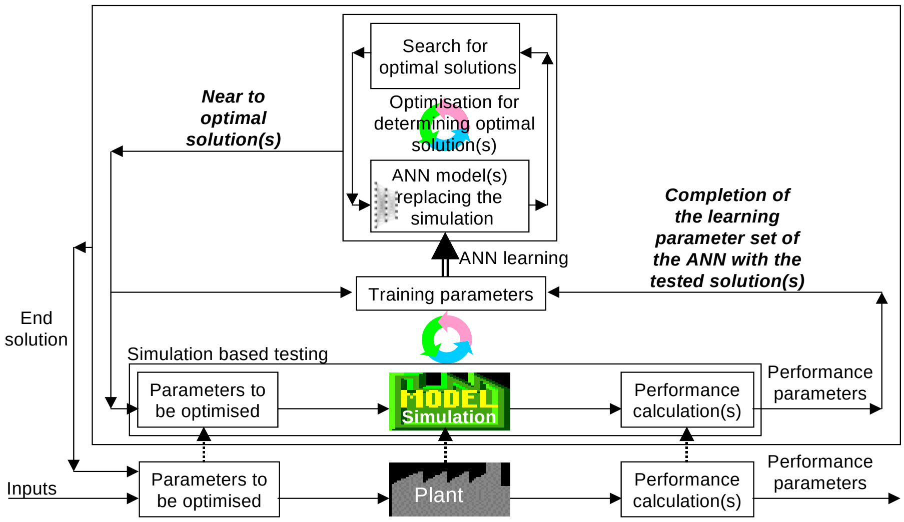

Figure 7: Concept of the hybrid, AI-, ML- and simulation-supported optimisation of production plants

It is appropriate to replace the time consuming simulation with ANN-based models initially trained by patterns generated by the plant or - in most cases - the simulation. An optimisation framework as the ProcessManager described above, can search for solutions by using the ANN model(s). Whether a found solution is appropriate, i.e., it is within the region appropriately realised by the ANN model(s), is to be checked by simulation. If this run indicates unexplored region, the related patterns are added to the training set(s) of the ANN(s) and after training, a new optimisation step is started. If the simulation provides with reinforcement, the found solutions are used for the determination of the system parameters searched for.

5.1 Industrial application

The above concept was applied for the optimisation of the production plant of a Hungarian firm producing one- and multi-layered printed wires. In a previous project the task was to analyse the production plant by using the SIMPLE++ simulation package and to initiate business-process reengineering measures if needed. The subject of optimisation in the project to be reported on here was to determine the geometrical (height and width) parameters of a given number of boards serving as raw material for the production. The aim was to maximise the average surface utilisation and to minimise the mean flow time.

The parameters to be determined influence the whole production, i.e., the machines used, their scheduling, part routing, etc. Moreover, the mapping between these parameters and the performance parameters of the plant is not invertable, consequently, in order to obtain the required results, the use of the previously developed simulation model of the plant was straightforward. Production orders were generated randomly based on the statistical data of a month, which could be considered as characteristic. A new algorithm was developed for placing the printed wires on the boards. Substituting the simulation for an appropriate neural network trained by the back propagation technique an acceleration of the optimisation with a factor of about 6000 was experienced. The average surface utilisation of the raw material was increased by about 20%, with the additional benefits of using only some, this way standardised boards as raw material, i.e. lower purchase prices, lower storage costs and better quality of the end products.

Some proposals for further improvement of the production were also given as some supplementary results of the project:

- introduction of a more flexible working time,
- modification of the production information system,
- pointing out the bottlenecks in the production,
- warehousing of some frequently ordered products,
- introduction of new operations in the production,
- extension of the simulation for the order processing and some preparatory phases of the production.

The success of the project indicates the applicability of the concept presented in this section, i.e., the hybrid, AI-, ML- and simulation-supported production optimisation.

6 SUMMARY

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 certain applications. A block oriented framework for modelling and optimisation of process chains was introduced and its applicability was illustrated by the results of the optimisation of cutting processes. The concept of the hybrid, AI-, ML- and simulation-supported optimisation of production plants was also outlined. Some results of an industrial project demonstrated the applicability of the concept where the task was to optimise the size spectrum of the ordered raw material at a plant producing one- and multi-layered printed wires. Further industrial applications of the concept and the developed modelling and optimisation framework are in the preparation phase.

7 ACKNOWLEDGEMENTS

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