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Human-robot collaboration in decentralized manufacturing systems: An approach for simulation-based evaluation of future intelligent production

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Abstract

The development towards decentralized manufacturing systems aims at increased flexibility and robustness by maintaining the level of productivity. In order to meet these requirements, human-robot collaboration is considered as basic framework within future intelligent manufacturing cells. For industrial implementation, the concepts of smart production need to be refined and their benefits have to be quantified. This paper introduces concepts for the design of decentralized manufacturing systems and a detailed simulation-based approach for evaluating the performance of the system. Particularly, the relationships between factory layout planning, production scheduling, and human-robot work distribution are investigated.

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Keywords: Flexible manufacturing system (FMS), Planning, Optimisation, Human-robot collaboration

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1. Introduction

Decentralized manufacturing systems (DMS) are of major interest within the concepts of Industry 4.0, the next industrial revolution. They face the tradeoff between increasing fluctuations in the market demands for highly individualized products and the demand of today's production systems for well-balanced and strongly deterministic production programs [1]. Therefore, they need to handle increased manufacturing complexity caused by decreased production volumes per product variant [2]. The basic design approach of DMS concentrates on highly flexible product and material transport units to allow individual and non-dedicated material flow paths by decentralized decision-making processes for each order. This approach has major impacts on the layout planning, the production scheduling and the work distribution regarding human-robot collaboration. In the context of layout planning, challenges regarding the optimal positioning of manufacturing cells as well as distributing process capabilities among these cells arise. Concerning production scheduling, increased flexibility is needed to allow improved utilization of information about the system's current state and the adaptation of production schedules. For a more efficient and ergonomic production, human-robot collaboration is a key concept and requires new approaches for distributing work tasks between humans and robots.

This work presents a holistic approach for the simulation-based evaluation of future intelligent production characterized by human-robot collaboration in decentralized manufacturing systems. In-depth explanations of dependencies between layout planning, production scheduling and human-robot work distribution are discussed.

The remainder of this paper is structured as follows. Chapter 2 provides the technical background with focus on future intelligent production, layout planning, production scheduling, and human-robot collaboration and finishes with the research demand and goal of this work. Chapter 3 introduces the concept of decentralized manufacturing systems (DMS) and an approach for a simulation-based evaluation of DMS. Main elements of the simulation concept are layout planning, scheduling and human-robot work

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distribution. Finally, Chapter 4 concludes the research progress and provides an outlook about future research needs.

2. Technical Background

Conditions that strongly influence the performance of manufacturing systems have changed dramatically in recent years [3]. In manufacturing, main reasons for inefficiencies in today’s production are increasing product individualization and shorter product life cycles whilst remaining competitive in almost saturated markets [1,2,4]. Zuehlke [4] states that the complexity of manufacturing systems increases in order to manage the market driven complexity increase of products. The smart factory, a conceptual approach described by Lucke et al. [3], aims at facing dynamic internal changes, e.g. machine breakdowns, and external changes, e.g. fluctuations in the market demand, by collecting and analyzing manufacturing information from physical objects as well as virtual planning systems. Bochmann et al. [5] introduce decentralized manufacturing systems as a more focused subcategory of the smart factory. The decentralization refers to the production layout, which dictates material flow, flexible scheduling of orders based on decentralized decision-making, and context-aware work distribution between humans and robots within the same manufacturing cell.

2.1. Layout Planning

Drira et al. [6] describe a facility layout as an arrangement of everything needed for production of goods or delivery of services. In this context, Heragu [7] defines a facility as an entity that allows any job, e.g. machine tools, manufacturing cells, departments or warehouses. Yang et al. [8] state that facility planning and material handling is crucial to achieve a high company's productivity and profitability. According to Francis et al. [9], material handling costs are 20% – 50% of the total operating expenses in manufacturing and they claim that a cost reduction of 10% – 30% can be achieved through effective facility planning. Singh and Sharma [10] define the facility layout problem (FLP) as the determination of the physical organization of a production system. Generally, Koopmanns and Beckmann [11] classified the FLP as a quadratic assignment problem (QAP). Since the QAP is NP-complete, where NP refers to ‘nondeterministic polynomial time’ and states that the required time to solve to problem with any currently known algorithm increases strongly with the size of the problem. Therefore, an exact solution is difficult to obtain and optimizations are often carried out on these kind of problems [12–14]. With respect to layout planning, the main optimization objective is to minimize material handling costs, but also research on multi-objective approaches exists [9].

Methods for solving the QAP are categorized in mathematical/exact algorithms and heuristics [15]. The fastest exact algorithms are branch-and-bound algorithms, but they can only solve QAPs consisting of maximal 20 objects within reasonable time due to high computational complexity [15]. Heuristics can be further subdivided into construction, improvement, hybrid, and graph theoretic algorithms [13,15]. Construction heuristics try to locate facilities iteratively until the complete layout is obtained [13]. Improvement heuristics try to improve an initial solution successively by systematic exchanges of the solutions’ characteristics. Examples for improvement heuristics are the CRAFT algorithm, simulated annealing, tabu search, and genetic algorithms [13,15]. Hybrid algorithms combine exact algorithms with heuristics to obtain more exact solutions in shorter time. Algorithms based on graph theory are often also construction algorithms. They represent the FLP as a weighted graph with relationships between the facilities and identify maximal planar subgraphs to obtain a solution [13].

2.2. Production Scheduling

According to Zobolas et al. [16], production scheduling problems are faced by every company that is engaged in the production of tangible goods. Due to more degrees of freedom (DoF) for the scheduling of orders in a smart factory, the production scheduling is of great importance and belongs to the category of shop production scheduling problems. Shop production scheduling problems are differentiated regarding their job arrival as static or dynamic, their inventory policy as open or closed, and their a priori knowledge about job processing times and machine availabilities as deterministic or probabilistic [16]. Additionally, a distinction based on the considered production environment as single or multi stage is made. For practical applications static, deterministic, multi stage shop scheduling problems are relevant [16].

With flow shop scheduling problem (FSSP) (see [17]), job shop scheduling problem (JSSP) (see [18]), and open shop scheduling problem (OSSP) (see [19]) three basic shop scheduling problems exist, which build the basis for more specific ones. Important extended problems are the flexible job shop scheduling problem (FJSSP) (see [18, 20]), the mixed shop scheduling problem (MSSP) (see [21]), and the group shop scheduling problem (GSSP) (see [22]). It is important to notice that extended shop scheduling problems are of at least equal complexity than the three basic problems and solving methods for basic problems can be applied to extended problems with little modifications [16]. With respect to DMS, none of the existing shop scheduling problem is capable of covering the whole dynamics and DoF. Thus, an extended shop scheduling problem needs to be defined and solution methods need to be developed.

2.3. Human-robot collaboration

The higher complexity and flexibility of decentralized manufacturing systems has to be handled in the workstations, which is a key element towards the factory of the future, as stated by Krueger et al. [23]. The human worker in the workstation is affected by these new manufacturing concepts. Repetitive work within an assembly line is replaced by fast changing situations in workstations of a decentralized production, which leads to a higher mental stress for the worker. Larger product varieties require increased mental flexibility. The cycle time is not constant anymore, but varies depending on the processes. Since each job can be different, the worker is unable to plan his next actions and can only react on the given situation in each cycle. Furthermore, quick changes in the number of workers in a workstation require effective teamwork and communication.

Within the fourth industrial revolution, the networked production is advancing, which is the base for new intelligent assistant systems. Such a new type of workplace is the human-robot shared workplace [24]. Connected sensors and advanced control software allow the implementation of assistant robots in assembly tasks. Until today, robots are working in cells for safety reasons. With the new generation of sensitive light-weight robots, any risk can be excluded because of their compliant behavior [25, 26]. Therefore, the collaboration is regulated in several standards.

Not only direct human-robot interaction is enabled, but also new manufacturing skills through force-controlled movements. Therefore, human-robot shared workplaces are assumed to be a basis for future intelligent production. They allow an optimal degree of automation in each workplace, and with the high flexibility of humans and the endurance of robots the strengths of both are combined to a highly efficient team. Therefore, ergonomics can be improved. Additionally, monotonous and repetitive jobs can be passed over to the robot and by focusing on value creating jobs the satisfaction and motivation of the worker can be affected positively. In fast changing situations and complex tasks, the worker can be assisted with information and intelligent work distribution, automatically followed by the robot. Overall, the higher efficiency leads to better productivity at lower cost while maintaining the level of quality.

Until today, simulations are only used for planning and offline programming of fully automated robotic assembly. Recent tools allow the integration of humans in the simulation to test the functionality of safety and protection zones (e.g. Siemens PLM Software [27]). Other simulations focusing on the human work allow the visualization of human movements within a process simulation and the extraction of ergonomic data (e.g. EMA [28]) from this virtual environment. Tools that are able to simulate the collaboration of humans and robots in a workstation, considering an adaptive behavior of the robot and process forces form the interaction of the human with the robot and the environment, are subject of current research. The new generation of compliant lightweight robots has not been integrated in commercial simulation tools, because they are not capable of simulating dynamic behaviors. First, dynamic models of the robots and the environment have to be implemented in order to simulate human-robot collaboration. Therefore, workstations are usually represented as blackboxes in simulations of manufacturing systems. The assembly steps within the workstations are considered as processes that only differ in their input, the time needed to complete the process, and their output.

2.4. Research Goals

Industrial applicability of decentralized manufacturing systems with human-robot collaboration requires fundamental evaluations of this concept. Within the considered fields of research, no evaluations are known due to the lack of conceptual work. In order to evaluate DMS, a simulation-based approach is introduced that covers important aspects and research demands to take dependencies between different concepts into account.

Regarding layout planning, common methods cannot consider highly flexible and individualized material flow paths. Additionally, the performance of a layout is affected by production scheduling and human-robot work distribution. Therefore, methods for production scheduling and human-robot work distribution are considered within the simulation and allow a more realistic evaluation of the decentralized manufacturing system. So far defined shop scheduling solutions do not cover the scheduling problem in a DMS completely. Hence, a combination of extended problems is proposed to cover this scheduling problem and an optimization method is applied.

In order to assess the benefits promised by human-robot collaboration, different types of human-robot shared workplaces have to be investigated. Therefore, this works aims at integrating human-robot shared workplaces in future production systems by presenting an algorithm for finding an optimal human-robot work distribution.

3. Simulation Concept

Since the concept of the smart factory introduces only a generic term with many different characteristics, we introduce the concept of DMS as a particular manifestation of the smart factory. Thereby, the concept of DMS concentrates on decentralized decision-making based on local information with the intention to cope with the increasing variant diversity in a manufacturing system. Based on decentralized decision-making processes, the vision is to allow each product to be produced along an individual material flow path. DMS are designed and dimensioned with the purpose to produce multiple variants or even related products in a single manufacturing system. This requires high flexibility and therefore fundamental modifications in comparison to traditional manufacturing systems need to be introduced:

- An important precondition for utilizing the advantages of decentralized decision-making based on local information is the presence of non-dedicated material flow paths as well as the absence of inflexible logistical couplings. Thus an individualized one piece flow can be introduced.
- Due to economic efficiency and limited spatial circumstances, it must be possible to combine compatible process capabilities, e.g. process capabilities with similar operating materials, tools or worker’s skill sets, on the same manufacturing cell. In this way, multi-purpose manufacturing cells offer different process capabilities and

thus enlarge the leeway in decision-making of the orders regarding their individual material flow path.

- In order to utilize state information of the manufacturing system for enabling the planning of and production along individual and state-optimal material flow paths, decentralized decision-making based on local information for each object is required.

The introduced concept of DMS emphasizes on decentralization aspects, which are often described in the visions of the smart factory.

3.1. Basic Problem

Generally, the introduced concept of DMS provides more DoF regarding layout planning, production scheduling as well as human-robot work distribution. Additionally, dependencies between the different optimization problems exist and a holistic simulation concept is required to represent the dynamic behavior of DMS, which is schematically shown in Figure 1.

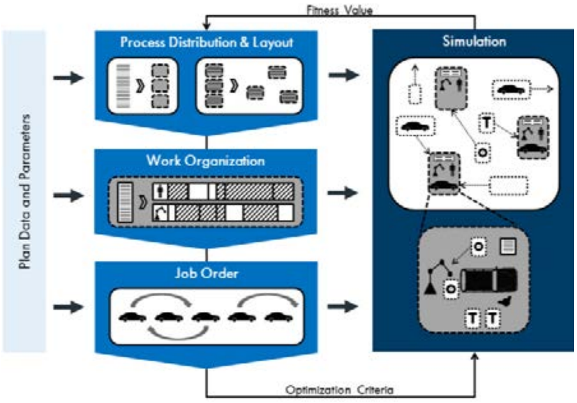

Figure 1: The basic optimization cycle. Plan data and parameters are used to generate the layout, the work distribution, and the job order. The simulation generates a fitness value based on the optimization criteria.

Layout planning and optimization is the first simulation objective. Due to increased routing flexibility of each product, the arrangement of manufacturing cells as well as the distribution of process capabilities among these cells is more complex and of greater significance for the systems' performance. However, an isolated consideration of this optimization problem is not sufficient since dependencies between the distribution of process capabilities and the suitability of a manufacturing cell for the application of human-robot collaboration exist. Furthermore, the performance of a planned production layout significantly depends on the quality of the scheduled production program. Thus, the three optimization problems shown in Figure 1 cannot be considered independently. Conventional optimization goals, e.g. minimal lead times, maximal throughput, high capacity utilization, remain important for each optimization problem. In order to restrict the optimization domain and thus allow a more target-oriented optimization procedure, basic information, as indicated on the left-hand side of Figure 1, is needed to characterize the optimization problem. The basic information mainly consists of planning data to characterize the production task, e.g. production volume, product information, and process information.

3.2. Layout Planning

Layout planning is based on the described basic information. With this, the determination and optimization of the number of workstations, the distribution of required process capabilities among workstations, and the location of workstations within the decentralized manufacturing system can be performed. For limiting the optimization domain, it is recommended to set a maximal value for the number of workstations. An adequate value is twice the number of required processes to allow the optimization to distribute each process to at least two workstations even if the borderline case with only one process capability per workstation eventuates. Thus, a robust system design can be achieved in any case. During the generation of an optimal layout, the distribution of process capabilities to workstations is not limited. But to assess the potential of decentralized manufacturing systems, relevant processes must be allocated to more than one workstation to enable flexible adaption to dynamical internal and external changes. Due to the fact that adding further process capabilities to a workstation increases the workstation's complexity, a cost function is introduced that takes the increasing cost into account. Furthermore, the distribution of the process capabilities is restricted by a compatibility matrix, which contains information whether it is possible to integrate processes on the same workstation or not. The information contained within the compatibility matrix is static and therefore integrated in the basic information. With respect to human-robot collaboration, an extension of the compatibility matrix is necessary since processes have different suitability for the application of human-robot collaboration (HRC). Therefore, during the layout planning process the values of the compatibility matrix are upgraded with HRC-suitability values for each process. By integrating the HRC-suitability into the objective function, layouts with higher HRC-suitability are generated.

After the determination of the number of workstations and the distribution of process capabilities among those, the spatial arrangement of the workstation needs to be defined. The developed method for finding an optimal location for the workstations is based on the modified triangulation procedure by Schmigalla [29]. In order to apply the procedure on DMS, its functionality is extended. Nevertheless, the main aspect for finding an optimal spatial arrangement is the minimization of transportation effort, in terms of distance or cost, for products as well as materials.

For finding an optimal layout with the previously mentioned restrictions, this work proposes the use of a genetic algorithm (GA). GAs are able to handle large optimization domains, which is the case for layout planning in DMS.

3.3. Production Scheduling

Given that the performance of a DMS greatly depends on the production layout as well as on the production schedule, it is almost impossible to evaluate the quality of a generated layout without an efficient production scheduling procedure. As introduced in section 2.3, three basic shop scheduling problems are defined in literature. However, none of these problems is capable to describe the production scheduling problem of a DMS. On the one hand side, this is caused again by the increased number of DoF, which cannot be completely covered by the basic shop scheduling problems. On the other hand side, interdependencies between layout planning and production scheduling increase the non-linearity of the problem and thereby lead to a more complex problem, which is not covered by the described basic shop scheduling problems. The most relevant scheduling problem for DMS is the GSSP, since it introduces groups with certain precedence relationships among different groups but without precedence relationships within the processes belonging to the same group. Nevertheless, the GSSP does not consider the existence of multiple workstations that have redundant process capabilities to a certain extent. Since the FJSSP takes this flexibility into account, the production scheduling within a DMS is a combination of both scheduling problems.

Since a production schedule is only optimal for a single layout variant, it is required to determine an optimal production schedule for each layout variant generated within the genetic algorithm explained in section 3.2. Because of the large amount of layout solutions generated by the GA, the optimization method applied to the scheduling problem needs to be less time-consuming. Therefore, a tabu-search (TS) is proposed to solve the scheduling problem in DMS.

3.4. Human-Robot Work Organization

In DMS, a higher level of complexity has to be handled in the workstations. Therefore, humans and robots have to collaborate in teams to maintain the flexibility and efficiency compared to conventional assembly. Workplaces are conventionally handled as blackboxes when planning the production layout. In simulations, they are represented as simple functions that take products, parts and tools as input to perform an assembly task in a certain time and generate a defined output. Dependencies within the workstation and interferences with the production are not considered. But the organization of the jobs within the workstation has a big influence on the performance of the whole production. For example the point of time within a production cycle at which a particular part is needed or a subtask is finished influences the occupancy and availability of transport systems in the production.

For optimizing the factory layout, the distribution of the processes to the workstations, as described in the previous section, is of high importance. Within the workstations, jobs have to be assigned to the robot in an intelligent way in order to support the human optimally. Therefore also the layout within the workstations, i.e. the position of products, parts and tools, must be considered. Finally, the processes within the workstation have to be integrated in the simulation of decentralized manufacturing systems in order to take the dependencies between the workstations and the production environment into account.

For the work distribution algorithm it is assumed that processes are already allocated to the workstations. Inputs are the work description of the processes, information about the workstation layout, and dependencies between products, parts and tools. The work descriptions are based on an MTM analysis, in which each movement that has to be done in order to perform a process is described. Since MTM only considers human work and requires an exact description of the work place, the method needs to be modified in order to cover HRC. The movement descriptions contain information about their type and associated containers, parts, and tools. From the parts' data base, detailed information about shape, weight, and location of assembly on the final product can be extracted. Further inputs are the actual skills and restrictions of the worker and the robot.

First, the types of movement in the processes are analyzed and compared with the skills of the human and the robot. Depending on the collaboration potential of a single movement, it is assigned either to the human, the robot, or both. In a second step, precedence dependencies between the tasks of the human and the robot are considered to generate an initial flow chart. Thereby, the most important criterion is a constant degree of utilization of the worker throughout the assembly cycle. Next, independent movements of human and robot are parallelized to compress the assembly cycle. Finally, non-utilized intervals of the robot are used to additionally assist the human, improve ergonomics, or decrease walking distances.

As a result, job instructions are generated for the human and the robot. The instructions can be used for a visual assistance system to guide the worker through the assembly cycle or to generate control inputs for robotic systems. Furthermore, parameters like the cycle time or occupancy rate, which are needed for the following optimization of the job order, can be extracted from the work distribution charts. The work distribution data can also be used in the simulation. Additional information about the assembly tasks is provided, e.g. the time when parts and tools are needed. The detailed representation of the processes in the workstations has a big influence on the actuality of the simulation of the whole production. By virtually performing the jobs of the worker and the robot in real time with the simulation of the decentralized manufacturing system, dependencies can be accurately considered.

4. Conclusion & Outlook

The presented research clarifies the concept of decentralized manufacturing systems and introduces a holistic approach for the evaluation of human-robot collaboration in decentralized manufacturing systems. Challenges regarding layout planning, human-robot work distribution, production scheduling are outlined and analyzed. Furthermore, dependencies between those topics are discussed and the need for a holistic approach of a simulation-based evaluation is pointed out.

The developed simulation concept aims at designing DMS for the optimal integration of HRC in multi-variant production. By implementing the proposed work distribution algorithm, the workstations are optimized for human-robot collaboration, but the degree of collaboration is usually not an optimization criterion in production. Future research will focus on an optimization algorithm that generates and evaluates multiple work distributions regarding key criteria in production. Furthermore, the integration of introduced concepts for layout planning and production scheduling in a self-developed simulation tool will be continued and improved. Additionally, the procedure for including HRC in DMS will be added to the simulation tool. Consequently, a simulation-based evaluation of the performance of DMS with HRC will be conducted.

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