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MONITORING PARAMETER BASED DETERMINATION OF PRODUCTION TOLERANCES

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Summary

One of the most important prerequisites of smooth, controlled manufacturing is the application of appropriate monitoring systems. Information about the production processes is dispatched to these systems in a form of measured parameters ahich can be used for accomplishing state analysis and feedback. The usually high number of processed data can be used for modelling production structures, when models capable to learn are applied. The paper describes the application of artificial neural networks built up on the base of monitoring parameters, to determine production tolerances. The behaviours of models, the method for determining tolerances and the representation for dependencies among parameters are also illustrated.

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.

In the CIRP survey on developments and trends in control and monitoring of machining processes, the necessity of sensor integration, sophisticated models, multimodel systems, and learning ability was outlined [1].

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 [4].

A number of reasons back the required models: design of processes, optimization of processes, control of processes, simulation of processes, and design of equipment [5].

Artificial neural networks (ANNs), neuro-fuzzy (NF) systems are general, multivariable, non-linear estimators, therefore, they offer a very effective process modelling approach. Such soft computing techniques seem to be a viable solution for the lower level of intelligent, hierarchical control and monitoring systems where abilities for real-time functioning, uncertainty handling, sensor integration, and learning are essential features. Successful attempts were also reported on in the literature [2], [3].

The paper is closely connected to the cluster called “Monitoring of complex production structures” of the “Digital enterprises, production networks” project realised in the frame of National Research and Development Programme of the Ministry of Education of Hungary. The cluster has several subjects grouped into three parts:

- Sensor integration, processing of huge data volume, handling of hidden dependencies and replace big models with smaller, dense connected sub-models are the subjects of the basic research part of the cluster.
- Further improvement and extension of the monitoring systems built up nowadays and a development of software, simulating the lamp production, and be connected to the developed monitoring systems, are the main targets of the R&D part.
- Demonstration and dissemination of the techniques and tools resulted by the previous two steps are the goals of the third part of the cluster.

The topic of the presented paper is connected to the first and second part of the cluster, as detailed in the next paragraphs.

2 AUTOMATIC INPUT-OUTPUT CONFIGURATION AND GENERATION OF MULTIPURPOSE ANN-BASED PROCESS MODELS

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 strongly influences the accuracy of the developed model, especially if dependencies between parameters are non-invertable. At different stages of production (e.g. in planning, optimization or control) tasks are different, consequently, the estimation capabilities of the related applied models vary, even if the same set of parameters is used. Instead of different models with different set of parameters, one general multipurpose model (Fig. 1.) is able to solve the same problems with higher efficiency.

The method for 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.

In order to accelerate the search for the ANN configuration, which complies with the accuracy requirements with the minimum number of input parameters, sequential forward search (SFS) algorithm is used. The search method is detailed in [6].

3 APPLICATION OF THE MULTIPURPOSE MODEL FOR VARIOUS ASSIGNMENTS

Because of the general nature of the multipurpose model, described in the previous paragraph, almost in every assignment, a part of input and a part of output variables of the model are known. During the solution the unknown part of the inputs and the outputs have to be determined by taking some constraints into account (Fig. 1.). Different known-unknown parameter settings (meaning different assignments) usually do not match the input-output configuration of the given, general ANN model, indicating, that a method is needed to determine values for the unknown parameters independently if they are inputs or outputs. An algorithm and its software realisation were developed to solve this task as detailed in [7].

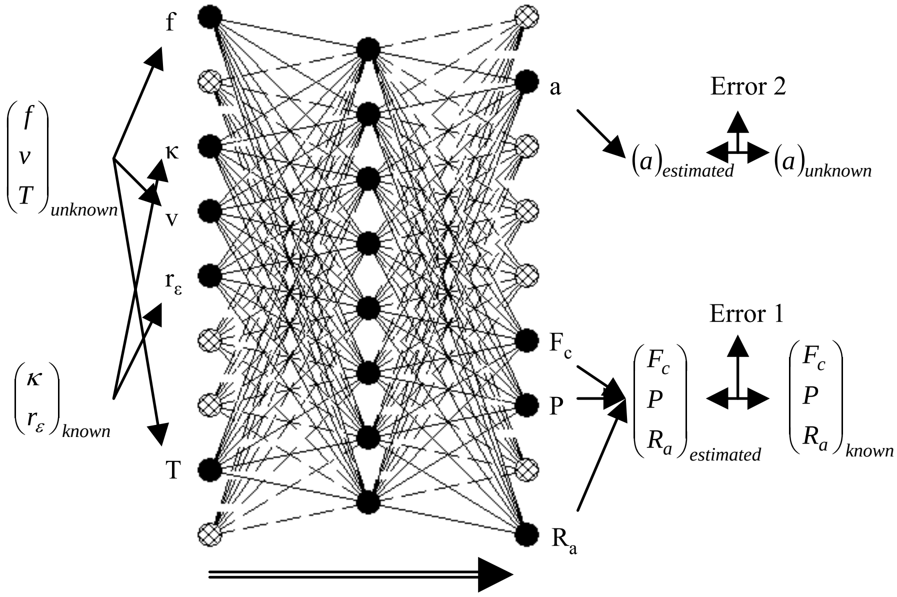

Fig. 1. The appropriate input-output configuration of the ANN based process model and the solution of an assignment determining the known-unknown state of the process parameters

4 APPLYING THE CONCEPT FOR DETECTING PROCESS RELATED TOLERANCES

The way of application of the method described in previous paragraphs is non-trivial and has several prerequisites like software, know-how, etc. To perform experimental tests could be another method for determining the appropriate tolerances for a given machining operation but this solution is usually more expensive and time consuming than the ANN based concept. Another aspect is the speed of measuring, which is sometimes very slow, and requires high precision.

To solve the problem the following method was applied:

- The solution starts with the data collection. For the analysed cutting experiments, three parameters of the process were changed in a wide range (depth of cut, feed, and speed), five parameters were measured (cutting temperature, three dimensions of cutting force and surface roughness) and one parameter was calculated (specific energy of cutting – shows the cutting energy per chip volume).
- A wide range of parameters, calculated from the original measured values, is the result of the second step.
- An ANN based process model was built up having the above mentioned parameters on its input or output side. Seven process parameters were involved in the analysed model building process. As result the cutting speed, feed, depth of cut and specific energy of cutting become the inputs, temperature, surface irregularity and force became the outputs of the ANN model.
- Some thousands of possible solutions for the given manufacturing operation were determined using the technique reviewed in the previous paragraph, which applies the above mentioned general process model. This high number of solutions enables to represent and show the dependencies among process parameters learnt by the ANN model. The dependencies are shown through two-dimensional diagrams having different shapes and colours related to different parameter settings. Some selected diagrams are shown in the Fig. 2.

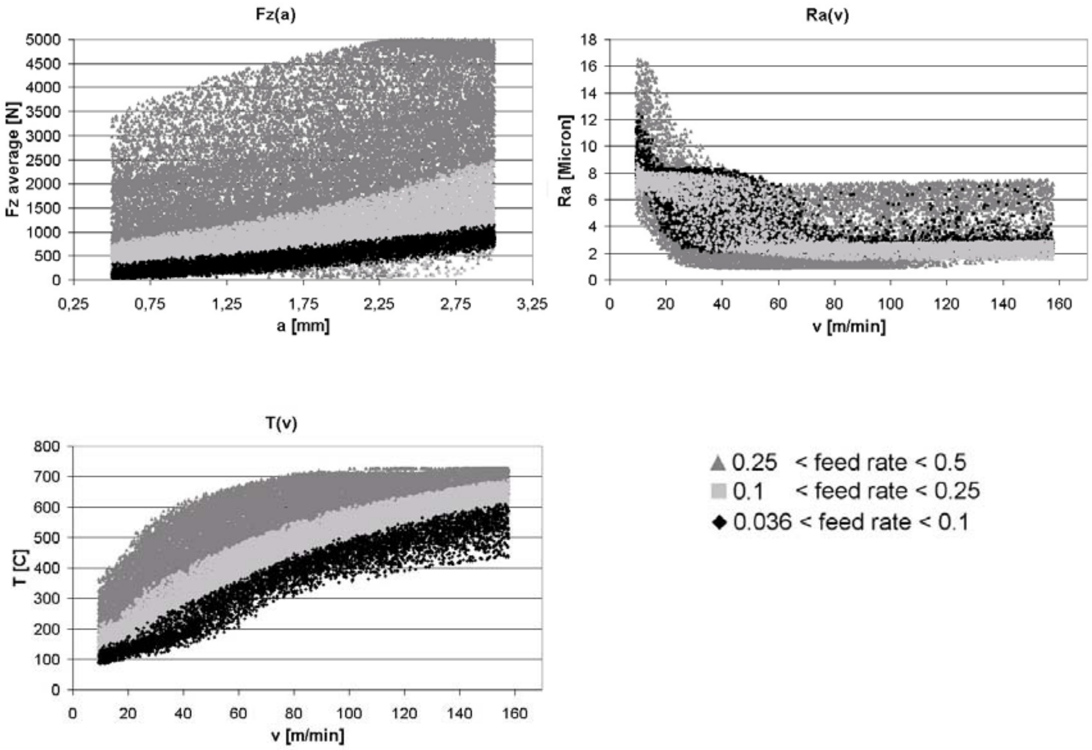

Fig. 2. Thirty thousand possible solutions of the analysed cutting process generated by the introduced method based on the ANN model of the process.

Solution zones in the Fig. 2. show not only several different, possible solutions of the given cutting process but they outline the trends and nature of the dependencies among process parameters and the required tolerances of different process circumstances, too. The nature of the investigated dependencies matches the ideas of engineers and the industrial observations showing that the introduced concept can be applied for determining tolerances of different industrial processes.

5 APPLYING THE INTRODUCED METHOD IN THE LAMP PRODUCTION INDUSTRY

The concept introduced in the previous paragraphs is an application-field independent solution.

The number of monitoring systems is increasing nowadays, consequently, the first step the data collection can be fulfilled more and more easily. This is the case in the lamp-production industry, too, namely several monitoring systems can be already found all over the word collecting more thousands of monitoring parameters inside a second. Process specialists and engineers are experts of the individual production steps having the know-how to define derivative parameters form the basic monitoring data. Software called “Neureca2” was developed to determine the appropriate input-output configuration of the ANN model resulting in the general model of the manufacturing process in question. The same software can be used to identify production tolerances while satisfying the predetermined manufacturing constraints. The tolerances are determined through a high number of generated solutions which satisfies the given production restrictions.

The introduced approach will be used to determine geometrical tolerances for the individual lamp parts influencing optical properties of produced lamps. The ratio of lamps having the required lighting parameters is used as a measure of the goodness of the geometrical tolerances. These parameters were measured and registered by monitoring systems during the production shifts of the past, consequently, there is a free space for using ANNs as models among production tolerances and this ratio.

6 CONCLUSIONS

The paper described a concept to determine parameter tolerances for machining processes. An experiment form the cutting field was performed and the results were analysed. The developed method was able to build up a general process model and to generate a huge number of different solutions for various engineering assignments with miscellaneous restrictions. Machining parameter tolerances come out through representing these solutions by diagrams as in the figure above.

7 ACKNOWLEDGEMENTS

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