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cognitive tolerance matching
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COGNITIVE OPTIMIZATION OF AN AUTOMOTIVE REAR-AXLE DRIVE PRODUCTION PROCESS

While optimizing tolerances in tolerance chains only single characteristics or objectives of single process steps are considered, there is no information exchange across all processes. Interdependencies between processes, materials, means of production and individuals acting in this environment as well as their effect on product variations are usually not fully understood. In order to face a dynamisation of process specification, interdependencies have to be identified and integrated in future production. The holistic consideration of the process chain focused on the allocation of tolerances allows detection of correlations and interdependencies in the production process itself. By this, process chain information is traced back to conduct the right optimizations at the right place in the process chain. But therefore intelligent controlling mechanisms are needed to analyze and optimize even complex production systems with multi-level interdependencies. Such a cognitive system is able to form the core of self-optimizing production system. Using this cognitive system, the production process of an automotive rear-axle drive is optimized in order to minimize disturbances created by structure-borne sound emissions. Therefore several cognitive technologies have been evaluated to fulfil specific tasks in process optimization.

1. INTRODUCTION

Due to an increasing amount of competitive pressure, the manufacturing industry faces a difficult situation. New competitors, who typically generate their competitive advantage through lower labour costs, are steadily improving the technology of their production capabilities and create a massive cut-throat competition [1]. Companies are forced to innovate continuously to maintain their leadership in production technology. At the same time, production or labour costs must be decreased and productivity increased, since changing consumer behaviour demands that even innovative products have to be placed on the market at the lowest possible price. Additionally, differences between customers' requirements and the company's innovation targets complicate business [2].

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Technologically demanding products are manufactured by adoption of modern production technology.

The increasing complexity of ambitious technological processes requires a new kind of controlling mechanisms, which can only be reached by sophisticated optimizations.

2. THE POLYLEMMA OF PRODUCTION

The demand for economical high quality products and efficient and effective production systems requires new methods to widen the optimal ‘operating range’ of the production system. In order to achieve less overall unit costs, the two main dilemmas of production technology must be solved, or at least be reduced.

The first dilemma exists between scale and scope, and the second between planning- and value-orientation. A production system that is focused on economies of scope is highly flexible and realizes one-piece-flow, i.e. there is no build-up at any given stage in the process. Products are produced for a specific customer rather than added to inventory. In contrast, a production system geared to economies of scale gains cost advantages by concentrating on robust, repeatable processes. Increasing product flexibility in this context is generally expensive and the main constraint in solving this dilemma. The second dilemma can be localized between value-oriented production with little or no planning efforts and an optimized, planning-oriented production. The combination of both dilemmas leads to the so-called polylemma of production (Fig. 1) [3].

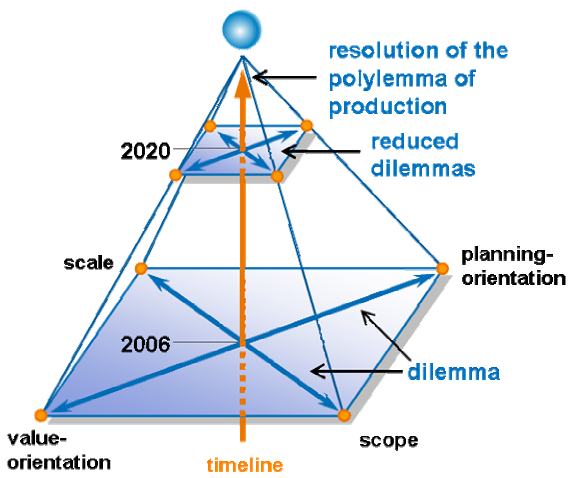

Fig. 1. The polylemma of production

To reduce this polylemma, new strategies for production systems are required. Self-optimizing production is one new approach which implements value-oriented activities with increased planning efficiency in order to enhance process and product quality. Self-optimization offers a new perspective on production and assembly systems by adapting the systems behaviour to dynamic objectives in technological and organizational areas. Previously acquired knowledge is transferred and used in new and similar production environments. An increase in the quality of the production system, which will secure sustained production for manufacturing companies, can thus be achieved [4].

3. SELF OPTIMIZATION

Due to changing conditions, the results of planning can lead to suboptimal operating points. Interactions between influencing elements and their effects on the products are usually not entirely known, which makes it impossible to deliver an accurate statement about the impact of changes on the total production system. Only single elements of a production system are ever in the focus of an optimization. Under these circumstances the behaviour of a production system cannot be predicted entirely, as some elements or sub-systems may affect others. A possible solution to this problem is a system designed to pursue different objectives and adapt its behaviour depending on the actual conditions. While a change in the system's behaviour is controlled externally, i.e. by humans, the decision's effect on the entire system is to be conceivably automated. The adaptation and modification of related elements would then be decided by a technical system.

This results in increased value-orientation as well as decreased planning effort, which both support the solution of the polylemma of production.

Self-optimizing elements can replace the current static planning and management processes in both organizational and technological fields [5]. The continuation of this idea leads to self-optimizing production as a concept of overall optimization. In any defined system, the principle of self-optimization describes the continuous repetition of the following three actions [6]: Analysis of the current situation, determination of the system targets and adaptation of the system behaviour.

In a broader sense, a self-optimizing system is able to accomplish a defined objective. While classic closed control loops dictate the behaviour of the system by means of externally introduced target parameters, a self-optimizing system, on the other hand, is able to redefine the various sub-objectives and adapt the control process dynamically.

In the following concepts, self-optimization is realised within technological processes, while also other levels of production systems can be focussed.

An identified issue is to dynamically adapt single objectives within a production process to reach the desired function of the product. While the function of the product is the superior objective, adapted objectives can be single dimensions of the product. A dynamisation of crucial process parameters will reduce costs, because other parameters can be expanded without losing the required product characteristics. Simultaneously, the flexibility of the production process in reference to changes of the product will increase significantly.

Within the research project ‘Integrative Production Technology for High-Wage Countries’ of RWTH Aachen University, a project to optimize production processes by applying cognitive technologies was defined, named ’Cognitive Tolerance Matching’.

The purpose is to analyze an entire production from manufacture to final assembly, monitoring the resulting quality, in order to initiate adequate optimizations. Interdependencies between variations in the production process and the resulting product have to be identified to build an adequate model of the processes. In order to detect these interdependencies, every parameter that can have an impact to the function of the final product is measured.

To conduct the optimizations, information is sent back to the correct place within the process chain. This requires intelligent controlling mechanisms. Thus the aim is to develop a control system for production processes using cognitive technologies, that is able to analyze and optimize even complex production systems with multi-level interdependencies. Such a cognitive system forms the core of a self-optimizing factory. [7]

Cognitive Tolerance Matching uses a cognitive architecture called Soar as well as technologies like artificial neural networks and data mining to build a cognitive system acting as a self-optimizing controlling application.

3.1. SOAR

Soar is a cognitive architecture based on the early systems of GPS and OPS5. In Soar, target-oriented problem solving takes place as a heuristic search in problem spaces. The search consists of a successive application of operators until the target situation is reached. In addition to classical planning systems, the search in the problem space is implemented in a complex decision cycle. For knowledge representation, Soar offers two concepts: a short-term and a long-term memory.

Information processing is conducted in two phases. In the first phase, the knowledge search phase, productions of the long-term memory, which work on the working memory, fire. This process generates new objects, which in turn activate other productions. In addition, preferences, which are used in the second phase, are generated. Then, the decision procedure selects an operator using the actual knowledge in the short-term memory. By successive application of operators, a target will be reached. In case of a dead end, a sub-target is generated to lead the search process out of the dead end. If the dead end cannot be solved in this way, problem space independent mechanisms like back-tracking are used. To avoid dead ends, a chunking learning mechanism is activated each time a route out of a dead end was found. If an agent finds itself in the same situation later, the learned rule fires and the dead end is avoided. Additionally, reinforcement learning remembers decisions by reward points given for reaching a target or a sub-target.

Soar is already used very successfully to simulate human behaviour, e.g. for robots and steering artificial enemies in flight simulators. First prototypes of a Soar-based systems for process optimizations are also very promising. [8].

3.2. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks can be described as a cognitive architecture with sub-symbolic information processing [9]. Artificial neurons are a technical approach of abstract modelling which emulates the processes of a biological nerve cell. Like a biological nerve cell, artificial neurons possess input channels used to detect signals in the form of input values and one output channel to provide output values.

An artificial neural network can be trained with sophisticated non-linear functions. Like in biological neural networks, the trained knowledge in artificial neural networks is represented in the weight structure of the neurons. In the case of supervised learning, the network is trained with a set of known input and corresponding output samples; the margin of error within the network can be identified using the set-actual comparison. [9]

3.3. DATA MINING

Data Mining tools and algorithms are used to detect structures within the production data, leading to knowledge that can be used to derive optimization decision. Data Mining also can be used to reduce model complexity by analysis of the influence of single parameters or characteristics. So data not being important can be identified in order to concentrate on important data.

3.4. A COGNITIVE SYSTEM ARCHITECTURE

With respect to the tasks mentioned, focus is to build a self-optimizing control system using the technologies described. In the following, a combination of data mining tools, artificial neural networks and Soar is introduced as a possible solution to optimize sophisticated production processes, arranged with regard to their ability to fulfil the tasks of cognitive information processing in production systems.

First, production data is analysed by data mining algorithms to reduce model complexity and to detect main influence parameters. Then, neural networks are trained to emulate the behaviour of the production system.

Soar generates decisions from existing rules and validates or extends them during their application. Soar conducts a variation of manufacturing parameters, learns from the effect of the particular application and transforms this knowledge into new rules.

Soar is the main element in the proposed architecture. It varies production parameters and neural networks subsequently evaluate these parameter sets. Finally, reinforcement learning allows Soar to also learn from the results. This ensures an effective and efficient search in the space of possible production parameters. The project team implemented a special clustering of achieved targets and a resulting distribution of reward points to enable

Soar to learn for future problems, so results from merely similar problems are taken into account.

The detailed interaction of the combined systems is organized as follows: Starting with a given vector of parameters and a basic set of rules, Soar conducts a variation of these parameters and sends it to the pre-trained neural network, which evaluates the parameter sets and sends obtained results, thus the product characteristics assumed to be produced in the real production system, back to Soar. The results are calculated using the networks' knowledge of the production processes.

This procedure is repeated until the results obtained by the neural network show conclusively that all product demands would be met in the actual production. Then this parameter set is used in the real production process. If the created product fulfils all the demands, Soar receives a success message. Otherwise this data will also be fed back, to be able to learn from any miscalculations and to correct the rules used. If derivations occur, the network will be re-trained. This enables the system to adapt to the new situation and to use its new knowledge for future decisions.

Decisions are therefore made by a systematic decision-making process performed by Soar. On the one hand Soar considers fixed rules of known correlations in the production system, on the other hand reinforcement learning is used to obtain further process knowledge. Improvements can be achieved systematically and more quickly than by algorithms that are not able to learn from similar, already solved problems.

4. CURRENT APPLICATIONS

4.1. BMW REAR AXLE DRIVE PRODUCTION

The appliance of the developed methods demands a use case which has been initiated in cooperation with WZL of the RWTH Aachen University, Fraunhofer IPT and BMW

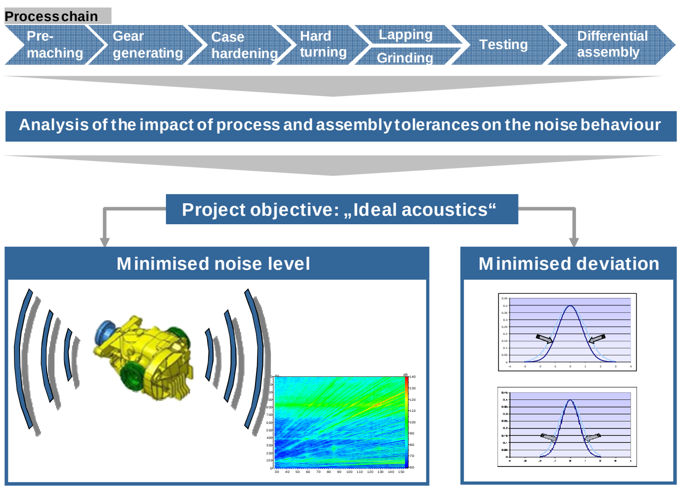

Fig. 2. Interrelationship between process chain and project objective

Group. For that purpose a project to optimize the emitted acoustic of rear-axle-transmissions has been defined. The challenge lies in the holistic examination of the entire process chain, implying the production of the gear tooth system for power transmission and the complete assembly process of the differential (Fig. 2).

Challenge

The effect regarding the driving comfort of modern vehicles represents an important criterion for customers deciding to buy a certain car. The acoustic behaviour can be regarded as a fundamental differentiating factor between cars. Therefore, the noise level of vehicles has become more important during the last years. The objective of the development and production of rear-axle-transmissions is consequently excellent noise behaviour in addition to its reliability. The challenge in production lies in controlling the tolerance chain and its interdependencies. As an example the position of the tooth contact can be observed, which is basically determined by the gear cutting. Distortion due to the hardening of the parts, the finish by lapping the gear sets and finally the assembly position in the casing can have a significant impact on the position of the tooth contact. In addition to the calibration of the process parameters, tolerances are the fundamental factor. This example demonstrates the complexity of this process chain.

The objective of the use case is to analyze the interactions of the various tolerances and its impact on the rear-axle-drive's noise behaviour. Optimizing the production process in the following will lead to improved competitiveness. Therefore, a 3-step approach is developed as follows:

1) Analysis of dependencies (Identifying most significant parameters), 2) Knowledge acquisition about the effects of each production parameter and tolerance and 3) Control of process parameters with Cognitive Tolerance Matching (CTM).

Analyzing the process chain

The analysis of dependencies within the process chain demands a consistent collection of measured data of a spot sample of a sufficient amount of parts. Therefore, a lot of 80 gear sets is accompanied during manufacturing and measured after each production step. For that purpose, special testing devices and above all 3D-coordinate measuring machines are used to check the flank of tooth topography and typical quality characteristics for tooth systems like true running and flank pitch. The objective is maximizing the information gain about the geometrical properties of the gear sets during the production process. Subsequent to the gear set production, inspected subassembly components are employed to assemble rear-axle transmissions using the checked gear sets. The assembly is completely documented, to gain information about the relative position between the drive pinion and the crown gear and in addition about the pre-load of the bearings. The noise behaviour is subsequently detected using a custom-built rear-axle-transmission acoustics test bench. The gauge for the emitted sound is the structure-borne noise applied to the first order of meshing. Matching the results of the test bench with the subjective evaluation of the noise behaviour of the rear-axle transmissions in the car by test operators shows excellent correlation.

The evaluation of the measured data turns out to be a great challenge because of the multiplicity of parameters, which cannot be handled by using basic statistical methods. An approach is the application of multivariate methods of analysis as well as data mining tools like artificial neural networks and regression trees. Particularly structure detection methods like previously mentioned data mining tools helps to analyse the interdependencies within the tolerance chain. An implementation of these methods however implies an exact data preparation including a correlation analysis within the data array to avoid highly correlating records and a variance analysis to delete records having a lack of information. The results of the examinations with data mining deliver the main factors having an impact on the rear-axle-transmission noise behaviour. Subsequently the effect of the main factors can be validated by series of tests using a method named design of experiments (DoE).

Controlling the process chain via CTM

Following the identification of the factors having the main impact on the noise behaviour and developing knowledge about their effect direction, strategies to implement cognitive control loops have to be modelled. Therefore, investigations must be carried out which parameters of the process chain can be measured in general and which ones must be measured in any case. Furthermore, the inspection cycle time in the process has to be considered and the measured data must be automatically prepared for continuous evaluation with CTM. Implementation of intervention zones for the CTM system is significant to control the production steps of capital importance. At this juncture the development leads from a quality backward stream to a quality forward stream in process direction. The objective is the functionally oriented production with the potential to reproduce parts having variations due to tolerances in a process step by adjusting the following one with CTM. This leads to improved noise behaviour with simultaneous consideration of minimisation of scrap and consequently to a continuous increase of competitiveness.

4.2. SHAFT-TO-COLLAR CONNECTION

In addition to the rear-axle drive application, a lot of development work is conducted with a much simpler manufacturing case. This is needed to instantly evaluate if Cognitive Tolerance Matching brings the expected results. To these ends, a simple shaft-to-collar connection has been developed. The connection combines elements of manufacture and assembly, which offer a lot of possibilities to influence the production process. This application will assist in the development and evaluation of cognitive technologies for production processes and serve as a demonstrator of the Cognitive Tolerance Matching system.

The connection consists of two rigidly connected collars fitted around a cylindrical shaft, which is designed to fail when a specified torque is applied to the shaft (Fig. 3). One collar features a tapered press fit. The turning parameters and the torque for assembly are defined by the cognitive system.

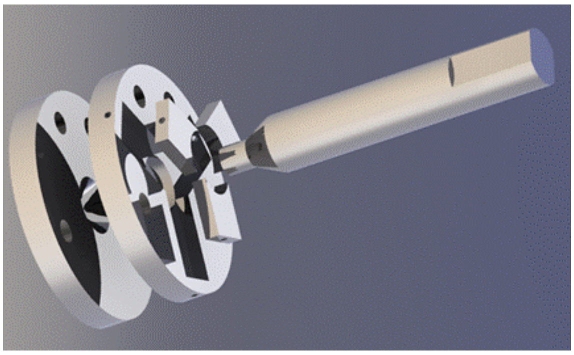

Fig. 3. Shaft-to-collar connection demonstrator

The second collar is composed of four separate parts, of which three smaller pieces form an inner ring, which can be tightened or loosened around the shaft manually. Adjusting the pressure exerted by the collar on the shaft changes the value of torque the connection can stand without slipping. The goal of the cognitive system is to reach a constant torque at which the whole connection begins to slip. Therefore it has to react to changing materials and other influences in manufacturing and assembly. In this manner, the self-optimizing system is able to accomplish the defined goal by redefining the sub-objectives and adapting the production process.

5. CONCLUSIONS

The production industry is under increasing pressure due to global competition. To retain economically important production, an exact understanding of the production process is mandatory. The new approach bases on self-optimizing elements, which simultaneously emphasize value-oriented processes and decrease the necessary manual planning effort. The underlying goal is the independent enhancement of system, process and product quality.

The approach presented in this paper deals with a cognitive controlling system for production systems, whose intelligent combination of Soar and artificial neural networks enables it to adapt to changing conditions quickly and efficiently.

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REFERENCES

[1] TSENG M., 2003, *Industry Development Perspectives: Global Distribution of Work and Market*, CIRP 53rd General Assembly, Montreal, Canada.
[2] SCHMITT R., SCHARRENBERG C., 2007, *Planning, Control and Improvement of Cross-site Production Process Chains*, Presented at the 2007 CIRP 40th National Seminar on Manufacturing Systems, Liverpool, GB.
[3] ORILSKI S., SCHUH G., 2007, *Roadmapping for Competitiveness of High Wage Countries*. Proceedings of the XVIII ISPIM Conference: On Innovation for Growth – the Challenges for East and West, Warsaw.
[4] SCHMITT R., BEAUJEAN P., 2007, *Selbstoptimierende Produktionssysteme*, ZWF – Zeitschrift für wirtschaftlichen Fabrikbetrieb, 102/9, 520-524.
[5] SCHOLZ-REITER B., HÖHNS H., 2007, *Selbststeuerung logistischer Prozesse mit Agentensystemen*, In: Schuh, G. (ed.): Produktionsplanung und – steuerung. Third Edition, Springer Verlag, Berlin, Heidelberg.
[6] FRANK U., GIESE H., KLEIN F., OBERSCHELP O., SCHMIDT A., SCHULZ B., VÖCKING H., WITTING K., 2004, *Selbstoptimierende Systeme im Maschinenbau*. *Definitionen und Konzepte*, HNI Verlag, Paderborn.
[7] SCHMITT R., BEAUJEAN P., KRISTES D., 2008, *Entrepreneurial Quality Management - A New Definition of Quality*, IEEE International Engineering Management Conference (IEMC-Europe 2008).
[8] Soar Technology. www.soartech.com