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Gentelligent processes in biologically inspired manufacturing

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ABSTRACT

Production systems have to meet quality requirements despite increasing product individuality, varying batch sizes and a scarcity of resources. The transfer of experience-based knowledge in a flexible and self-optimizing production and process planning offers the potential to meet these challenges. Biological systems solve conceptually similar challenges pertaining to the transfer of knowledge, flexibility of individual reactions and adaptation over time. Thus, in the context of digital transformation, mechanisms derived from biology are interpreted and applied to the knowledge domain of production technology. To be able to exploit the potential of bio-inspired production systems, genetic and intelligent properties of technical components and machines were identified and brought together under the concept of "Gentelligence". Expanding upon this concept with the new idea of process-DNA and biologically inspired optimization algorithms facilitates a more flexible, learning and self-optimizing production, which is shown in three different applications. By using the new concept of gentelligent process planning it is possible to determine machine-specific process parameters in turning processes in order to ensure appropriate roughness within the requirements. Furthermore, the combination of the concept with a material removal simulation allows the determination of the resulting process force in tool grinding for subsequent unknown workpiece geometries. As a result of using the process-DNA, a workpiece-independent knowledge transfer and thus process adaptation for shape error compensation becomes possible. Gentelligent production scheduling enables a process-parallel, holistically optimized machine allocation, and as a result, a significantly reduced lead time.

Introduction

Today, production systems are challenged with an increasing individuality of products in varying batch sizes. Additionally, the processes must be resource-efficient and economical. Flexibility and self-optimization are key factors for an economic production. Increasing flexibility and at the same time meeting the quality requirements of diverse products is a major challenge. The transfer of experience-based knowledge in a flexible and self-optimizing process planning and production scheduling offers the potential to meet these challenges.

Solutions based on biology enable the implementation of flexible and self-optimizing production systems including a transfer of knowledge. Thus, in the context of digital transformation, dependencies and correlations derived from biology are interpreted and applied to the knowledge domain of production technology [1]. Moreover, the concept of biological transformation, based on insights from life sciences and tools of digitalization like artificial intelligence, introduces a new dimension of sustainable production [2]. With regards to manufacturing technology, the connection between genetics and intelligence appears very promising in addressing the aforementioned challenges [3,4].

Within the Colaborative Research Centre (CRC) 653 this idea was already adressed in 2005 by defining the term "gentelligence" [5]. Interdisciplinary research has laid a broad foundation for the use of biologically inspired manufacturing. More than 450 publications had been released leading up to the completion of the CRC 653 in 2017 [6]. In addition, the Institute for Product Development and Machine Design (IPeG) was established in 2010 at the Leibniz University in Hanover, Germany, which continues to research methods for product development throughout the entire life cycle and across generations under the heading of "technical inheritance" [7].

This publication enhances the concept of gentelligence with the new idea of process-DNA as a biologically inspired method for knowledge transfer by using process components of simulation, process and quality data. It is shown how biologically inspired algorithms can be integrated to optimize process and production

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planning. Three different applications demonstrate, how the vison of extended gentelligent manufacturing is brought into practice. The use cases from the areas of process planning and production scheduling demonstrate a wide range of possible applications for the new concept as well as the potential which can be tapped.

State of the art

Biologicalisation in production

Bio-intelligent manufacturing represents a new field of research with the potential to change the traditional value creation drastically by using bio-inspired manufacturing technologies, which have to be targeted as a field of further action [8]. By using biological manufacturing methods, flexibility, adaptability as well as the structure and behavior of natural life forms and organisms can be applied to production [9]. Furthermore, biologically inspired intelligent manufacturing provides a tool for a sustainable and resource efficient production by combining biological principles with digitalization [10].

The growing variety of products leads to increasing complexity within the tasks of process planning as well as production planning and control (PPC) [11]. For this reason, both areas require optimization, which is often achieved by biologically inspired approaches. For example, a genetic algorithm is a process, characterized by DNA approaches. Zhang et al. [12] use this in in order to solve the issue of flexible job shop scheduling. In process planning, genetic algorithms are also applied within several approaches [13]. Another solution for job shop scheduling optimization is based on particle swarms [14]. Particle swarm optimization is also used in process planning in order to improve set-up [15]. Moreover, a similar approach to that used by ant colonies can be implemented in route determination of production systems as well as in planning and control decisions [16,17]. Ant colonies are frequently examined in connection with flexible manufacturing systems [18,19] but are also used in the optimization of process planning [20,21]. The concept of DNA based on Ueda et al. [22] is used for the self-optimizing control of transport units.

To solve these optimization problems, prediction models are often required. By modelling complex systems, multi-objective optimizations can be carried out, for which biologically inspired methods are also widely used. Artificial neural networks (ANN) are used to map complex relationships in production. ANN are used in process planning to optimize cutting parameters [23] or to determine the processing sequence [24–29].

However, the above mentioned approaches are only components of a bio-inspired production. Thus, the potential for improvement is also limited to the individual optimization scenarios. An overview of more superordinate concepts can be found in publications by Dias-Ferreira et al. [30] and Byrne et al. [1]. According to Dias-Ferreira et al. [30] modern bio-inspired production systems encompass bionic manufacturing systems (BMS), holonic manufacturing systems [31], reconfigurable manufacturing systems [32] and evolvable production systems [33]. Byrne et al. [1] also mention BMS and holonic as well as agent-based systems as bio-inspired approaches for production systems to realize a biological transformation in manufacturing.

Agent-based applications are examined in biological PPC approaches [34] as well as in process planning [35,36]. The main added values of agent technology are flexibility, control, decentralization and robustness in manufacturing [37]. Holonic manufacturing systems consist of autonomous modules with a distributed control and combine the best characteristics of hierarchical and heterarchical organization. Most applications focus on dynamic scheduling [38,39] or real-time production rescheduling [40].

The previous approaches cover an essential part of production system management, but a complete integration of all tasks related to process planning as well as production planning and control is missing. A concept is needed which allows bio-intelligent manufacturing in one complete system. Intelligence is defined based on Albus [41] as the ability of a system to act appropriately in an unfamiliar environment to increase the probability of success and support the system's ultimate goal. According to Albus, intelligence develops in natural systems over the lifetime of an individual via maturation and learning as well as over generations by evolution. Learning is not required in order to be intelligent, but rather intelligence must be gained as a result of experience. Learning is defined as consolidating short-term memory into long-term memory and exhibiting altered behavior influenced by such recollections. Biological intelligence is defined as the ability to meet the ultimate goal of biological creatures, which is gene propagation. The success criteria are defined by the process of natural selection [41].

The information and values which a system has stored in its memory are very important and must be involved. Thus, an essential part of the overall concept for bio-intelligent manufacturing should be the ability of lifelong learning of all production units. To address this aspect, the following section introduces the concept of gentelligence.

Concept of gentelligence

To be able to exploit the potential of bio-inspired production systems completely, the concept of technical inheritance and especially the idea of "gentelligence" was developed within the CRC 653 in 2005. The aim was to develop components that independently monitor their condition, know their life expectancy and, if necessary, independently initiate an inspection. To achieve this goal, the combination of genetic and intelligent properties were identified as key features of technical components and machines.

As shown in Fig. 1 genetic properties enable the transfer of information to subsequent product generations. For this purpose, this information (e.g. geometry, material, process parameter) is stored as static and unalterable data in the component.

Intelligence is intended to ensure lifelong learning during production and use of products. It is created by the component's technical ability to autonomously and inherently store and process information (e.g. the effects of mechanical and thermal load during their production and life-cycle). Suitable materials and sensor technologies are integrated into the components for this purpose. The entirety of the collected information is inherently connected to the gentelligent component and always accessible. The use of such gentelligent components in production opens up new degrees of

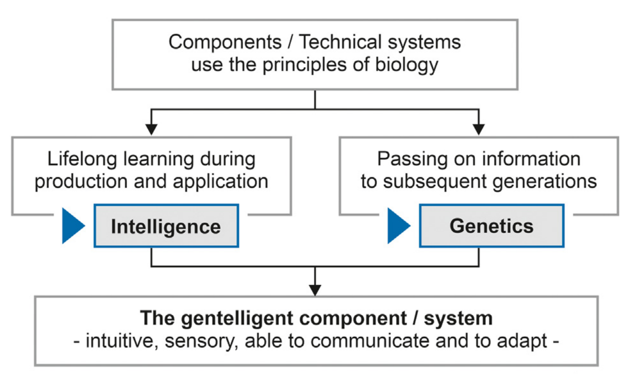

Fig. 1. Definition of gentelligence [5].

freedom for planning, control and monitoring of complex production processes. However, the large amount of available production information initially increases the complexity of the production organization. To solve this challenge, the concept of the virtual planner was developed to aid in the organization of a gentelligent production and to exploit the potential of intelligent components [5].

As shown in Fig. 2, the virtual planner enables the networking of all information relevant to the production process in a closed information structure and integrates the tasks of process planning, process adaption as well as PPC in one system. As a result, it virtually links the autonomous and gentelligent production units to cyber-physical systems with the aim of realizing a flexible and undisturbed production [42]. The consistent feedback and processing of information creates a knowledge database that enables continuous improvement of the virtual planner's functionalities, transforming it into a gentelligent planner.

Gentelligent process planning

Concept of process-DNA

The usual process steps of process planning to generate the NC-code for manufacturing are extended comprehensively within the following concept. A gentelligent process planning will be realized by using process-DNA within the virtual planner.

For an improved transfer of knowledge in machining, the database of the virtual planner uses the principle of “process-DNA” which is derived from biology and visualized in Fig. 3. Similar to the storage of information contained within genetic sequences in biology, the existing historical data from previous processes and workpiece generations can be stored for later use. For this purpose, the process is divided into generalizable process increments. These increments represent the process-DNA, which is then used to enable the knowledge transfer.

Process-DNA is defined as a combination of time-dependent and shape-independent attributes which define local cutting conditions as identifiers (IDs) and different data types which are linked to these identifiers.

The ID in combination with the linked data is used in a way which is conceptionally similar to that of DNA in biology, which also stores and encodes information, in that case relating to the development and function of a living being. Specifically, the ID, which is also described as a set of features, can be used to transfer information about historical processes or quality data to new workpiece geometries, local workpiece positions or process states. Each increment can be enriched with local process data (e.g. forces, spindle torque or drive currents) and quality data related to the product (e.g. shape deviations or surface roughness). In the case of machining processes with complex cutting conditions, which change locally and as a function of time, a numerical material removal simulation is used for the calculation. The simulation can be understood as a soft sensor and makes it possible to include the local and time-dependent cutting conditions of each increment as simulation data and identifiers in the process-DNA.

The machining knowledge is generally applied by a so-called genetic knowledge transfer. Every process generates data, which is the reason why the process-DNA will be constantly changed and added to. Similar components lead to similar genes, while the level of knowledge and diversity is considerably increased by data from entirely different components or processes. Errors and uncertainties in the derived process models can be understood as an analogy to mutations, which, under certain circumstances, can have a positive effect on the validity of the model. On the other hand, these mutations also bear the risk of creating expensive errors which require careful revision.

Fig. 4 details the underlying approach for using process-DNA in the concept of gentelligent process planning. It is illustrated, how the knowledge obtained from the manufacturing processes of previous workpieces can be applied independently to the process and the shape of the current workpiece. In this context, the knowledge is stored in shape-independent features of local cutting conditions as identifiers in order to apply knowledge to a new process situation or workpiece shape. This is accomplished by

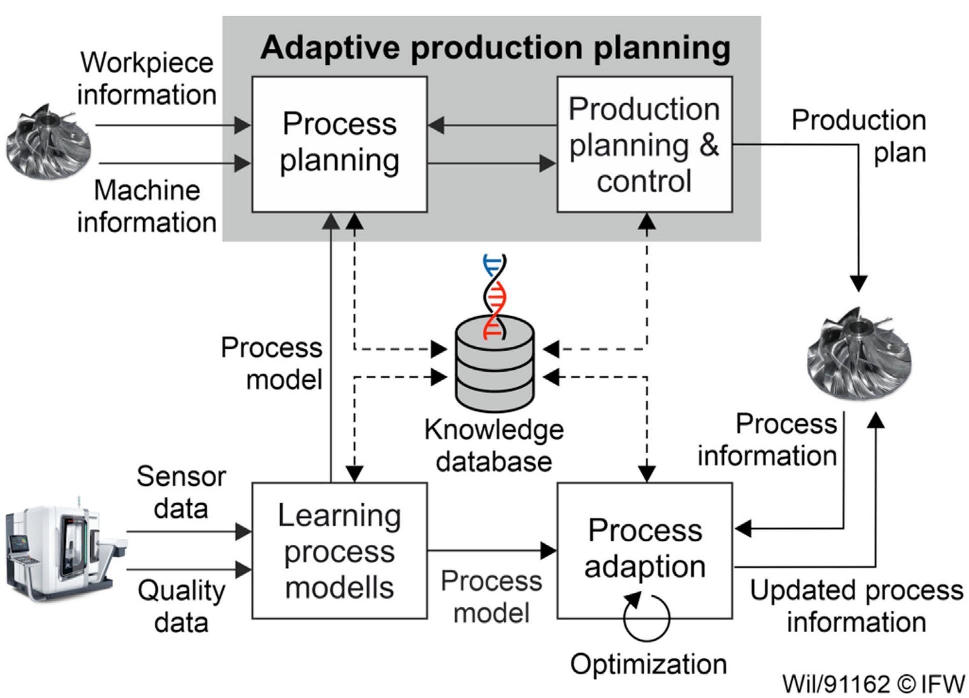

Fig. 2. Virtual planner for gentelligent manufacturing (based on Ref. [58]).

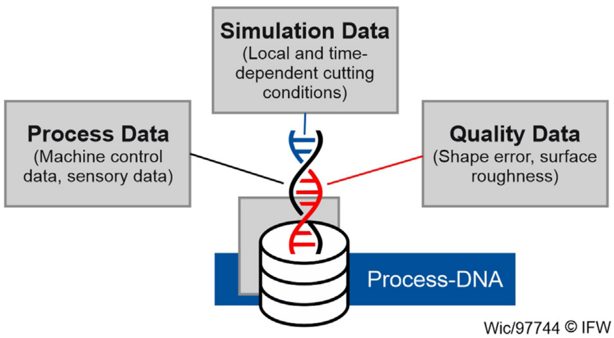

Fig. 3. Concept of process-DNA.

using the initial NC-code, which results out of Computer Aided Manufacturing (CAM) during process planning, in a previous material removal simulation to calculate the local cutting conditions of the actual workpiece. These are used as identifiers or indicators of the current process situation. The learning models, which have been constructed prior to this with the historical data in the process-DNA, are used to make predictions for the local process or quality target values.

It is thereby possible to transfer knowledge regarding a specific process state or local shape to the manufacturing process of the current workpiece. Afterwards, an automatic adaption of the initial NC-code will be conducted based on the gentelligent methods in the optimization phase. The aim is to predict and improve the resulting workpiece quality and process performance by optimizing the process parameters and adapting the tool paths.

Machine learning algorithms are applied to extract the knowledge from different data types in the process-DNA. Based on learning process models, suitable process parameters are selected with the help of biologically inspired heuristics and iteratively optimized with respect to target values. The optimization process is also biology inspired and can be carried out by a particle swarm optimization. Process data as well as information about materials, tools and the corresponding quality values of past processes are used as gentelligent input for modelling the process-DNA. Additionally, simulation data can be used to gain detailed information about processes with locally changing cutting conditions. In the context of gentelligent process planning, a material removal simulation can be implemented as a preliminary simulation of new processes based on the NC-code. It is thus possible to calculate the local cutting conditions as indicators for the learning process models to make predictions for the process adaption in the optimization loop. Furthermore, a process parallel simulation can be implemented on the basis of the real axis positions to calculate the local cutting conditions based on the real movements of the machine tool. In this way, the database can be expanded with the realistic local cutting conditions of each process during production. This information is used to gain further process knowledge, such as the correlation between the tool engagement and measured cutting forces [43].

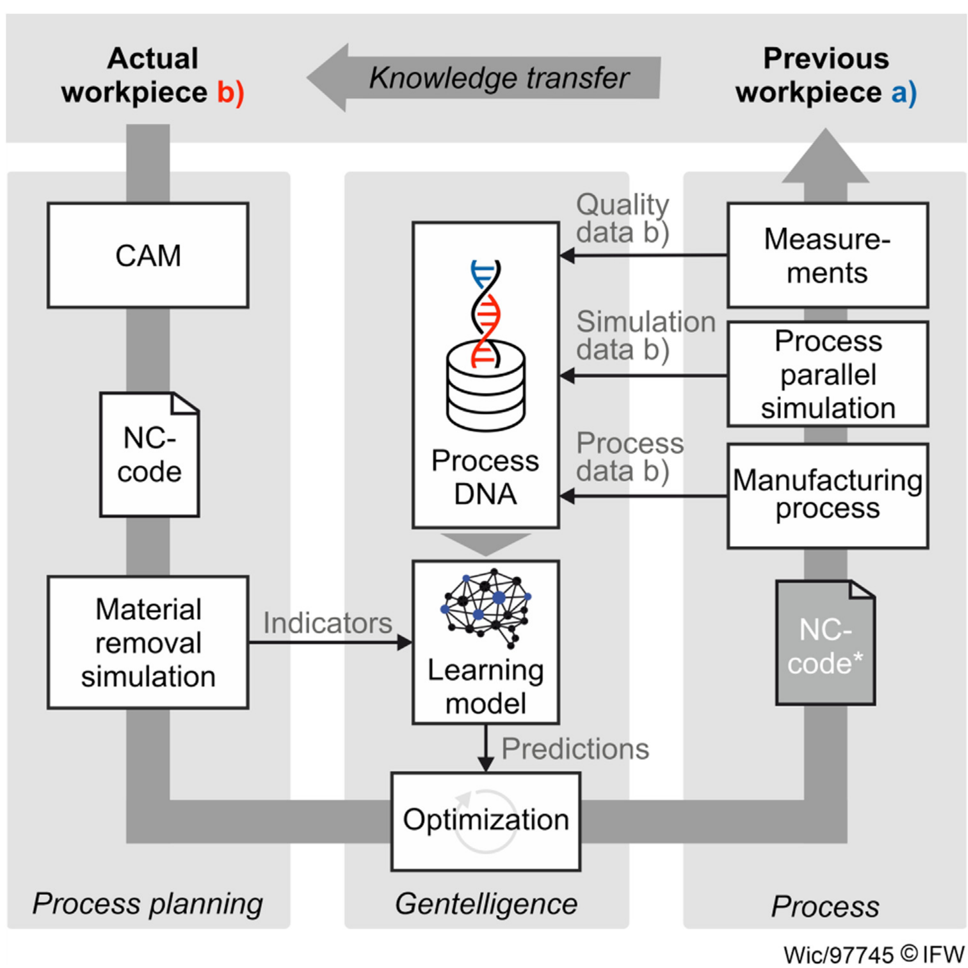

Fig. 4. Concept of gentelligent process planning.

Previous investigations defined the parameters of a process-DNA based approach to knowledge transfer in the gentelligent process planning of milling processes [44]. It was established using workpieces of two unique geometries that a support vector machine (SVM) model which had only been trained with data from one workpiece geometry can also be used to predict the resulting shape error for another workpiece geometry successfully. The maximum shape error can be decreased for both geometries based on an adjusted tool path generated with the prediction model based on information from the first workpiece [44].

Having already demonstrated the potential of the new approach for milling processes, the applicability for turning and grinding processes is examined in the following. The different engagement conditions as well as the strength of the characteristics of the input variables to the target variable in turning and tool grinding require a different number of input variables. The main influence of the feed rate on the surface roughness is already understood for turning processes [45]. Therefore, the process behavior can be represented by gentelligent feedback information. In contrast, helical groove grinding processes of cylindrical round tools are characterized by a complicated 5-axis kinematics with a complex curved contact zone and locally varying loads on the grinding wheel [46]. The resulting shape error caused by the grinding forces and the workpiece deflection is one of the main challenges [47,48]. A process adaption is necessary to compensate the shape deviation. A transfer of machining knowledge between different workpiece geometries would be very helpful in cases with small batch sizes to reduce the setup times for process run-in.

Knowledge-based planning of turning processes

In order to reschedule production orders rapidly, a method is required that quickly determines alternative process parameters, e.g., cutting speed, feed rate, while maintaining the capabilities of the respective machine. In addition, the process parameters must be selected in such a way that a required target value (here surface roughness) can be met. The following approach was developed to provide optimized process parameters for turning that enables automated knowledge-based detailed process planning. Fig. 5 shows the procedure for the determination of new process parameters via optimization.

The aim is not to improve the prediction of roughness in general, but to present a method that enables machines to predict the roughness to be achieved and thus derive machine-specific process parameters. The procedure accesses the process-DNA consisting of past process parameter of one specific machine in a knowledge database. The first step is to extract the required information from the DNA by sequencing. The Process DNA is composed of historical process data, coupled with the underlying features of the geometry (shape element) with constant cutting conditions. For this purpose, the recorded process data is analyzed by a self-programmed allocation algorithm and divided into part-related form elements. By using time stamps of the data, a relation to the process control variables can be established. Enriched with the recorded quality variables and tool information, the database is used to train the machine learning-based process model. Applying this process model, a process adaptation is carried out by determining and optimizing new process parameters. For this

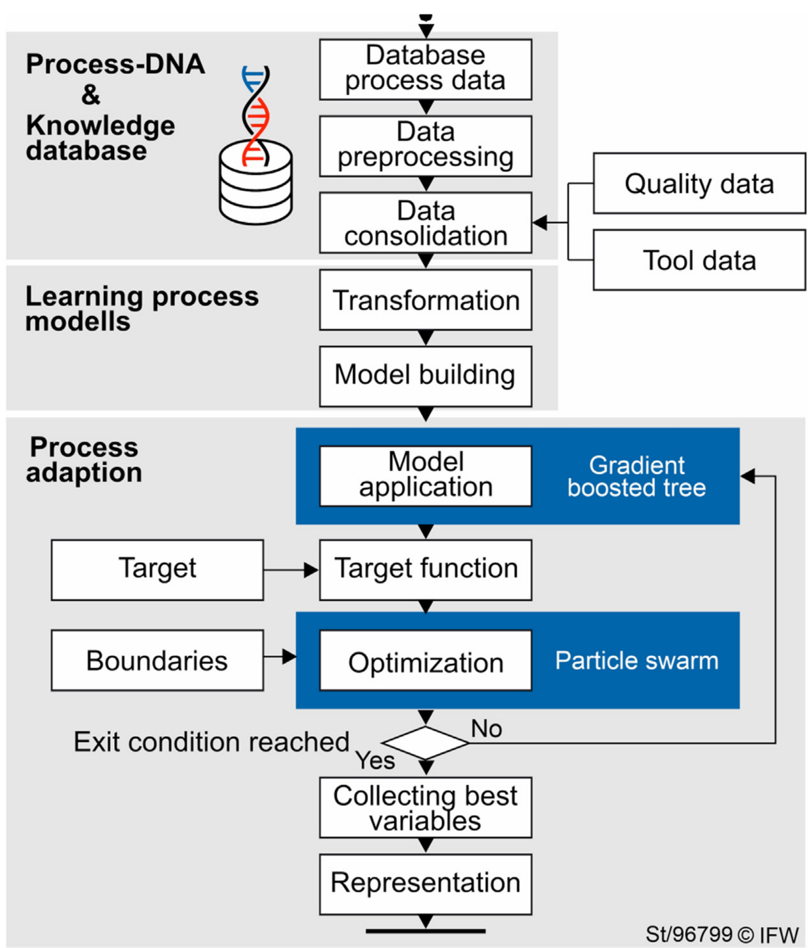

Fig. 5. Procedure for determining new process parameters.

purpose, an iterative sequence of process model, target value comparison and optimization within the given boundaries is used. The number of selectable alternatives is determined by the number of iterations.

To determine suitable process parameters for turning, surface roughness was selected as the target value for process modelling. As relevant input parameters, gentelligent information was selected such as feed rate f, cutting speed v_c, cutting depth a_p and identity of the tools in question. The tools are summarized as categories by combining setting angle and corner radius. Here, W1 ($r_\varepsilon = 0{,}8$ mm, $\kappa = 93°$), W2 ($r_\varepsilon = 0{,}4$ mm, $\kappa = 45°$), and W3 ($r_\varepsilon = 0{,}8$ mm, $\kappa = 95°$) were used for machining. For process modelling a weak learner is used as regression method, e.g. a gradient boosted tree algorithm. The basis of this algorithm is a decision tree, which arranges decision rules according to a biological tree structure (recurring division into two branches) to solve complex problems [49]. In the next step, the model for predicting the surface roughness Rz is built by applying a hyperparameter optimization. For validation, the data set was divided into training and test data. The evaluation was carried out by repeating the learning process 5000-times, varying the training and test data.

The optimization and determination of new process parameters takes place by applying the model to predict surface roughness of new process parameters determined by a metaheuristic. The aim is to achieve an exact surface roughness by combining feed rate, cutting speed, and cutting depth by an optimization algorithm. Thus, alternative process parameters are determined to achieve the required roughness. An optimization regarding tool wear is not included in the model. In order to meet the goal of a quick response, a metaheuristic is used. Nevertheless, a wear analysis of the alternative process control variables can be performed. As optimization algorithm, the use of a particle swarm optimization, is implemented. The metaheuristic provides a better result for optimization problems in many cases compared to other common metaheuristics, while comparatively few parameters have to be selected [50]. Derived from swarm intelligence in biology, cognitive and social weighting factors are applied to solve optimization problems [51]. The particle movements of the swarm are limited in the solution area by the properties of the machine tool, the tool itself, and the roughness model. Thus, the solution area is always adapted according to the requirements and stable process parameters are ensured. The algorithm searches for the best global position of all used particles. The swarm contains 50 particles at 20 iterations and a randomly selected start position. An adjustment of the hyperparameters is done by grid search.

The target function is defined as squared deviation of the desired target roughness to the predicted roughness. The optimization run is performed 25 times to create 25 different alternatives. As a recommendation, a list of specific process parameters is represented. From this list, the respective process parameters can be selected or further processed.

To evaluate the accuracy of the function, the particle swarm optimization was applied to a recorded data set and checked for quality and uncertainties. The relative difference (x) of the target (y) and the predicted roughness (y_{pred}) were considered, as shown

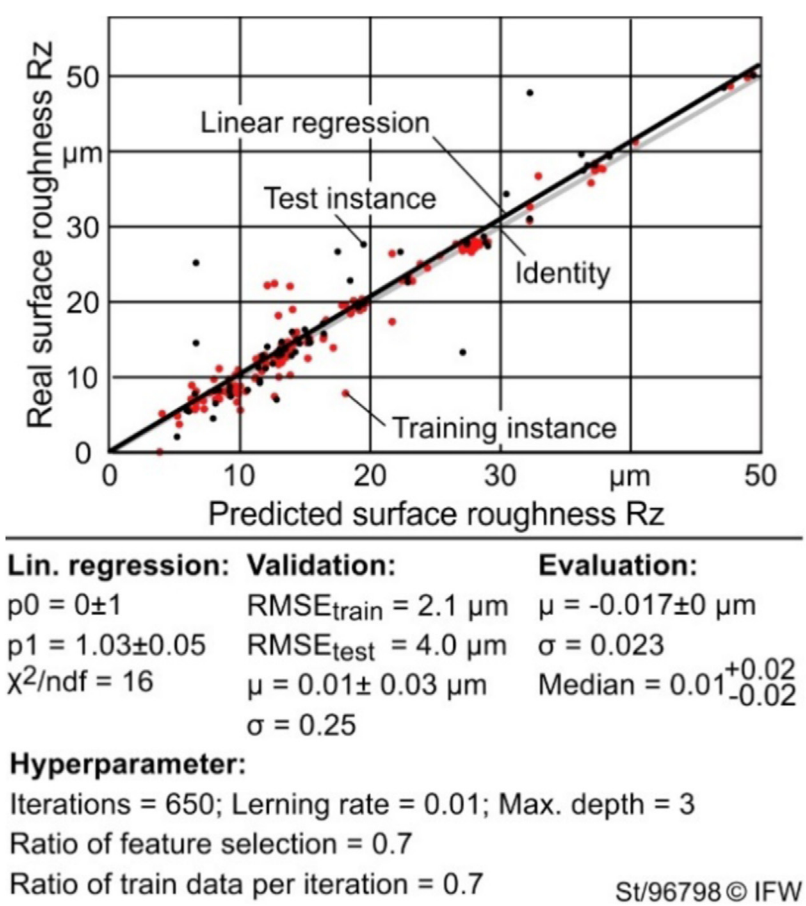

Fig. 6. Validation of the process model.

in Eq. 1. For this purpose, 25 repetitions were carried out in steps of one per target variable (in a range of 7–50 μm) to determine process parameters for one tool each.

$$x = 2 \cdot \frac{\left(y - y_{pred}\right)}{\left(y + y_{pred}\right)} \tag{1}$$

The application was implemented as a software assistance system in Visual C# and Python. The collection of the data set and the tests for evaluation have been carried out on a DMG MORI CNC universal lathe NEF 400. The scope of the data set includes 242 test work pieces. An unalloyed steel (1.503) was used as material. The surface roughness was measured by a mobile roughness tester Hommel Etamic W5 (measuring range/resolution: ±100 μm/6 nm [52]). In Fig. 6, the results of the model evaluation of the process model are shown by a comparison of the predicted surface roughness to the real surface roughness.

A linear regression based on test instances shows a reasonable approximation of the identity. It has been established that on average, the predicted and real surface roughness show a relative difference in the lower percentage range (an accuracy of 99%) with a precision of approximately 25%. On repeating tests, the model shows a mean value of the relative difference of 0.017 μm with a standard deviation of 2.3 μm. The negative relative difference leads to the conclusion that, based on the recorded data, the average results contain an upward skew. Of particular interest is the difference between the RMSE of the training (2.1 μm) and the RMSE of the test set (4.0 μm). This deviation exhibits a generalization gap of the model, which can be attributed to the limited number of instances of 242. The results of the particle swarm optimization analysis are shown in Fig. 7.

On average, the relative difference of the target and the predicted surface roughness based on optimized process parameters depended on the tools selected. Tool W2 shows a suitable application in the area of higher target values (20–50 μm), whereas tool W1 and W3 tend to perform better in the lower target range (7–20 μm). The differences between tool W1 and W3 can be attributed to the distribution of the input data. Tool W1 has fewer values in the range (20–30 μm). In contrast, there are several values within this range in the input data for tool W3. For tool W1, there are also significantly more input data, see Fig. 8. The mentioned algorithm reacts sensitively to the amount and distribution of the input data, which causes these differences.

Even with small data sets of a few hundred instances, the system allows for applicable process parameters for manufacturing in the turning process at a specified surface roughness Rz. For example, using the proposed process parameters, a roughness between approx. 8.7–10.7 μm was achieved in tests using all tools, with a target value of 10 μm, as shown in Fig. 8. In these tests the process parameters determined by the system deviated from the target value by approx. 7–12 %. The tests show a small deviation value of 7% for tool W2, for which there are significantly more input instances than for the comparison tools. A further improvement of the model and increasing generalization of the method is expected by an extension of the data set.

By selecting the regression method and subsequently ensuring its precision, the practical requirements are met. The focus is on

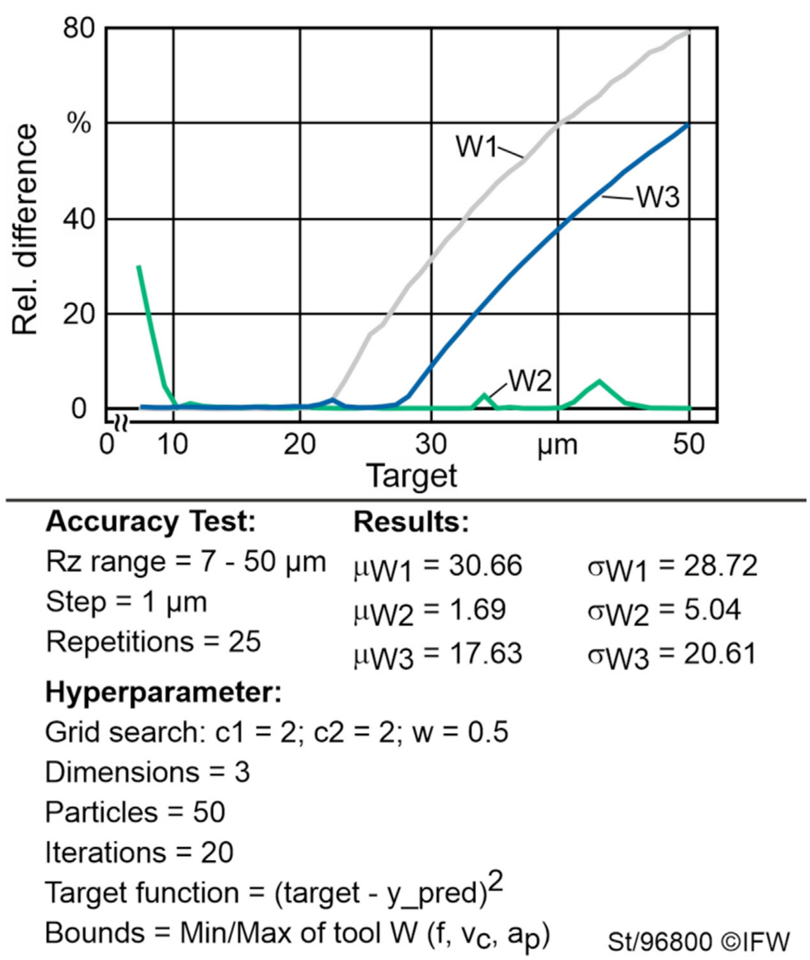

Fig. 7. Analysis of the particle swarm optimization.

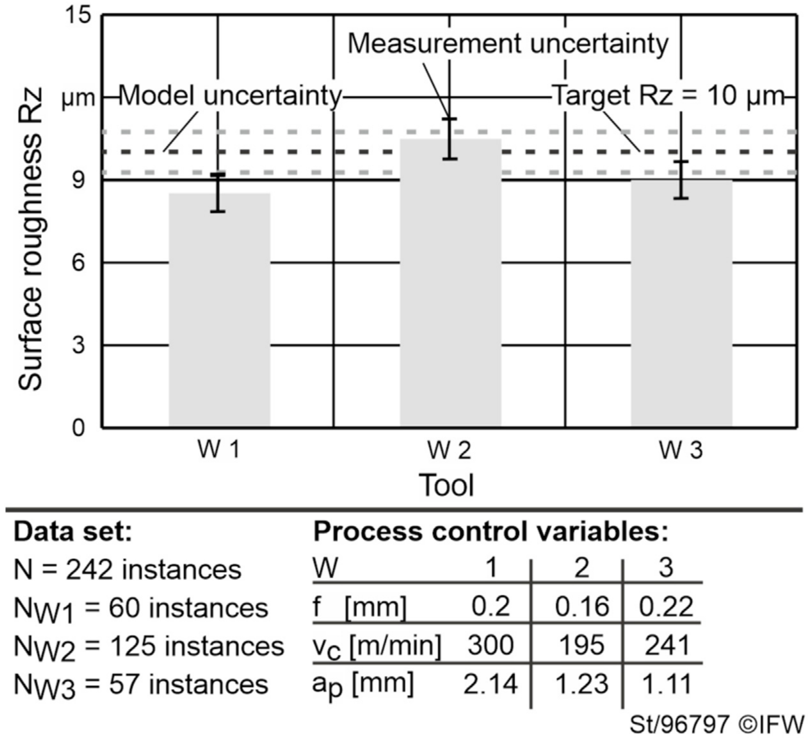

Fig. 8. Spot check of knowledge-based process planning.

the fact that the target value surface roughness can be determined in a wide range (depending on the roughness values available in the historical data) new process parameters recommended within the range. Using a gradient boosted tree, it was possible to minimize the number of required input instances. With the help of the developed automated knowledge-based detailed process planning it is possible to determine machine-specific process parameters in the turning process with a required cross-tool surface roughness. Cross-tool means in this case that the algorithm selects the tool with which the roughness can be achieved. Furthermore, this enables inheritance across component generations and provides a quick response for scheduling.

The presented algorithm can suggest new tool categories (different setting angles and corner radii) and process parameters by learning with the historical tool categories and process control variables. The knowledge implied in the data is thus transferred to other components (inheritance). In addition, the automatic determination of new process control variables speeds up detailed process planning, allowing for quick response in case of rescheduling. The application of biologically inspired algorithms (here the combination of a gradient boosted tree and a particle swarm optimization) based on the process-DNA, helps to achieve satisfactory results even with a small number of instances, to store knowledge for detailed process planning and to transfer it to other processes. The property of the biology-based algorithms also supports traceability and thus enables fast, traceable results. A current major limitation of the model is the present low number of instances, which reduces precision and generalized application.

Adaption of tool grinding processes

The following approach is developed to realize a process adaption and a knowledge transfer in tool grinding processes. These methods of the virtual planner are used to predict and compensate resulting shape errors and optimize the process parameters. Similar to the previous section 3.2 learning process models and the concept of process-DNA are applied. In contrast to turning processes, tool grinding processes are characterized by a complicated 5-axis kinematics with a complex curved contact zone. To describe the local cutting conditions, material removal simulations are needed. In addition, the challenges of small batch sizes and extensive set-up experiments require a transfer of knowledge between different workpiece geometries.

To solve these challenges, an automatic adaption of the NC-code based on the concept of gentelligent process planning is used, as shown in Fig. 4. Moreover, a knowledge transfer between different workpiece geometries realized by the concept of process-DNA is investigated. To build up the specific process-DNA for the tool grinding process, a material removal simulation with grinding wheel segments is used. Thereby, the grinding process is divided into individual process increments for which the corresponding local cutting conditions are calculated as the simulation data of the process-DNA. In the investigations, the dexel-based material removal simulation software IFW CutS [53] is applied to analyse the complex curved contact zone along the axial position of the grinding wheel. In this study, the grinding wheel is divided into 40 disc-shaped segments with a width of b_i = 0.25 mm. For each segment, the maximum geometrical contact length l_g, equivalent chip thickness h_{eq} and material removal rate Q'_w were calculated. The local simulation data will be combined in a vector of shape-independent features, which are represented here by typical grinding parameters. These are combined in the vector X.

$$X = \left(Q^{'}_{W}, l_g, h_{eq}\right) \tag{2}$$

The grinding parameters in the vector X represent the influences of the workpiece geometry, grinding wheel diameter, local grinding wheel infeed a_e, grinding wheel shape and the process parameters feed rate v_f and cutting speed v_c. For the simulation of the local cutting conditions, the workpiece is discretized with a Cartesian multi-dexel model. The dexel grid distance is set to 80 μm and the time steps of the simulation to 0.1 s aiming for a compromise between accuracy and computational effort. The grinding wheel is described by a triangular mesh. The secant errors depend on the accuracy of the tessellation file. This has to be considered regarding to the quality of the simulation. IFW CutS is used for pre-simulations. It is able to use the same NC-code as the real machine tool, if a parameterized machine model exists. To realize a permanent calculation of simulation data for the process based on the real movements of the machine tool to create a larger dataset in the process-DNA, the usage of a process parallel material removal simulation as an additional soft sensor is investigated.

In order to implement a process parallel simulation as a soft sensor, the real axis positions out of the machine control are used to navigate the simulation. For the investigations a Walter Vision 400 L machine tool with a FANUC machine control (Series 30i-MODEL B) is used. The proprietary interface FANUC Focas 2 is used as the gateway. The axis values are read out via a LAN port and transferred to IFW CutS. The process parallel simulation generates simultaneously to the process itself the local cutting conditions for the process-DNA. The material removal on the cylindrical workpiece is displayed in soft real time. The system can continue to work in a stable manner, even if individual implementation steps may take longer or the quality of the result is affected. In addition to the axis data, other internal control data such as the spindle power, the currents of the axis drives or the unexpected spindle load torque can be also read out at a frequency of 70 Hz. Fig. 9 depicts the kinematic model of the grinding machine and the process parallel simulation.

The simulated local cutting conditions of the process increments are subsequently extended by local process data, which can be measured by sensors or extracted from the machine control. Pre-investigations showed that the spindle load torque (DTRQ) has a proportional correlation to the resulting process force.

Direct force measurements are only possible on a tool grinding machine with a cost intensive integration of a 3-component dynamometer, which is not feasible for industrial use. Process data, which can be read out directly from standard machine control systems, is much more suitable.

DTRQ can be extracted directly from the FANUC machine control and is determined by using the unexpected disturbance torque detection function. It is calculated by the difference between the measured spindle torque $M_{S,meas}$ and the expected spindle torque $M_{S,exp}$ relative to the maximum motor torque. $M_{S,exp}$ is calculated by including the actual cutting speed. The unit of DTRQ is given in percent, as it is set in relation to the maximum motor torque. All torque values are based on the measured and expected currents of the spindle. In this context, DTRQ is used accordingly to predict the resulting total force F_{res} for the tool grinding process. Previous approaches in which empirical models are used tend to be rigid. By using the process value DTRQ, existing models can be adapted to new conditions by permanently reading out current data. In preliminary surface grinding studies, a conversion equation based on force measurements with a 3-component dynamometer was developed for DTRQ [54]. After examination of all forces and DTRQ values the resulting force can be calculated as:

$$F_{res} = DTRQ \cdot (0.833 \cdot v_c + 22.5) \tag{3}$$

The equation includes a correction factor, which depends on the cutting speed. This factor compensates the deviation of the spindle motors torque at higher cutting speeds. The deviation is caused by field weakening or an increase of the spindle motor temperature.

To further extend the process-DNA with quality data, the local shape error of the workpiece is measured. In the case of helical groove grinding, the core diameter deviation can be used as an indicator for the resulting shape error. For a derivation of the local simulation, process and quality data, machine learning methods are used finally to create learning process models.

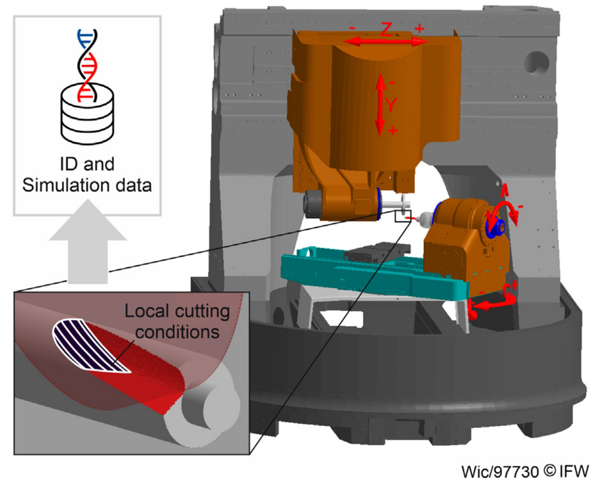

Fig. 9. Process parallel material removal simulation.

For further investigation, a preliminary SVM model is derived. The process-DNA as the database of this modelling is formed by the simulated local grinding parameters, which are combined in the vector X as well as the DTRQ values out of the machine control. The values are used as an input for a SVM regression to derive a prediction model of DTRQ, which is used to calculate the resulting process force with Eq. (3).

The approach of a knowledge transfer by process-DNA has been validated in tool grinding experiments with different workpiece geometries. For this reason, helical groove grinding processes of drilling tools are carried out on a Walter Vision 400L machine tool in which the process force prediction is investigated. In the experiments, Tigra T10MG cemented carbide rods with a diameter of 6 mm and a length of 93 mm are used. Two experimental test series are performed. First, the geometry of a workpiece A (helical angle $\lambda = 30°$, core diameter $d_c = 1.8$ mm) is kept constant to gain data-based experience for this geometry. In a full factorial design, the process parameters v_c and v_f are varied in ten different settings to collect the shape-independent features as the simulation data by the process parallel simulation. The features are the local values of the grinding parameters Q'_w, l_g and h_{eq} in the vector X.

In addition, the simultaneous recording of the process value DTRQ is conducted directly from the machine tool. Both data categories generate a database for the machine learning model to predict the process force. An SVM model is build up with a coefficient of determination $R^2 = 0.99$ and a mean absolute error MAE = 0.075. By using the force translation equation (Eq. (3)), the DTRQ value is converted afterwards into a force value. The MAE value of the SVM model leads to an uncertainty in the prediction of the process force of 2.6 N. In the second series, the workpiece geometry is varied to workpiece B ($\lambda = 20°$, $d_c = 2.3$ mm). The vector of workpiece-independent features is used as the identifier for the circumstances of the following component B. For the prediction of the resulting force F_{res} of both workpieces, the SVM model generated by the data of component A is used to calculate the DTRQ value. By using the translation equation, F_{res} is determined. Fig. 10 shows the results of the knowledge transfer using the process-DNA for component A and B. The process forces of the experiment for workpiece A and the validation for workpiece B are calculated by using the measured DTRQ value to show the model accuracy.

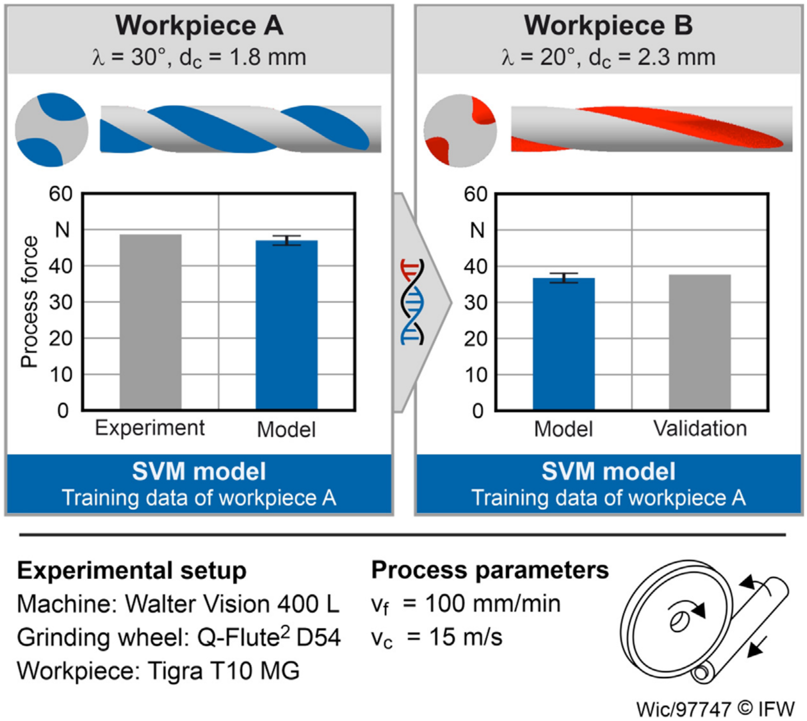

Fig. 10. Validation of knowledge transfer in tool grinding.

As expected, it is shown that geometry B leads to a changed process force for the same process parameters v_c and v_f due to a change in core diameter and a smaller helix angle. In addition to the verification of the expected force behaviour, it is thus possible to predict the resulting force value on the basis of the model accuracy.

Using the NC-code for the process of geometry B, a preliminary simulation is carried out to calculate the vector of workpiece-independent features. By using the prediction model of component A and the specific process-DNA it is possible to determine the force for a subsequent process with a deviation of 2.6%. A feature-based knowledge transfer by using the process-DNA is thus possible. The presented data and results demonstrate the application possibilities of the process DNA for a knowledge transfer and are regarded as an example of its utilization. Similar results were achieved in other grinding experiments in which 60 data points differ according to the workpiece geometry ($\lambda = 3–40°$, $d_c = 1.3–3.4$ mm), process parameters ($v_c = 12–21$ m/s, $v_f = 50–300$ mm/min) and dressing conditions of the grinding wheel.

The grinding process of round tools needs a specific process adaption to compensate the shape error caused by the grinding forces. Additionally, the process parameters have to be optimized. Currently, these problems are solved by adapting the process in expensive experimental run-in tests. The result is a resource-

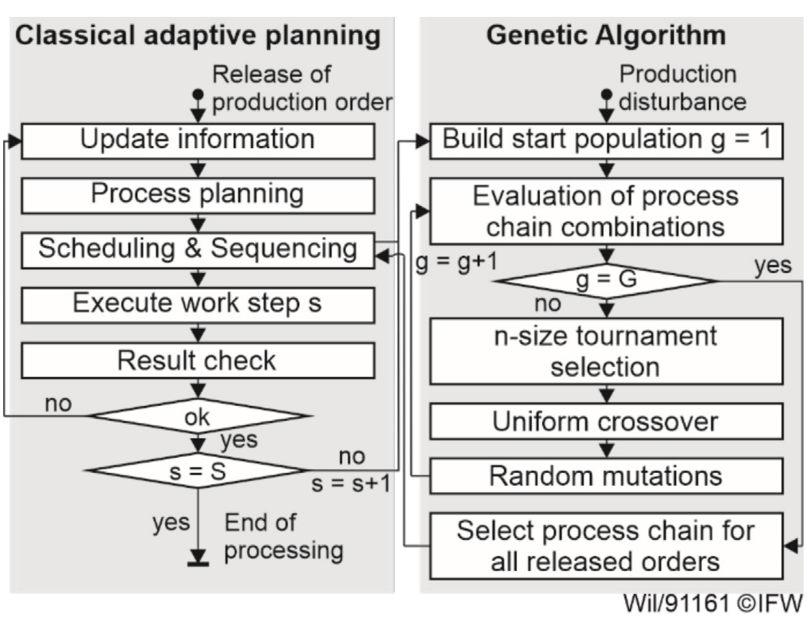

Fig. 11. Optimized adaptive production planning.

wasting process planning. The presented approach is able to predict the process force for the specific situation. By using the concept of process-DNA, knowledge can be extrapolated and transferred to new geometries without the need for additional experiments.

In future research, the predicted force will be used to compensate the shape error by grinding path adaption according to the concept of gentelligent process planning. The aim is a NC-code adaption for shape error compensation and process parameter optimization.

Gentelligent production scheduling

Based on the presented methods for automated process planning, potentials can also be increased in the area of production scheduling. As shown in Fig. 2, a complete integration of process planning and PPC for so-called adaptive production planning by Denkena et al. [55] is realized. The virtual planner links the process chain alternatives and job status information stored on the gentelligent workpiece (cf. [56]) with the latest status information from production units (e.g. availability of machines, workers). Production scheduling is carried out continuously and process parallel to each order, so that the most recent information is always the basis for control decision [57]. The processing times required to evaluate the alternative process chains can be derived from the automated knowledge based process planning, which is presented in chapter "Knowledge-based planning of turning processes". In order to optimize the machine assignments holistically, a bio-inspired genetic algorithm is used in the following to expand the concept of classical adaptive production planning (cf. Fig. 11).

The individuals of the genetic algorithm represent valid process chain combinations for all released orders. The combinations of the start population are randomly drawn from the quantity of all available combinations. To evaluate the fitness of a solution, orders are planned using forward scheduling. The priority sequence in which the work steps are considered is defined by the order release time. The resulting total production time and costs as well as the total reject rate, as a measure of the realized quality, can be evaluated individually or can be weighted and included in a multi-criteria fitness function. Meaningful additional optimization targets, such as due time delivery and minimum work in process, can be easily added at any time to the fitness function due to its modular structure. The selection for a new generation of process plan combinations is implemented as an n-size tournament selection, with n = 3. Three individuals of the parent generation are randomly selected and the best of these three is transferred to the crossover pool for the child generation. This process is repeated until the population size is reached. The selected individuals are crossed with each other in a uniform crossover, randomly interspersed mutations swap single genomes of an individual and thus increase the search space. In order to avoid a deterioration of the solution found, the overall best individual of a parent generation is always transferred unchanged to the child generation.

The potential for savings through the use of this gentelligent production scheduling concept is examined with an exemplary

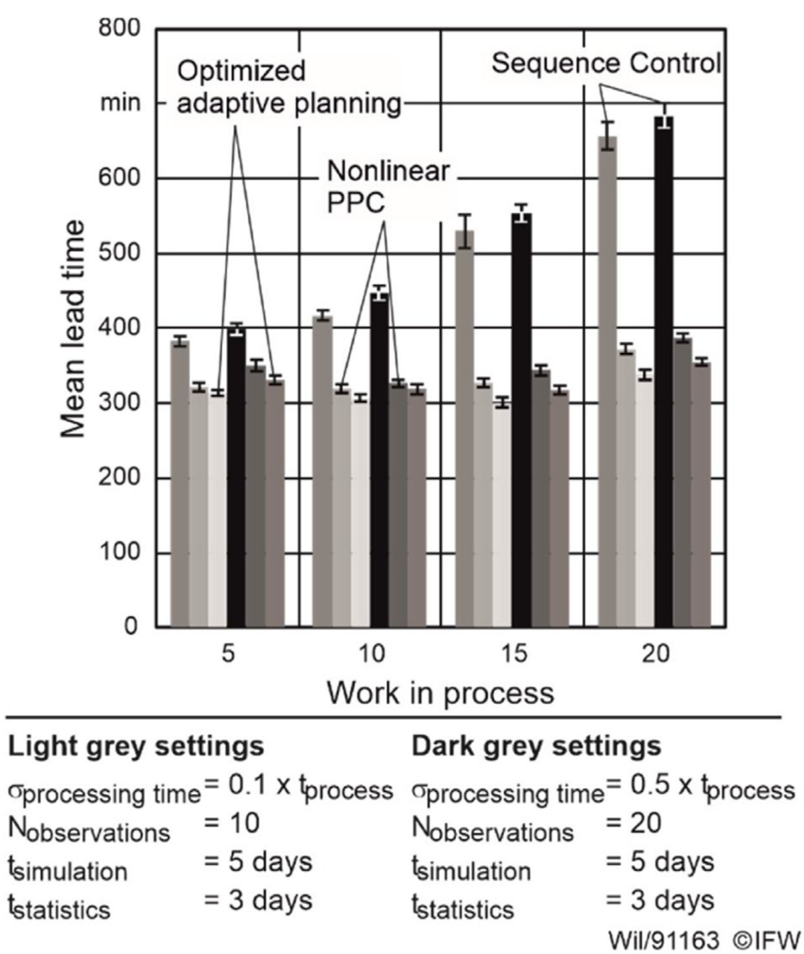

Fig. 12. Mean lead time for different PPC approaches.

workshop production. This is implemented as a simulation model in the material flow simulation software Tecnomatix Plant Simulation. It consists of three alternative machines for the turning, milling and drilling operations and a further nine grinding machines. In addition, there is a machining center that can perform turning, milling and drilling operations. The machines differ in terms of their machining speed, the component quality produced (reject rate) and the respective machine hour rate. The work program provides for the cyclic production of 15 different orders. The number of required operations ranges from two to four. For each order, the available machines as well as machine and operation-specific, stochastically fluctuating processing times are stored in the simulation model. In addition, each machine is assigned an individual reject rate and a machine hour rate. The capacity utilization can be adjusted by varying the number of simultaneously released orders (work in process).

In order to investigate the potential of the new approach, it will be used in the test scenario at different levels of capacity utilization. In the first step, only the resulting average lead time is considered. For this investigation, the fitness function of the genetic algorithm only takes the total production time into account. The simulation time $t_{simulation}$ is five days. In order to exclude ramp-up effects at the beginning of the simulation study, only the last three days are used to record statistical values ($t_{statistics}$). To be able to make a statement about the effect of differently strong fluctuating processing times on the performance of the optimized adaptive production planning, experiments with low and high standard deviation of processing times (10% and 50% of the target processing time) are carried out. To statistically verify the results, the experiments with low standard deviation are repeated ten times ($N_{observations} = 10$), for the experiments with high standard deviation $N_{observations}$ is set to 20. The impact of the workload of the production system on the suitability of the optimized adaptive production planning is investigated by varying the work in process.

A simple control rule (sequence control) and nonlinear PPC are used to evaluate the performance of the new approach. Via the sequence control, possible successor machines of a workstation are always supplied with new orders one after the other. Consequently, all machines allocate approximately the same number of orders. However, differences in processing time, quality or costs are not considered. The nonlinear PPC uses the same genetic and forward scheduling algorithms as the advanced adaptive production planning but standard stochastic effects, such as fluctuating processing times, do not trigger any new scheduling.

Fig. 12 shows that optimized adaptive planning provides better results than the reference methods in all considered scenarios. In particular, it is shown that both nonlinear PPC and optimized adaptive production planning are significantly more stable against load increases than the sequence control.

For instance, with a work in process of 5 orders and a low standard deviation of the processing time, the new approach delivers a lead time that is 18% shorter than that of the sequence control. With a work in process of 20 orders, the average lead time achieved is about 48% lower. The results for a high standard deviation of the processing time are almost identical (17% and 48%). The advantages of the optimized adaptive planning compared to nonlinear PPC are fewer. However, with on average 2.22% to 9.26% and a probability of error of 0.1, they are still in the statistically significant range in most cases.

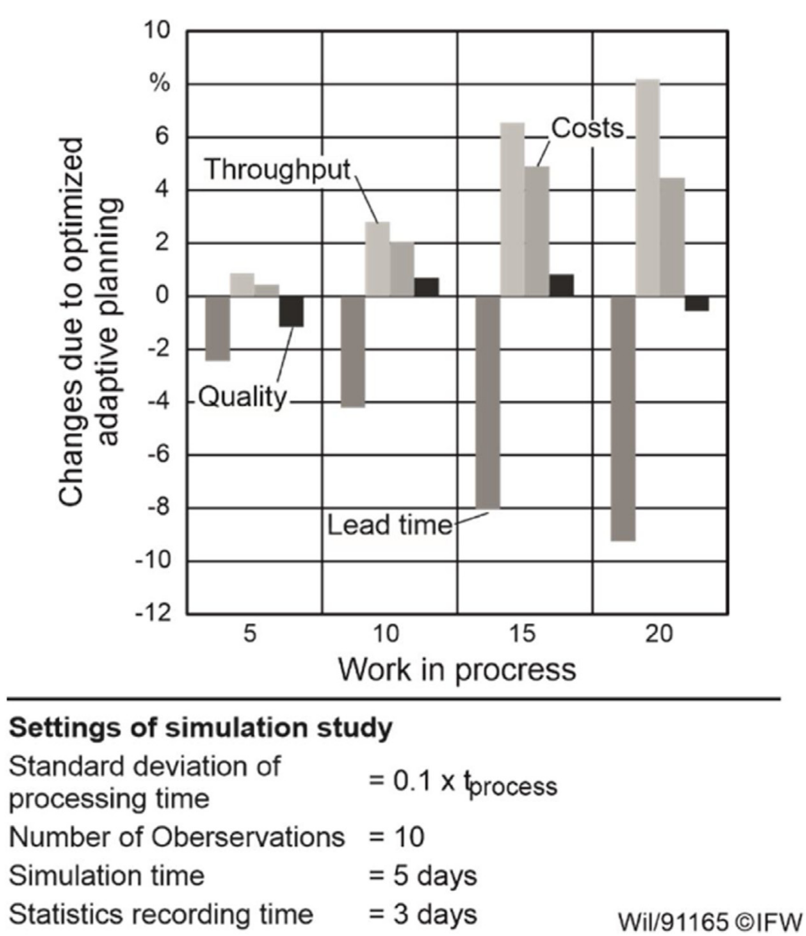

Fig. 13. Advantages of optimized adaptive production planning with low processing time deviations.

Comparing nonlinear PPC and optimized adaptive production planning in detail shows that by re-evaluating the production situation more frequently, it is possible to react faster to unexpected queues caused by fluctuations in processing time and to shorten them. In general, this effect is not as strong at very low utilization of the production system, as there is still sufficient buffer capacity available. As a result, the improvements in throughput and lead time shown in Fig. 13 for five released jobs are rather small at +0.87% and −2.44% respectively.

For higher utilization rates, more significant improvements of both key performance indicators (KPI) can be achieved. The throughput increases by up to 8.18%, the lead time decreases by a maximum of 9.26%. The rising costs of between 0.42% and 4.92% indicate that, for the improvement of throughput and lead time, orders originally planned on fast machines are regularly shifted to slower ones. This is due to the fact that in the present application scenario, the slower machines also have the highest machine hour rates. However, as new machines often have the highest machine hour rates in practice, the results presented here are more like a worst-case scenario. With regard to the quality achieved, a variety of effects overlap, which is why it is not possible to explain clearly why the reject rate hardly changes in all the scenarios considered. In general, the redistribution of orders to slower machines to reduce queues seems to be carried out in such a way that machines with both lower and higher reject rates are selected. All in all, the overall quality produced thus remains almost constant over all four utilization scenarios. Again, the selected configuration of the test use case plays an important role. If the KPI under consideration behave differently in other application scenarios and possibly deteriorate too much, the multi-criteria fitness function enables the production planner to intervene by means of targeted weighting.

Beyond the effects mentioned above, it is confirmed that the intensity of processing time deviation does not clearly influence the advantages of optimized adaptive planning. As already stated in the high-level comparison (cf. results of Fig. 12), the trends remain basically the same for all the KPI considered if the standard deviation of processing time is increased to 50%.

Conclusion

Systems with genetic and intelligent properties which enable the transfer of biological principles are referred to as “gentelligent systems”. This allows the field of manufacturing to exploit the benefits of genetic concepts such as inheritance of information and lifelong learning.

The use of gentelligent components in manufacturing opens up new degrees of freedom for planning, control and monitoring of complex production processes. However, the large amount of available production information initially increases the complexity of the production organization. To account for this complexity, the idea of process-DNA was integrated into the virtual planner for gentelligent manufacturing. As a result autonomous and gentelligent production units can be linked virtually and existing data from previous workpiece and process generations are made accessible for a knowledge transfer. In addition, it was shown how a combination with biologically inspired optimization algorithms enables an optimized process and production planning within this concept, thus enabling flexible and undisturbed production.

Three different use-cases were presented to elaborate upon the potential of gentelligent systems in biologically inspired manufacturing. Detailed analyses proved, that using process-DNA in combination with biologically inspired optimization algorithms enables automated, knowledge-based, and detailed planning of turning processes. Machine-specific process parameters can be determined to reach the required surface roughness. The overall margin of error adds up to 7.6%. The process parameters determined in a spot test, by the system, deviated from the target value by less than 12%. Considering the uncertainties, the determined values remain within the expected range.

For tool grinding it was shown that the concept of process-DNA allows workpiece-independent knowledge transfer and improves the process adaption. By using an SVM model derived from data of the first workpiece geometry combined with the specific process-DNA of a new workpiece geometry as an indicator, it was possible to determine the resulting force for the subsequent process with a deviation of 2.6%.

Using a genetic algorithm for gentelligent production scheduling within the framework of adaptive production planning showed great potential for optimizing the performance of flexible job shops. Compared to simple control rules the evaluation of the new approach with bio-inspired optimization showed lead time reductions over 48% for high capacity utilization.

The results presented within this paper show that the use of gentelligent systems can unleash great potential in the field of manufacturing. In order to realize the full potential of the concept, however, diverse further research is necessary. For example, the transfer of knowledge within the concept of process-DNA will be additionally investigated for other tool elements in further grinding experiments. Moreover, it is currently being investigated, to which extent multi-agent systems are suitable in combination with reinforcement learning for the decentralized but holistically optimized control of a gentelligent production system. In addition, the adaptability of the planning and control algorithms in the event of changes to the framework conditions (e.g.: new machines) have to be investigated. Here, the area of transfer learning offers interesting perspectives.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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