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Agent-Based Systems, cognition-based, self-optimisation, rear-axle-drive

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COGNITION-BASED SELF-OPTIMISATION OF AN AUTOMOTIVE REAR-AXLE-DRIVE PRODUCTION PROCESS

The production of automotive rear-axle drives is a complex process. This is due to many involved process steps, factors and interdependencies between processes, materials, means of production and individuals acting in this environment. In general their effect on product variations is not fully comprehended. Hence, a holistic analytical model is only possible in parts of the production. In this paper a modular approach is presented to make the production more flexible and enable it to react faster on product variations. This is achieved by a Cognitive Production System (CPS), which is based on accumulating, storing and processing of process knowledge so that it can be applied to similar cases. Through the combination and interaction of Cognitive Tolerance Matching (CTM) and Agent-based Systems the performance of the CPS is enhanced. The work discusses the set-up of such a CPS for the production of automotive rear-axle-drives with the focus on the failure state agent.

1. INTRODUCTION

Rear axles are a key component for automobiles with high function integration. This will be intensified in the future due to the increasing customer demands. The manufacturing of rear-axle-drives is currently characterised by many variants at medium lot sizes. This poses a “scale vs. scope” conflict. Depending on the variant even different manufacturing processes are involved. The adaption of adequate values for manufacturing parameters from one variant to another is difficult. This leads to a high planning effort for every new variant. Due to the challenging market the customer does not accept that these additional planning efforts are included in the product prize. This poses a conflict of value vs. planning orientation. Thus, to keep the present development expertise for these components in high-wage countries the manufacturing of rear-axle-drives has to be reorganised.

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2. SELF-OPTIMISATION

The approach for this reorganisation is based on cognitive methods, which should increase the dynamic and flexibility (value-oriented) of an inelastic (plan-orientated) production. Value-orientation focuses on the direct value adding processes (less planning, preparation, handling and transport), while planning-orientation focuses on extensive planning to optimise value-adding (modelling, simulation, information gathering) [1].

Through modularity and configuration logics for both, product and production system, as well as advanced production technologies the dichotomy between economies-of-scope and economies-of-scale can be resolved. Additionally, the concept of individualised production enables a high level of rear-axle variety and dynamics at mass production costs. Through a self-optimised production system the considerable planning effort for the variants is reduced by transferring already acquired knowledge to new, but similar cases.

To solve the described conflict, set-up and non-productive times have to be reduced to a minimum. The whole integrated process chain has to be modelled and simulated. Permissible tolerances for each process have to be assigned regarding the function of the final part and not only the single process step.

The key issue is to achieve a higher degree of self-optimisation within production systems. This objective requires a rigorous increase of transparency that can be achieved through object-to-object communication. In order to realise one-piece-flow the design and realisation of products must have minimum set-up efforts. The reduction of these efforts will lead to lower labour and production costs. Another particular aim is to identify the model structure of coupled subsystems reduced towards detailed comprehension of their complex interaction.

3. COGNITIVE METHODS FOR SELF-OPTIMISATION

An autonomous control and synchronisation can be realised through distributed multi agent systems (MAS). MAS employ intelligent system modules which autonomously act on lower hierarchical levels. Especially for flexible manufacturing systems, agent-based systems are an innovative approach to split the responsibility of the accomplishment of different tasks, interacting constantly with each other in order to achieve the main goal of controlling the production.

The modelling of the control of a production or assembly system with an agent-based structure aims at the optimization of the efficiency of the available hardware resources for the production process [2-4]. Even though various definitions for agent-based systems can be found, it is widely agreed upon that an agent is an entity (software module) perceiving its environment with sensors and is able to give feedback to its environment using actuators [2].

Main aspects that can be modelled and autonomously handled by different agents among a flexible and self-optimised cognitive production system are the control of various manufacturing and assembly processes, e.g. recommendation for optimal process parameters, the control of sensors and actuators to perceive and interact with the process and the cognitive software elements (for evaluating the quality state and taking decisions).

An agent pursuits autonomously one or more goals, while staying in contact with other agents of the production system to achieve these goals. Before the agent decides for a specific action it considers its perception of the environment, its goals, its knowledge and experience (Fig. 1).

The development of the software module for an agent focuses onto the decomposition of a problem and responsibility into small autonomous entities. These entities follow certain principles to perform their local and global distributed actions, e.g. encapsulation, goal-orientation, reactivity, autonomy, proactivity, interaction, persistence, adaptability intelligence and learning aptitude [3],[5].

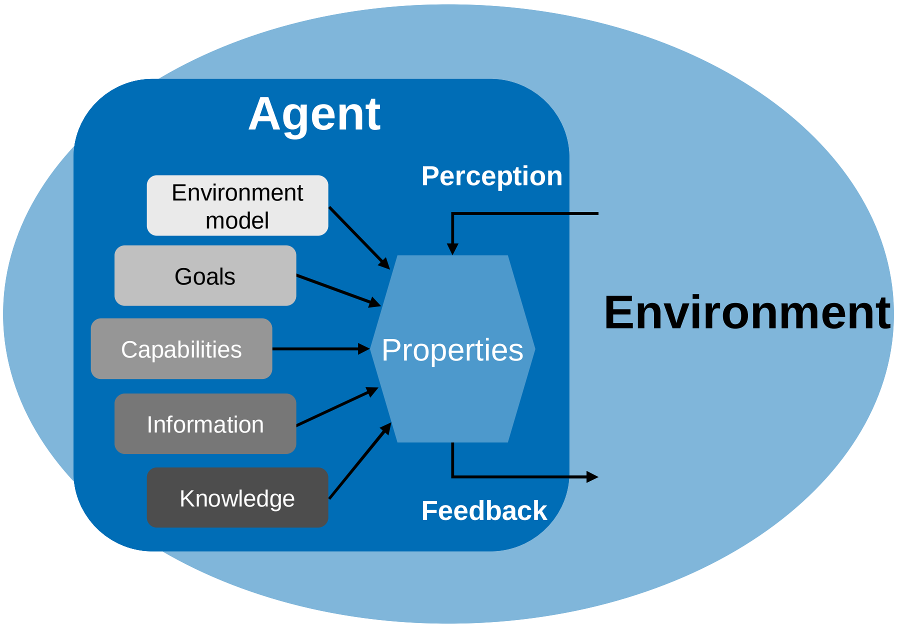

Fig. 1. Model and Function of a software agent

The utilisation of agent-based production control has at least 3 advantages [6]. With the structure of an agent-based system further agents (soft- and hardware) may be added without having to program the control logic anew. Furthermore, they are based on the principles of distributed systems. This allows the application of various operational systems and the communication between different hardware systems using the same communication protocol and medium. In addition, the agents' ability to cooperate or concur with other agents is the main reason for the desired operational autonomy of the production system.

The agents of a multi-agent system can be distinguished by their ability and responsibility. A certain hierarchy between different agents regarding their functionality does not exist. Basically, all agents work and interact on the same software level. They exchange information and services to achieve their goals. However, regarding the organisation of the modelling a certain hierarchy can be valuable and helpful for the process comprehension. By this the level of complexity for the implementation and the importance of the agents' functionality are emphasized.

Such modular MAS are ideal for the implementation of cognitive elements, which are based on the notion of intelligent technical systems. A fundamental precondition is an entirely modular hardware and software design enabling rapid exchange and fast integration of subsystems. The introduction of cognitive elements within the production control system is usually implemented with methods of artificial intelligence, also known as knowledge-based systems. These provide the basis for knowledge representation and inference skills, in order to accomplish cognitive tasks such as reasoning, planning and learning [7],[8].

An important incident, for which the MAS must react quickly, occurs when a manufacturing or assembly process becomes unstable. Indicators for this are a higher process variation or a systematic shift of the expected outcome. If a process operates outside of the defined tolerances, it is controlled by the so-called Failure State Agent (Fig. 2).

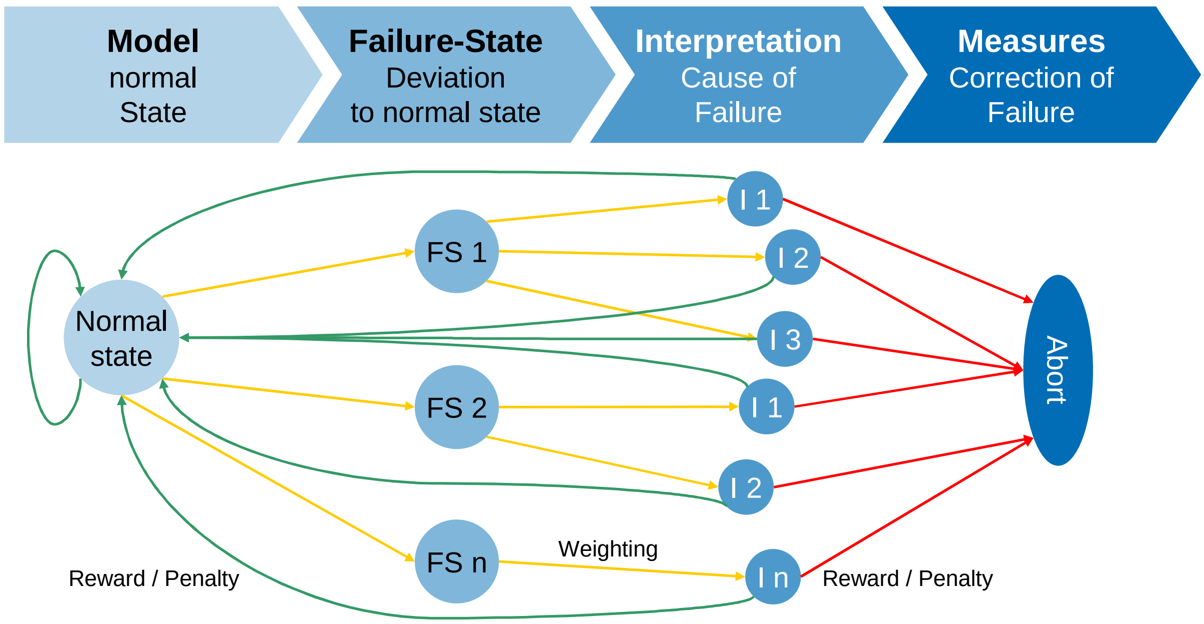

Fig. 2. Functionality of the failure state systematic

This agent continuously checks the actual state of a process and compares it to the normal state. The normal state is characterised by a nominal value and permissible tolerances. In case that the actual process deviation is too high a failure state is diagnosed. It can happen, that several failure states occur simultaneously. So it is necessary to prioritise them when it comes to the search for the cause of the failure and its interpretation. One failure state may have different causes, which require also different countermeasures. Which countermeasure is the most adequate to regain the stable normal state is assessed by using methods of reinforcement learning. Within the process simulation certain solutions of the problem, e.g. adjustment of manufacturing parameters, are rewarded if they lead to an improvement of the target characteristic. In case another combination of parameter value leads even to a higher deviation it is assigned with a penalty. So the next time a similar case occurs the solution path that has been awarded a penalty is then excluded. Only the most promising failure interpretations are pursuit. By this a significant reduction of simulation time and hence reaction time for a failure state is possible. The optimal countermeasure is then stored in the knowledge base together with the failure state and the failure cause. The failure state agent communicates the countermeasure to an Actuator Agent that takes care of the process adjustment. The Failure State Agents checks again the actual state to obtain the effect of the devised countermeasure.

4. APPLICATION SCENARIO AUTOMOTIVE REAR-AXLE-DRIVE

Subsequently the set-up for a Cognitive Production System (CPS) using Agent-Bases systems is outlined for the rear-axle-drive production. The descriptions focus on the gear set, which is a major component in the rear-axle-drive. To be optimised is the acoustic emission of the rear-axle-transmission. The acoustic behaviour is a fundamental differentiating factor between cars. Also the customer reacts sensitively on annoying acoustic emissions. Therefore, the noise level of vehicles has become more important during the last years. The acoustic emission is influenced by a lot of factors along the whole production process. Hence, an intentional adjustment is difficult. The physical interactions and effects of single process parameters onto the emission are up to know not fully comprehended.

So the aim is to develop rear-axle-transmissions with an optimized acoustic characteristic but at the same reliability of conventional drives. The challenge is the control of the tolerance chain and its interdependencies. For instance, the position of the tooth contact is basically determined by the gear cutting. Distortion due to the case hardening of the blank, the finish by lapping the gear sets and the assembly position in the gear housing can have a significant impact on the position of the tooth contact. Manufacturing deviations inevitably lead to a distortion and shifting of the wear pattern. How big these deviations could be depends on the tolerances and the desired functionality of the final assembly.

The proposed CPS combines the agent-bases system with the method of cognitive tolerance matching (CTM) [9]. The CPS is shown schematically in Fig. 3.

By CTM subsequent process steps can react flexibly on process deviations, e.g. by adding components that compensate a clearance at the final assembly of the rear-axle-drive. The Failure State Agent diagnoses deviations from the defined nominal state of the process providing the desired part functionality at the end. The actual state of the process is acquired with sensors and measurement devices. The measurement data are combined to characteristics, which are compared to the nominal values. In case impermissible deviations occur, the Failure State Agent initiates a cause-effect analysis to trace back the origin of the deviation. Here the learned knowledge of the CTM optimization module can recommend enhanced countermeasure to regain the normal state. New failure states are fed to the CTM optimization module, which calculates possible solutions using reinforcement learning. New failure states are stored in a database, so the cognitive production system learns with new situations. The combination of these methods improves the knowledge exchange to have a self-optimised and more sophisticated cognitive production system closing the loop to the production process.

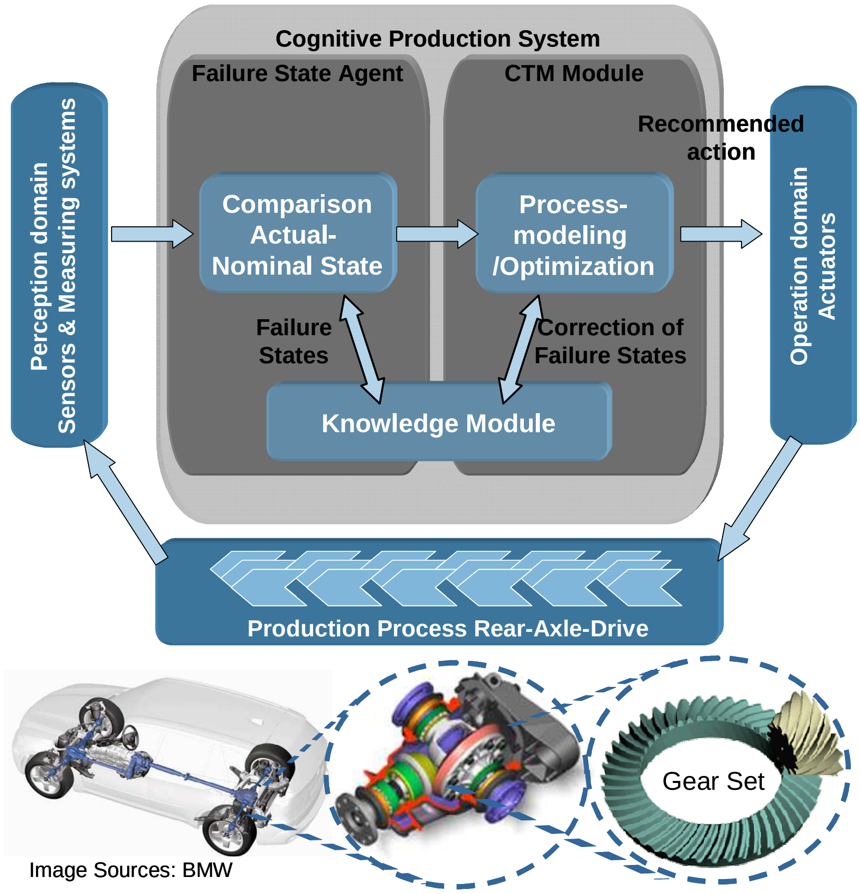

Fig. 3. Cognitive Production System for Automotive Rear-Axle-Drive combining Failure State Agent and Cognitive Tolerance Matching

It is important that the production process is systematically divided into sequential steps, in which different features of the manufacturing process and the intermediate product must be monitored to provide an assessment of the actual state. With this modular separation the search for causes and adjustment is facilitated. In addition, through the monitoring the knowledge about each single manufacturing and assembly step increases. This could also benefit other entities in the product development process, e.g. for the construction of new rear-axle-variants. Here the knowledge about the process variation is important when it comes to the definition of the tolerances.

A disadvantage of the process separation described above is that they are pre-planned and rigid in their sequence. If multiple variations of the production sequence are possible, all of the required steps need to be planned in advance. To be more flexible the integrated CTM module can decide which step to do next. The decision is based on the acquired information of the sensors and preceding production steps. This requires a representation of the product properties as a function of the product and process tolerances and the sensors and metrology devices to acquire and process measurement data about the current system state. The possible options that can be recommended are then that an intermediate part is reworked or the measured deviation is compensated in a subsequent process step. The decision is derived regarding the effort necessary to do the specific action. To be able to recommend adequate actions the involved processes have to be modelled to that extent that a sufficient similarity to the real case exists.

The application of cognitive aspects for technical systems aims at their capability for intelligent decision making. The modelling and implementation of such cognitive capabilities is supported by knowledge-based systems. These systems are a base for the knowledge representation and visualisation as well as for the inference and learning aptitude, which are desirable for the dynamic and adaptive systems.

Compared to conventional approaches for programming knowledge-based systems reveal a distinct separation of the knowledge representation and knowledge processing [7]. Therefore, several knowledge-based approaches use the same core structure, which contains a knowledge base for the storage of data and an inference module for the knowledge processing. The knowledge base can store two different knowledge categories [7]. These categories are case-specific and rule-based knowledge. The first category refers only to the actual problem case, e.g. facts resulting from process observations or analyses results. The rule-based knowledge is the core of the knowledge base as it comprises knowledge related to the domain (theoretical knowledge and experience) and general knowledge (heuristic knowledge to solve problems, optimization rules or knowledge about work pieces and correlations of the real process).

A Failure State Agent can be supported by an expert system, which is a special knowledge-based system. The distinct characteristic between the expert and the knowledge-based system is the origin of the knowledge in the knowledge base. For an expert system the knowledge is derived from human experts, who have an adequate education and sufficient experience in the specific field. Also the comprehension of the involved processes is essential [7]. The rule-based knowledge of an intelligent agent comprises a lot of „IF-THEN“-rules. These represent the systematic of the production process of the rear-axle-drive. Thus, various information about the production process are stored, e.g. the different components for the differential assembly, their tolerances, the measurement system to prove the conformity of the work piece and the characteristic of the actuators to adjust the production process. Nevertheless, the intelligent agent needs further input information from the planning agent to trigger the rules of the knowledge base. Due to this the Failure State Agent receives a sequence of manufacturing and assembly processes from the Planning Agent. Also the desired quality level of the final product is transmitted. This assures the proactive and preventive character of the agent. Then the agent coordinates the measurement and testing operations and delegate tasks to the measurement agents to supervise and acquire the actual process state. First Failure States have to be identified. A Failure State is given when a significant deviation between actual and nominal state is observed. Base for this diagnosis is the evaluation of measurement data of the sensors in the perception domain. The process state is evaluated by the rule-based knowledge of the expert agent. The agent can explain the actual state comprehensively and transparently (logic to derive failure state).

In case a Failure State has been observed, the cause of this failure has to be found and be interpreted. In several cases the measurement analyses can be used to derive countermeasures to correct the failures state and re-establish the normal state. The coupling of a certain failure state with a possible solution and countermeasure uses the experience and knowledge of similar cases in the knowledge base. For new cases the information pair is stored in the knowledge base. So the cognitive production system learns with every new case increasing the knowledge about the production process. This improves the reactivity and flexibility. This is because validated measures for a failure state are found faster and more cases are available for the failure interpretation and process adjustment.

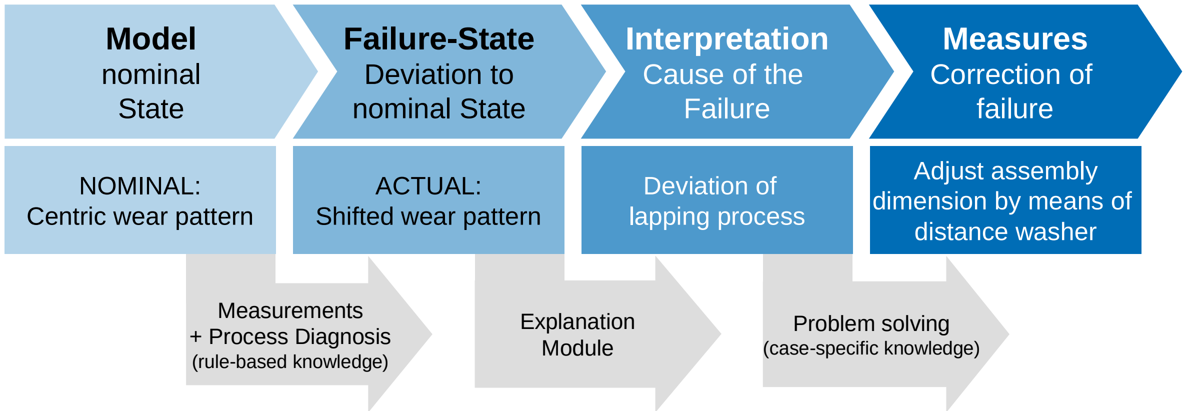

Fig. 4. Procedure to detect and correct failure states for the example wear pattern for gear sets

How the procedure for the failure state agent constitutes for the rear-axle-drive is shown in Fig. 4 for the example of the wear pattern for the gear set. The wear pattern is one of the most relevant factors regarding the acoustic emission. The wear pattern is influenced by a lot of previous production steps, e.g. the case hardening or lapping. The production processes influence the tooth flank geometry of the bevel and crown gear. Also depending on the pairing of both gears at the final assembly of the differential the wear pattern may vary.

First, the nominal state of the wear pattern and the permissible tolerances have to be defined. This is usually done by the construction department, which is also defining the gear geometry. The nominal wear pattern can be described by a set of characteristics. Usually wear pattern reveal an elliptic shape and are located in the middle of the tooth flank. Possible characteristics are the length of the major and minor axis, the coverage area, the angles between axes and flank edges and the edge distances. Undesirable wear pattern are for instance when the coverage area is too small, the shape is shifted to one edge or the pattern is divided into several smaller ellipses. The wear pattern is assessed at the Single-Flank working test, which is performed after the final lapping process. For this the single flanks of both gears are sprayed with paint. This paint is squeezed out at those areas where the corresponding flanks are in contact. After several revolutions the distinct wear pattern becomes visible.

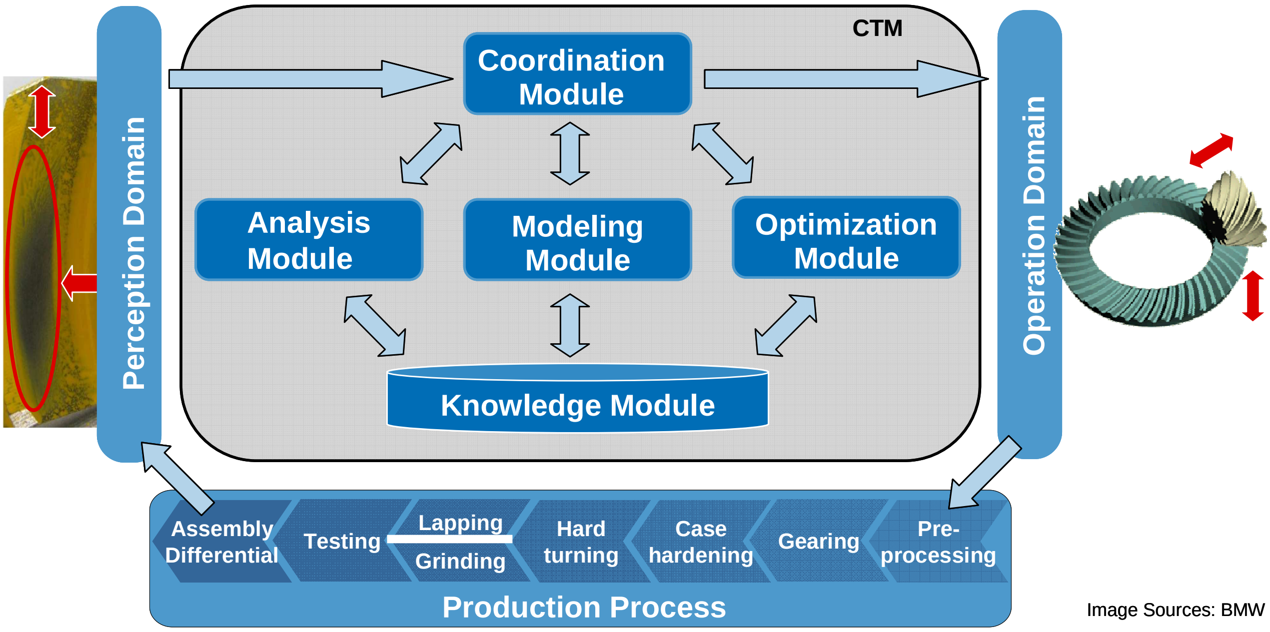

Fig. 5. Procedure to react upon a perceived wear pattern shift by means of Cognitive Tolerance Matching

The actual wear pattern can be acquired using industrial machine vision systems. The characteristics are then derived by means of image processing. The comparison to the nominal state reveals if an impermissible process deviation occurred. In case of too high deviations a failure state is diagnosed. This is followed by the search for the cause that leads to the process deviation. Having analysed similar cases, which are already stored in the knowledge base a likely cause for the deviation is a variation of the lapping process. In detail the lapping is influenced itself by a lot of factors, e.g. lapping time, particle size, fluid. Using then the methods of CTM a solution can be found that the part concerned can still be taken for the final assembly. A countermeasure could be to add a distance washer so that the bevel gear is shifted relatively towards the crown gear. To find the adequate thickness of the distance washer the correlation of the gear shift onto the wear pattern shift has to be known. The schematic procedure of CTM for this example is illustrated in Fig. 5.

5. CONCLUSIONS

The work presented a new approach for a Cognitive Production System based on the combination of Cognitive Tolerance Matching and Agent-Bases System to achieve a higher degree of self-optimisation for complex production processes. With this Cognitive Production System the conflict area between value-oriented processes and necessary planning efforts is decreased. The approach is outlined for an automotive rear-axle-drive, which is an assembly with many different variants. Base for the Cognitive Production System is the collecting and processing of process knowledge, which can be adapted to similar cases. The knowledge acquisition is done by sensors while the knowledge processing is performed by means of a knowledge-based system. The underlying goal is the independent enhancement of system, process and product quality, whereas the focus is on the final product functionality. Through the interaction of CTM with the agent-bases system the cause-effect analysis for occurred failure states is improved. The storage of pairs of failure states and adequate countermeasures accelerates the process simulation when similar cases happen. By this the CPS is able to react faster and with more robustness on impermissible process deviations.

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