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OPTIMISATION OF PRODUCTION SYSTEMS USING SIMULATION AND ARTIFICIAL INTELLIGENCE TECHNIQUES

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Summary

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.

1 INTRODUCTION

Reliable process models are extremely important in different fields of computer integrated manufacturing [1]. 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.

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]. Obviously, machine learning (ML) techniques can enhance the performance of any KBHS architecture, i.e. embedded, parallel, co-operative, intelligent front-end. 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 [2].

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 [3]. Successful applications in manufacturing were reported on in the literature [4], [5].

3 HYBRID MODELLING AND OPTIMISATION OF PROCESESS AND PROCESS CHAINS

The sequence of production operations can be modelled by a chain of operations connected by their input-output parameters [6], [7]. In the following space a block-oriented software named 'ProcessManager' will be introduced for optimising operations and/or production chains according to criteria handled by the usual weighting technique. It can be considered as an extension of the modelling and search techniques introduced for single processes.

ProcessManager incorporates (Fig. 1):

- Definition of the elements of the process chain.
- Determination of the process models in a hybrid way, 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.

Fig. 2 illustrates the application of ProcessManager for three-criterion optimisation according to the interests of the customer (minimisation of the surface roughness), owner of the company (profit/productivity maximisation) and the production engineer (maximisation of process stability through the a/f ratio). Parameters resulted by the optimisation of the plate turning operation are illustrated by 3D-plots in Fig. 2.

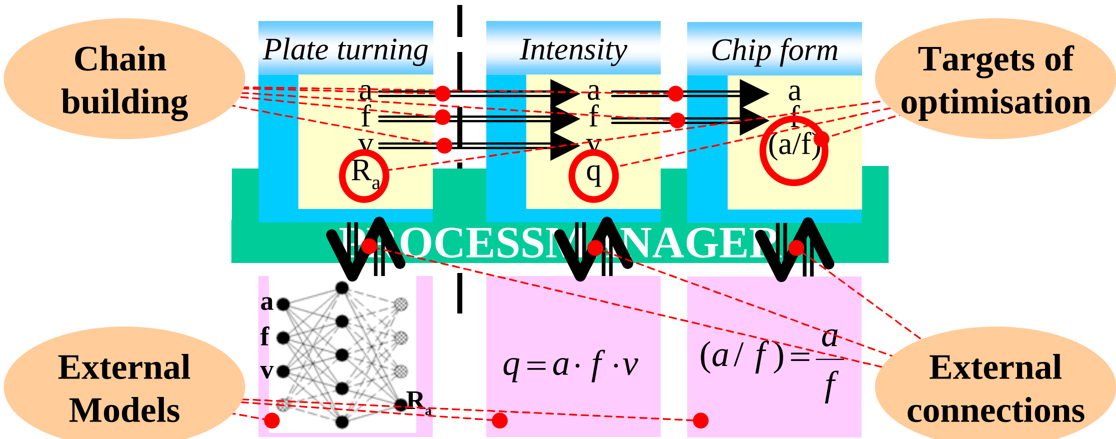

Fig. 1. Hybrid modelling and optimisation by ProcessManager (model of the plate turning operation with optimisation criteria)

Ratios of the weighting factors of the three variables to be optimised are represented along the axes in the Fig. 2. The 'surfaces' are to be used together, i.e., the moving along the plane marked by Ra (surface roughness) and a/f (parameter related to process stability) occurs on each of the diagrams at the same time. The corner marked by q indicates the position where the criteria of the company owner is the most important and the movement along the axes Ra and a/f represents that the criteria of the customer and the engineer are more and more important with respect to q.

It is worth mentioning that the results illustrated here are based on ANN models generated with measured data.

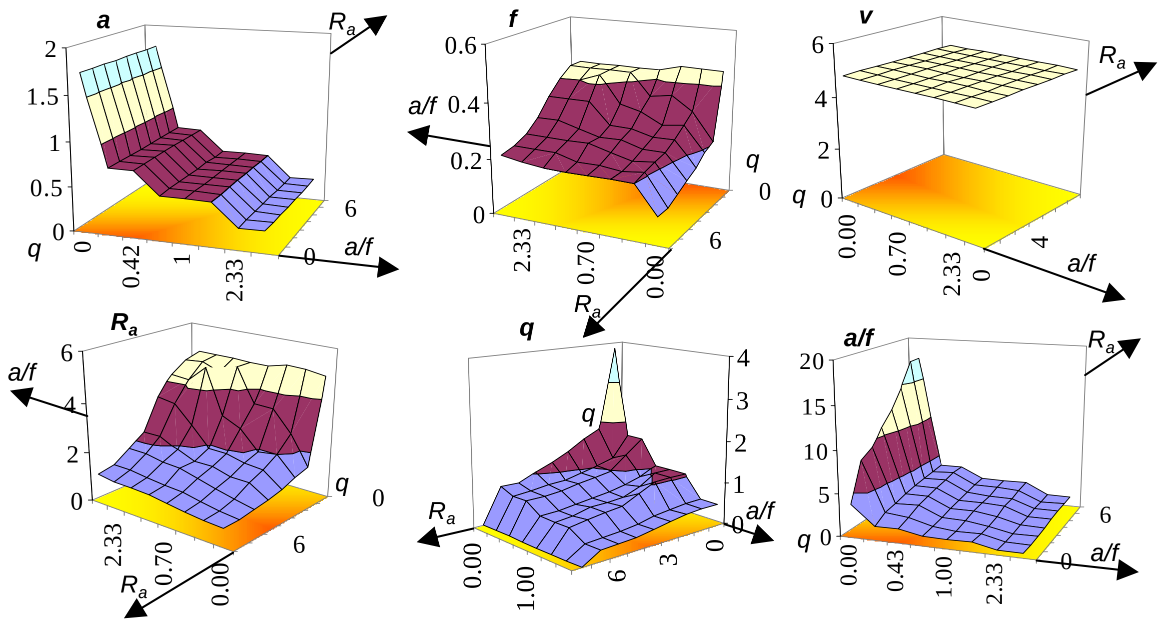

Fig. 2. Parameters resulted by the threefold optimisation of the plate turning operation

4 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 [7]. 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 Fig. 3.

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.

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.

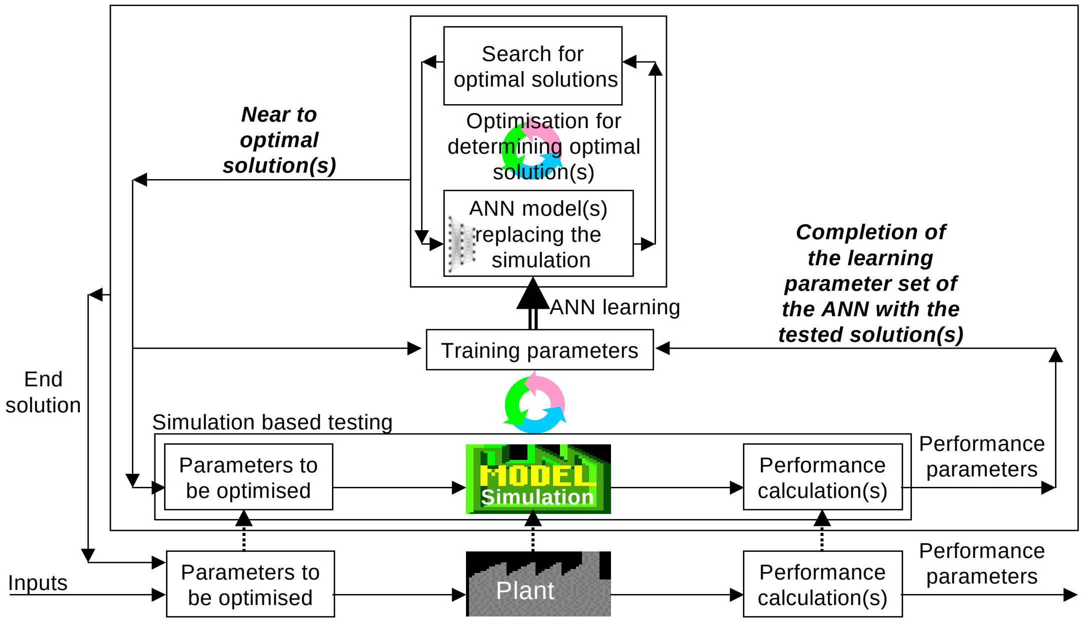

Fig. 3. Concept of the hybrid, AI-, ML- and simulation-supported optimisation of production plants

4.1. 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, like 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 and 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.

5 CONCLUDING REMARKS

A block oriented framework for modelling and optimisation of process chains was introduced in the paper 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.

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