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Similarities of high and low levels of production with respect to assignments and solution techniques

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Abstract—This paper highlights similarities between higher and lower levels of production, focusing on assignments and solution techniques. Various production levels are examined with respect to several aspects (complexity of relations, large number of parameters) and typical generic tasks ("classical" modelling, problem solving, optimization and submodel decomposition). For each issue, the paper highlights that due to similarities, the same classes of methods based on artificial neural networks (ANN) can be used for different levels of production, outlining a uniform approach.

Keywords: production levels, modeling, neural networks

1. INTRODUCTION

Optimizing the efficiency of production has always been a vital issue and is recently getting much attention due to increasing competition between manufacturers. This, of course, calls for substantial improvement of planning, control and monitoring of production processes and manufacturing systems. While opinions differ as to where the borders of various production levels should be drawn (see Horváth et al. [1], Tóth [2], Luttervelt et al. [3] and Tóth et al. [4] for a general overview), it can be observed that all levels share some basic characteristics, such as high complexity (which, however, can be broken up to subsystems, as shown later) and a high number of relevant system parameters. This observation raises the assumption that suitable unified methods can be set up and used for handling production on its various levels, allowing an integrated treatment of manufacturing.

This paper presents a family of methods based on artificial neural networks whose successful application in various levels of manufacturing supports the aforementioned idea. First, basic properties are highlighted which are common to various production levels (such as complexity due to the large number of interdependencies, as well as a large number of system parameters). Hereafter, a family of ANN-based methods is presented through practical application examples where ANN models are used to solve key classes of problems (classical modelling of complex systems with missing data, unknown input/output arrangement and uncertainties, basic problem solving, optimization and decomposition of a complex system to a net of simple submodels). The examples are selected to span a wide range of production levels, which will shed light on the universal applicability of the methods.

2. COMPLEXITY

Significant complexity can be encountered in all levels of production. At the lowest level, even a single production step is usually performed using a very complex machine. Here, a few fundamental, relatively simple relations can be set up for some physical properties. However, none of these can be fully decoupled from the dense network of interdependencies—this eventually obstructs the efficient use of conventional analytic modelling and evaluation techniques. As an example, cutting and machining processes can be mentioned (see Markos et al. [5], Monostori et al. [6] and Dolinšek et al. [7]). To give an idea of the complexity of cutting processes, Fig. 1 shows the main parameter groups connected to key phenomena, as well as their interdependencies.

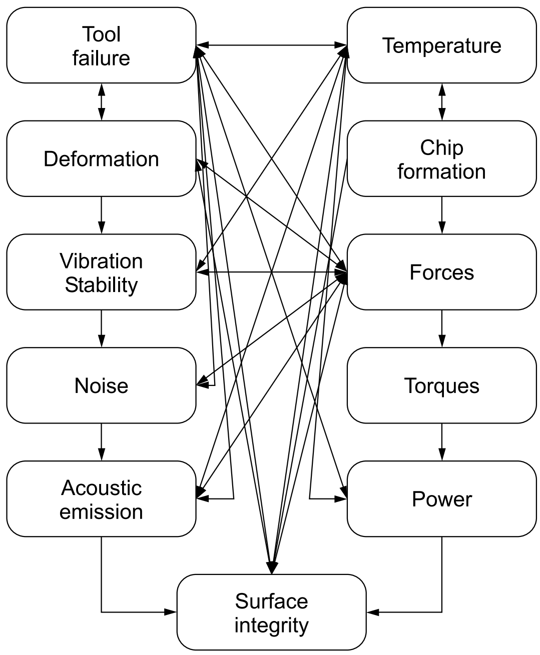

Figure 1: Key physical phenomena of a machining process and their interdependencies

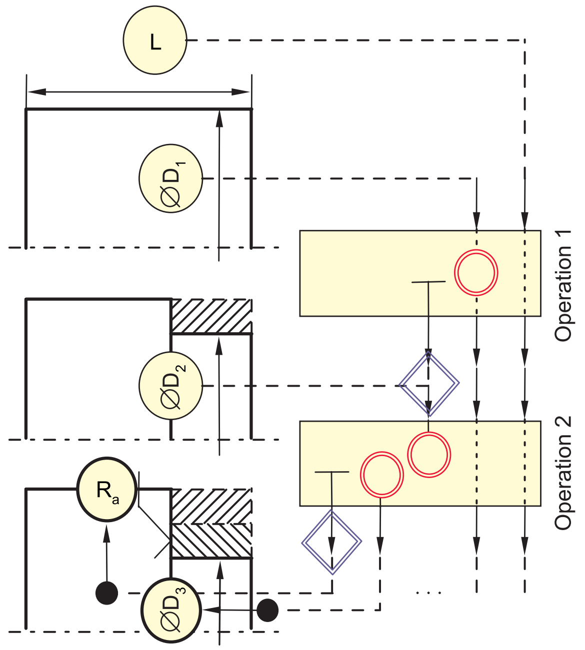

Figure 2: Main steps of a multistage material removal process for turning an axle. The subsequent execution of manufacturing processes introduces complicated interdependencies, so that even a higher level production model's complexity is similar to that of low-level process models

The concatenation of several production steps and their integration into a larger system brings about new interdependencies (Fig. 2). This has two main reasons. First, the result of a given production step (such as surface quality in machining and cutting, see [7]) can largely influence the parameters of a subsequent stage, even if the goal of the latter would not be influenced by deviations encountered in the preceding step. Second, the different subsystems have to work together as one production system where even decisions—such as work assignment to one machine or another—may depend on the result of a given production step. Even if phenomena inherent to subsystems are neglected in a higher level arrangement, the integration of several lower level systems into a higher level network adds new interdependencies, so that the complexity of production systems does not necessarily decrease while examining higher levels of hierarchy. This is demonstrated, e. g., by the results of a production modelling, planning and control project (*Digital Factory*), as reported by Monostori et al. [8].

In addition to the complexity of production systems, some parameters can even change their nature from being an independent one (input) to being a dependent one (output). The input/output nature of a parameter may either alter due to changing task prefernces, or it may be uncertain owing to sparse knowledge of the interdependencies within the process. Altogether, it can be seen that the following fundamental phenomena can be encountered in all levels of production:

- complexity due to numerous interdependencies and
- varying input/output nature of parameters.

3. LARGE NUMBER OF PARAMETERS

Another difficulty in handling production systems is the large number of parameters in their corresponding models. Even if some related features can be arranged in groups, their total number alone can be a serious hindrance for the application of conventional approaches (not to speak of the dense network of interdependencies, as mentioned before). The number of relevant physical properties can easily reach the range of a hundred parameters, as demonstrated by the cutting process (Markos et al. [5]), and even the features of a part of the process (such as chip formation, see Viharos et al. [9]) are numerous.

The same phenomenon can be observed in higher levels of production—the number of parameters is often too high to tackle problems related to the system with conventional means, and artificial intelligence techniques have to be used for simulation, decision support etc. (see Monostori et al. [10]).

4. CLASSICAL MODELLING

Is sufficient measurement information available, the first step towards handling a production system, no matter at what level, is the creation of an adequate model. This is essential for setting up planning and control methods, as well as for testing and validating them in a simulation environment before practical application.

Production processes are characterised by nonlinear relations, usually contain significant uncertainty and may change during production. Conventional methods, such as differential equations or rudimentary interpolation, may describe the relation of a few typical process parameters, yet they fail to handle the entire process of interest in its full complexity, deal with its uncertainties and adapt to its changes.

Therefore, artificial intelligence (AI) techniques have been used for long to deal with modelling production processes. One possible AI technique is the use of artificial neural networks (ANN)—as proposed and successfully demonstrated in practice in various works by Viharos et al. Application of these networks in lower levels of production is shown in [9] for simulating chip formation in turning and milling processes and in [5] for modelling surface quality properties of a cutting process depending on various technical parameters. Application of ANN's for modelling higher levels of production was proposed in [10], where a more efficient successor of the previously mentioned concept is extended to process chains and entire production plants, while [11] shows the application of various AI and machine learning techniques for the design of manufacturing processes and production systems.

Two key features of the novel ANN-based method of Viharos et al. are highlighted in [12]. *First, the proposed network architecture can cope with changing input/output assignments.* These can either change due to the nature of a given subtask (in addition to the question of which parameters are considered known or given and which are to be found), or are unknown and to be determined by the learning be-

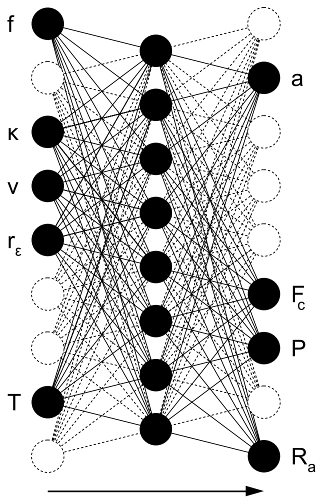

Figure 3: Protected (dotted) and unprotected (solid) states of different neurons and corresponding weights

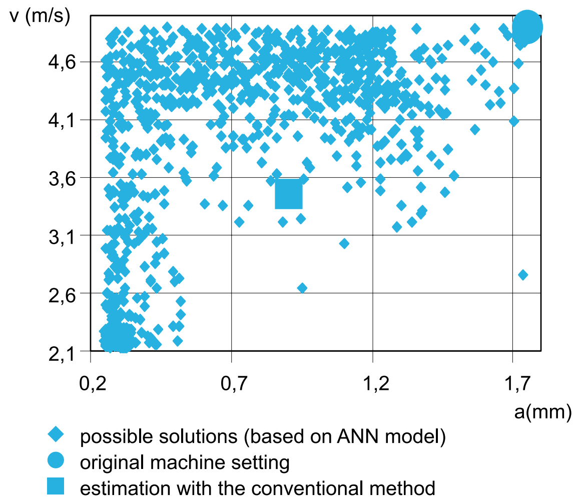

Figure 4: A thousand possible machine settings which produce a prescribed surface roughness

havior of the neural network. Independently of the specific reason an uncertain input/output arrangement may have, an automatic search method facilitates meeting the best choice. Here, possible output candidates are selected and the learning performance (learning speed and accuracy) of the ANN is monitored, keeping allowable tolerances of the given parameter in mind. Should the training of the ANN for a given input/output arrangement succeed, the selected variable becomes eligible for being an output. *This automatic search can also detect non-invertable relations*, as in their case, training the input/output arrangement corresponding to their inverse fails. An important characteristic of the method is the unchanging topology of the network where, as shown in Fig. 3, unused neurons and links are not deleted but only protected from being altered during learning.

A similar method is applied when *incomplete data sets* are encountered. While numerous methods paste up missing components in training and test data by interpolation, the concept of Viharos et al. does not make this necessary. *Here, weights corresponding to missing data are protected and remain omitted by the given learning step.* As shown by the results (see [12]), this is suitable for handling incomplete data. *Moreover, "impaired" training vectors often bring better learning results if data vectros to be learned contain redundant information.*

5. PROBLEM SOLVING

Having once assembled the general, multi-purpose ANN-based model as described above, it can be used to solve a wide variety of problems. The key to the model's versatility arises, aside from the fact that it is among the best models attainable with an ANN of a given size and topology, from the possibility of both direct and indirect use. Is a parameter—considered unknown in a given problem—equivalent to an output of the ANN, direct estimation can be performed. Should unknown parameters of a problem be inputs of the network, an indirect approach can be used which is also suitable for non-invertable relations.

Numerous practical application examples for low levels of production (metal cutting again, as in various examples mentioned before) are given in [6]:

- The output of an ANN can determine operation order and assignment of resources to work centers.
- The generic model can facilitate the determination of cutting settings, tool selection etc. to maintain prescribed quality.
- Attainable fields of machine parameters can be explored by ANN-based simulation.
- Expected tool life and monitoring parameters can be estimated and an early warning can be issued according to them.
- Adaptive control of machine settings can be realized to satisfy a given processing requirement.

In [13, 14], the role of a proper input-output search is shown in picking out non-invertable relations to learn them the correct way. Should a non-invertable relation be encountered, learning it imposes no hindrance to a correctly configured ANN, however, the non-invertable nature does show in the high number of solutions found in an indirect problem solution process, as shown in Fig. 4.

Still an application example for lower levels of manufacturing, [15] shows another case for multiple solutions of a non-invertable relation. An example is shown in Fig. 5 where solutions had to be found for a set of multiple prescribed parameters of a cutting process. In [15], the influence of the simultaneous selection of several requirements is examined from the point of view of estimation accuracy.

An example for the use of the generic ANN model in higher levels of production is given in [10] where various problems related to efficiency improvement had to be solved in manufacturing processes of multilayer printed circuit boards.

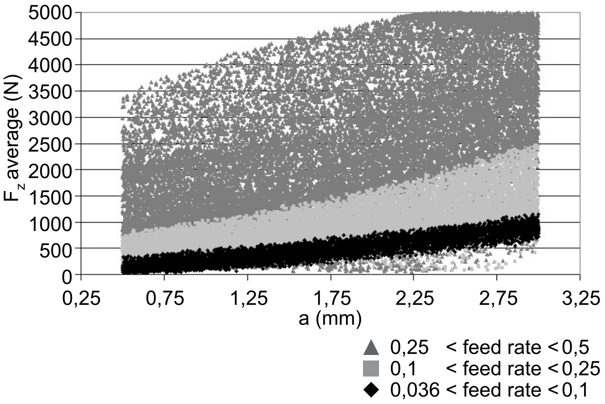

Figure 5: Thirty thousand possible solutions to a cutting problem obtained from an ANN model of the process

6. OPTIMIZATION

Depending on the nature of the model and the problem, finding a solution (or a set of solutions) may require iterative search or optimization. In fact, this is the case every time the ANN-based model is used in an indirect way to obtain a solution where a valid interval for unknown inputs and outputs is to be determined. In this case, following constraints are imposed on the iterative search:

- Condition regarding known output parameters—complying with this contraint ensures that a valid solution estimates known output parameters by forward calculation within specified bouds of estimation error.

- Condition regarding unknown input parameters—this is determined by the valid domain of inputs of the ANN model which is assumed to be covered by the set of training data.

- Condition regarding unknown output parameters—determined by the valid range of the ANN's output, a prospective solution is only accepted if the unknown output remains in this acceptable range.

An application example of iterative optimization with such constraints is shown by Viharos et al. [16] where *simulated annealing* is used to obtain a set of valid solutions to manufacturing problems. Also, the technique initially applied to only one production step is extended in [16] to a higher level of production: The block-oriented *ProcessManager* framework presented in [16] can deal with an entire process chain where the result of an earlier step may influence all subsequent steps.

Even higher levels of production are handled in [10] where a hybrid optimisation technique (supported by AI, machine learning (ML) and simulation) is used to find an optimal arrangement of manufacturing processes within a production plant. A substantial gain in optimization time (acceleration by a factor of 6000) is reached by substituting discrete event simulation with ANN's trained by results of earlier simulation runs.

7. SUBMODEL DECOMPOSITION

The complexity of production systems implies models which—due to the high number of parameters and the dense network of interrelations—can be handled as a whole only at huge computational costs. It is thus advantageous to decompose these complex models to several smaller interconnected submodels which can be easily handled one by one. For this purpose, a submodel finding approach combining feature selection and artificial neural networks—a culmination of the ANN-based techniques presented before—was developed by Viharos [17, 18]. The application of the algorithm has two main prerequisites:

- A data set of sufficient size has to be supplied, e. g., in form of a database table where columns represent the variables to describe the system and each row stands for these variables recorded at a given time.

- Since in subsequent parts of the algorithm, an artificial neural network is employed to test whether a given variable can be estimated using other parameters, a maximal tolerable error has to be assigned to each variable when estimating it with an ANN model.

Having fulfilled these requirements, an algorithm can be run which uses ANN's to validate proposed submodels. In the most "conventional" case, the assignment of potential inputs and outputs as well as the isolation of proposed submodel structures is done in a separate block, prior to any ANN training, as proposed by earlier approaches (e. g., Caelli et al. [19]). Departing from this rigid setup, one can allow the structure of the interconnected submodels to be determined dynamically during learning.

The novel method presented in [20] allows the flexible configuration of submodels, as well as free assignment of a given variable for input or output. As shown before, the highest number of outputs is selected in an input/output search based on ANN learning performance. However, attempting to learn a potential output by an ANN can only signalize that there is a dependency "somewhere within the set of selected variables" but cannot weed out parameters totally independent of the given subsystem. This would result in a single ANN struggling to learn the entire structure in question, therefore, the reduction to smaller, easy-to-handle submodels must be cared for by other means. While the vast majority of such approaches determines the submodel structures before any ANN training takes place, this new method identifies the submodel structures dynamically, leaning on the results of earlier ANN training periods.

This is accomplished by an extended feature selection algorithm—developed by Viharos et al.—running on the complete set of variables and setting up a decision tree for submodel selection. This can be considered a set of *assumptions*, to be either *verified* or *rejected* by the ANN algorithm. The latter begins validating a given part of the submodel structure—at a given point in the decision tree—and delivers first training results. Examining these and removing the successfully learned submodel form the "pool" of unclassified

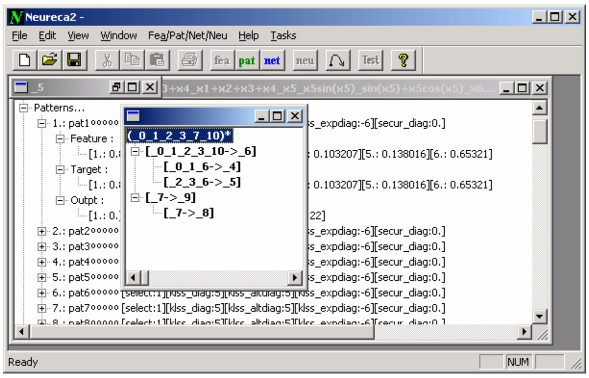

Figure 6: A simple case of submodel decomposition. The net of accepted submodels consists, in this example, of five main relations (in brackets), partitioning a system containing eleven description parameters. The fourth row in the window shows that the algorithm identified a submodel with parameters 2, 3 and 6 as inputs for the estimation of output 5. The four identified submodels have common parameters, e. g., parameter 6 is estimated by the submodel shown in the second row, but it is to be found among the input variables of the next two submodels, too. Thus, a structure of interconnected submodels can be recognized additionally to the identification of its individual parts.

variables, feature selection is run again on the remaining data set and the decision tree is reconfigured if needed. Hereafter, ANN training takes place again. Thus, the method does not separate preselection and ANN training into disjoint tasks—in fact, *feature selection and training complement each other with their alternate execution* until all submodels are identified and learned.

Having completed the decomposition, the following results are obtained (see also Figs. 6,7):

- A set of valid submodels, each containing a minimal set of the system's parameters with as many of them labeled as output as the ANN algorithm could find.
- A set of rejected submodels. These were originally proposed as submodels by the feature selection procedure but were judged invalid by the ANN algorithm. Storing these discarded patterns is useful for an early pruning of submodel candidates bound to fail.
- Since the valid submodels were spotted while ANN's were learning their parameter dependencies, this knowledge is readily accessible and applicable for problem solving as a network separate neural nets, each of them representing one submodel.

Fig. 7 shows a screenshot of an actual industrial application in a rather low level of manufacturing where a production line is modelled using more than sixty parameters. In [17] and [18], another industrial application is shown for an intermediate level of production.

Currently ongoing research activities, as described by Viharos et al. in [21], are aimed at extending submodel decomposition towards an agent-based framework where knowledge specific to an agent is mapped onto a given submodel.

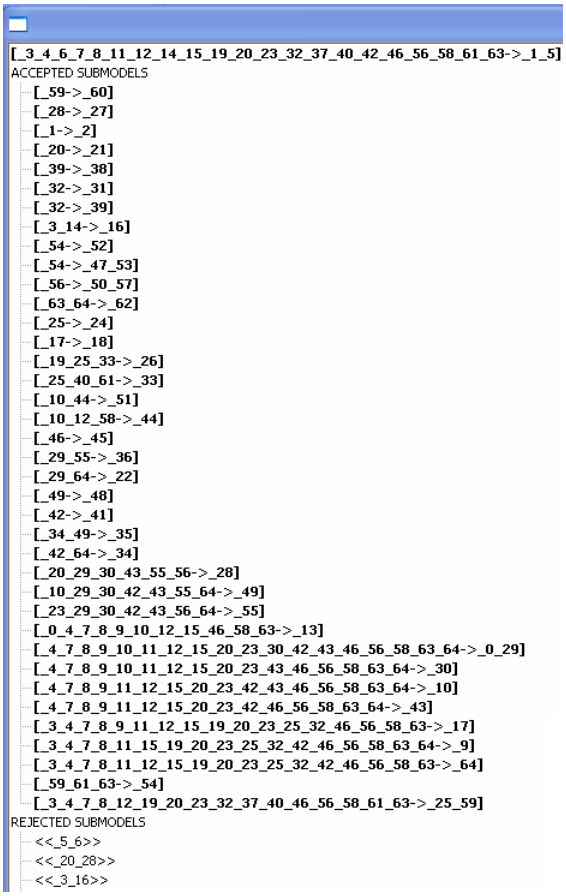

Figure 7: Result of submodel decomposition in an industrial example with a large number of system parameters

The feasibility of this generalisation is assumed because of remarkable analogies between ANN-based submodels and agents: the fact of decomposability, the existence of localised knowledge with strongly limited connections beyond a given neighborhood, a network architecture, learning or adaptive behavior and estimation or prediction abilities. Additionally to the submodel principle, the automatic decomposition approach itself is expected to be applicable to autonomous agents as well, moreover, agents could be dynamically set up, grouped or split up according to various efficiency criteria, such as learning ability or skills of predicting relevant events.

It is envisaged that such a multi-agent system can be erected as a higher level envelope for lower level production control to determine an efficient initial layout of entire production plants or provide decision support for their reorganisation.

8. CONCLUSION

The first part of this paper highlighted fundamental phenomena equally shared by higher and lower levels of manufacturing (complexity due to a dense network of interdependencies, and a large number of relevant system parameters). To handle these in various types of problems, a family of ANN-based methods was presented (classical modelling, problem solving, optimization and submodel decomposition) which can be equally applied in lower and higher hierarchical levels of production. To demonstrate their versatile applicability, examples of practical use were shown for various levels of manufacturing systems. While submodel decomposition, combined with a flexible multi-agent system, is still subject to research, previous examples support the assumption that the submodel decomposition technique, applied this far only to monitor production lines, can be used in the highest hierarchical levels of a production plant as well.

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