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A holistic approach for the cognitive control of production systems

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ABSTRACT

Increasing dynamics and a turbulent environment force industrial enterprises to ensure a highly efficient production. The field of production planning and control (PPC) and the sustainable optimization of its methods are hereby of utmost importance. This paper introduces a concept for a cognitive production planning and control system, in which so-called smart products store knowledge about the production process and its current state. The RFID (radio frequency identification) technology presents a promising approach to realize those smart products, to enhance the information management on the shop floor and to offer a precise image of individual product states in the production process. The knowledge on production sequences is represented in a graph-based model. The developed concept represents the executable production of every single resource in capability profiles that are used for the allocation of production steps to resources. Material transports are realized by an anticipatory transport control, which updates its model parameters autonomously. During runtime, the product-specific operation times are measured and stored on the smart product, which is subsequently used to update the overall planning data. Thus, the introduced production planning and control system is able to react to unforeseen events (e.g. missing material, insufficient product quality) and autonomously adapts the planning data to the actual elapsed values of the real production. First experiments showed promising results for the approach to provide and process information directly on the shop floor: the idleness of resources due to errors was reduced by 41% from 19.4% to 8.0% during a 3 h test run. The waiting time of resources caused by missing material can be reduced in specific cases by 17.7%.

1. Introduction

In recent years, global economic competition and a shift from seller markets to buyer markets have induced increasing dynamics and a turbulent environment for industrial enterprises [25]. Propagated concepts such as mass customization and individualization promised the creation of unique products that satisfy the needs of nearly every customer [29]. This trend has been accompanied by uncertainties for production enterprises in terms of an increasing number of products, product variants with specific configurations, large-scale fluctuations in demand and random dispatching of orders [18,28]. Therefore, companies can only compete successfully if they offer products and services that meet the customer's individual requirements without sacrificing cost effectiveness, product quality and on-time delivery [7,14,27].

Regarding the aforementioned boundary conditions, the control of production systems is becoming increasingly complex, because of growing requirements with regard to flexibility and productivity as well as a decreasing predictability of processes [4]. In order to face the changed boundary conditions, manufacturing systems must be primarily collaborative, flexible and responsive [14]. On the one hand, these requirements comprehend a shift of capabilities and decision functions from the central system to its dynamically interacting single sub-systems [1]. On the other hand, real-time information from the manufacturing system, the production process and the individual product has to be continuously integrated in production planning and control instances. Thus, an essential element for the shift from off-line planning systems to on-line and closed-loop control systems can be achieved [27].

2. State of the art

2.1. Production planning and control methods

Many researchers have identified the necessity to develop novel manufacturing paradigms in order to achieve higher degrees of flexibility, adaptability, autonomy and intelligence of production systems [8,12,24]. The quasi-standard of rigid, hierarchical control architectures in today's industry has been unable to cope with the new challenges, since the production schedules and plans are known to become ineffective after a short time on the shop floor. Established production planning and control systems are therefore vulnerable to abrupt changes, unforeseen events and supply

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stockouts in production processes and do not allow a real-time computation of sophisticated decision models [4,10]. Furthermore, with the increasing size and scope of central-planning-based Manufacturing Execution Systems, the structural complexity of these systems is growing rapidly [12,18]. Due to the growing dynamics and consequently necessary modifications in scheduling, the planning level cannot anticipate all constraints and limitations on the execution level [20].

The shift to concepts such as mass customization and individualization pushed the development of methods and concepts in agile manufacturing with a clustering of manufacturing systems into sub-systems and modules. Thus, single resources and units within the production system are able to increase their autonomy and are therefore capable of making certain decisions without external instructions from a central control system. As a consequence, a reduction of the complexity in the physical structure as well as in the information system shall be obtained [18].

Reconfigurable manufacturing systems (RMS) can be reconfigured both on the overall system's structure level and on the machine level (e.g. machine hardware and control software) [8]. Other research approaches went even further and propagated decentralized or heterarchical manufacturing systems, in which intelligent products control the production in cooperation with intelligent resources, each represented by associated software entities. Among these solutions, high level concepts such as multi-agent systems and holonic manufacturing systems (HMS) [9,12,21,24] can be found. In those agent-based manufacturing systems, centralized, hierarchical control architectures are replaced by a group of loosely connected agents. Thereby, each agent, which is a software entity, represents fundamental processing units (e.g. machines), orders and products [22–24]. By order of their physical counterparts, the software entities negotiate production control strategies between each other [11]. Thereby, a distribution of responsibility, tasks and resources is gained, which results in a high robustness and adaptability against disruptions and reorganizations [11].

To ensure sustainable quality and good performance of manufacturing processes, production systems must further have the ability to react to disturbances in coherence with overall performance targets. Therefore, several authors have identified the ultimate requirement as being the establishment of sensor–actuator-networks in production environments [14,20,27]. Sensors are used to capture current states of resources and products and feed this information back to the respective controllers [18]. In recent years, research work focuses especially on the increase of flexibility and adaptability in production environments by acquiring and using information from resources and machines. In addition, the radio frequency identification (RFID) technology has been identified as an instrument for the tracking and tracing of products and workpieces [10,22]. Moreover, this Auto-ID technology contains potential to store essential information of the individual product (e.g. quality), which was barely utilized [27]. In most production environments, the workpiece flow is passive and is handled or transformed only by active resources [17]. However, it is inevitable that the individual product and its current state is considered in order to improve flexibility in production management [6,26].

2.2. Principles of self-optimization in production planning

The principle of self-optimization is recognized as a viable solution to face the turbulent environment of production systems. Early concepts in this area are Autonomous Production Cells (APC), where parts of the production are organized as a company within a company [13,15]. The concept of APC focuses mainly on the fault-tolerant operation of production systems and provides solutions, how to efficiently organize a factory. However, this concept provides no specific means for production planning and control, but performs this task by skilled humans.

A strong research focus on self-optimizing systems can be recognized in logistics system. With ALEM (Autonomous Logistics Engineering Methodology), a methodology to build up self-optimizing production systems is introduced. It consists of the three parts: ALEM-N (notation), ALEM-P (process) and ALEM-T (tool), which provide a view concept (ALEM-N), a guideline (ALEM-P) and a software tool (ALEM-T). The procedure model hereby offers a guideline, how to model a logistic system with respect to principles of self-optimization. However, the guideline does not name the specific principles of self-optimization that need to be implemented. An agent-based algorithm is used to validate the principal approach. Although the procedure model provides a possibility to introduce elements of self-optimization into logistic systems, it does not provide solutions for assembly processes as a vital element of production [19]. In addition, it can be enhanced by methods to continuously update and optimize the necessary planning data.

3. Cognitive production system

3.1. Overall goal

A promising approach for a sustainable enhancement of the flexibility and adaptability in production systems is the integration of artificial cognitive capabilities. These Cognitive Technical Systems (CTS) are equipped with artificial sensors and actuators, are integrated and embedded into physical systems and act in a physical world. They differ from other technical systems in that they perform cognitive control and have cognitive capabilities such as perception, reasoning, learning and planning.

The paradigm "cognition" in terms of the factory denotes that machines and processes are equipped with cognitive capabilities. In technical terms, this comprises sensors and actuators that enable machines and processes to assess and increase their scope of operation autonomously. Models for knowledge and learning equip the factory with information about its capabilities and help to expand the abilities of the machines and processes. While performing their tasks, the production environment acquires models of production processes, machine capabilities, workpieces and their properties as well as the relevant contexts of production processes. These models are continuously updated to adapt to changes in the environment and are then used to optimize action selection and parameterization. Thus, unequalled levels of flexibility, reliability, adaptability and efficiency are reached by providing machine controllers, automated production resources, planning processes and whole factory environments with artificial cognitive capabilities.

3.2. Concept overview

The basis for the realization of a flexible and adaptive production system is a holistic communication and control infrastructure that is illustrated in Fig. 1. The proposed infrastructure consists of the system control level, the process control level and the planning level. In the context of this paper, the system control level is responsible for the physical execution of the production process. Thus, it will not be further detailed.

The global planning level administrates, coordinates and dispatches the incoming orders to the production system. The respective order data (e.g. slack time), the current boundary conditions (e.g. machine availability) and the overall system utilization (e.g. capacity utilization) are the prerequisites for the job release. Based on the specification of the order and an economical evaluation (e.g. machine costs), the global planning level allocates the respective