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A Systematic Approach to Task Assignment and Production Planning in Disassembly with Employee Skills

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Abstract

An emerging shortage of resources fosters a development for strategies for the circularity of products and resources. Due to the different states of returned end-of-life products, the complexity for employees in disassembly increases. This work aims to provide an approach for an optimal allocation of disassembly tasks to individual employees and therefore enable a basis for planning and control in disassembly. At first, a task description is provided based on which a standardized time for operations is considered. Second, a link is created between the task description and the product state. Depending on the product state the time determined prior can be adjusted. Third, human skills are considered in manufacturing. It is assumed that within a production system there are different employees with different, developing skill sets. Based on specific skills, a task-to-person-is conducted. Using the information gathered, a Digital Twin (DT) that includes the human nature of the employees and their state is created to enable a simulation of tasks and thereby also a learning system for "first-time-seen" products. When facing complex tasks, the cognitive load and human's fatigue are decisive for performance and thereby the time required for execution. Completing these steps, a multi-stage concept is created that enables a more precise disassembly planning that can be shown in the case study on the example of components of electric vehicles.

Keywords: Human Digital Twin; Disassembly; Industry 4.0; Process Planning and Control

1. Introduction and Basics

Despite the advance of automation, a large number of activities remains manual in both assembly and disassembly. With a constant increase in complexity in the production system [1], humans are still the most flexible resource [2]. At the same time, it is crucial that humans and technology are considered jointly and that technology is accepted by humans [3] so that a beneficial co-existence can be achieved. Humans play a central role and it has also been shown quantitatively that if humans are actively involved in decision-making or planning, better results can be achieved [4, 5]. Of particular interest are the competencies of humans, indicating an advantage of a skill-based approach [6, 7]. Moreover, different approaches include differences in performance with respect to employee efficiency [8] or fatigue [9].

However, especially in the representation of production systems, human workers are often modelled as an unchangeable resource with equal properties [6] not reflecting.

In Industry 4.0, a large amount of data is generated in complex systems. Digital twins offer a possibility to investigate complex processes and thus make statements with respect to reality [10]. At the same time, digital twins allow the simulation of processes and procedures in order to make better decisions, sometimes in real time. Based on the aforementioned lack of the integration of the human in simulation, to ensure a better,

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holistic mapping of complex (production) systems, "the question is no longer whether to integrate humans as part of complex systems, but how to do so" [11]. To integrate humans into a digital twin, so-called human digital twins can be used [11]. Depending on the scope of consideration, different variables, from physiological (e.g. eye movement) to personality, are included [12]. This can provide information about the current state of the human and thus create a better understanding of the human being [11].

Thereby, fields with a large number of manual processes are of particular interest where humans have the biggest impacts. An interesting use case here is the disassembly of end-of-life (EOL) products, which is characterized by high uncertainties with respect to product type and condition [4] and a variance of up to 15% can be observed for the set-up and process time [13]. Human-related uncertainties in planning and control are thus further exacerbated in the disassembly use case due to product-related uncertainties.

In this contribution, a conceptual approach is presented that enables consideration of both human-related and product-related uncertainties and thereby improves control of the production system, but at the same time suggests measures for improvement of production planning. Based on this, the goal is to perform an optimization on the overall system level that provides both human welfare and cost-optimal solutions. This contribution is structured as follows: In section 2 an overview on the current state of the art is provided. In section 3 a conceptual approach to address the identified research gap is described. To conclude, in section 4 an outlook and the description of a case study for validation is provided.

2. State of the Art

Although the field of disassembly planning is a younger field than assembly planning, it is a field of increasing interest. In the following, exemplary approaches considering the listed subjects are examined: exemplary publications within the field of human digital twins, approaches to planning and control with the involvement of the human being, and dynamic models for learning about the human in assembly and disassembly. In addition, approaches to planning and control including product related uncertainties are presented.

2.1. Human Digital Twin in Production Systems and Human in Production System

In different publications models for human digital twins are introduced (e.g. [14], [15], [16], [17], [18]), and have also been used for production planning and the allocation of tasks [19]. A large number of publications on the human digital twin can be located in the field of collaboration between humans and machines, robots in particular. For example, [20] created a human digital twin aiming at optimizing the collaboration between humans and automated guided vehicles (AGV). The focus is on the investigation of safety in the collaboration with AGV, for which a prediction of the movement of the human is of great importance. The presented architecture provides a valuable basis, however, planning and control in production are only of subordinate importance.

In addition to the digital representation, the human being itself is also examined in the production system. [21] investigate how stress affects the error rate of humans using fuzzy logics. First, empirical data was collected for this purpose, which was then used to create a simulation. Product quality was considered as a key characteristic. However, the effects on planning and control were not discussed further at this point. [22] suggest a reinforcement learning approach that enables a human-oriented control to dispatch tasks amongst different workers. However, besides the availability of the worker and the task execution time, no further data on the human being is captured in order to provide a more precise representation. [23] use different reward functions in reinforcement learning to reflect different human behavior and therefore improve simulation results. However, the human's properties are not considered in detail.

2.2. Human-involved Planning and Control in (Dis-) Assembly

In this subarea a variety of approaches is found, mainly focusing on human-robot collaboration. For example, [24] present an approach to planning in disassembly. Here, the focus is on the derivation of the disassembly sequence based on CAD models as well as the allocation of tasks to humans and robots. Based on this, recommendations are be made for product development for future product design. However, the considered times of the processes are static for each worker and the human does not play a significant role in the allocation neither is a dynamic model presented for the human.

Human fatigue has also been considered in the context of human-robot-collaboration [25]. Considering the time required for a human to disassemble as a dynamic variable related to fatigue, the optimal task distribution between human and robot changes. The target value of the optimization is the total time for disassembly [25].

For the best possible allocation of tasks in assembly, including age-appropriate tasks, [7] divide possible tasks into four classes based on required expertise and physiological load. Aiming at minimizing both cycle time and physiological load employees are directly included and asked for their evaluation.

[4] use a genetic algorithm (NSGA-II) to schedule disassembly. Processing times and ergonomics are included and a real use case is considered. Nevertheless, this is not enriched with a simulation and it is unclear how unknown workers and their skills are handled. In addition, uncertainties that may be present in EOL products with respect to their state, as well as the current state of the human, are not discussed. The focus of [26] is on creating a framework for integrating humans into an IoT environment and the underlying ontology-based data model. This is implemented using the middleware CHARIOT. Individual workers in the system are represented as agents, which are again supplemented by a so-called task dispatcher agent that performs the assignment of tasks to humans. In addition to the availability of humans, health data

is collected to ensure the worker's well-being. However, a simulative integration of human and product related uncertainties is not made.

2.3. Consideration of Uncertainty in Disassembly

Uncertainties in disassembly relate to a variety of aspects. Product condition, time of return as well as quantity are uncertain; at the same time, the human behavior is out of control. Uncertainties related to product and human are considered in the approach of [27]. They assume that human expertise is crucial for dealing with product-related uncertainty. Based on a heuristic, a disassembly sequence at minimum cost is calculated. [28] address product-related uncertainty. Times used to perform a task are assumed to be unknown. A Monte Carlo simulation is used to select at which station which product should be processed. However, the relation to humans is not established. [8] formulate a model for task allocation in disassembly for whose solution they use a so-called Discrete Flower Pollination Algorithm is used. Different efficiencies of humans are also considered, but these are not further broken down in terms of fatigue or stress. Due to the high variances in disassembly, the times for disassembly operations are considered with high uncertainties (i.e. random number). But, no learning approach is used that allows successive tightening and improvement of the human model neither does a simulation exist.

2.4. Learning Approaches in (Dis-) Assembly Planning

Both aspects in manual disassembly, the human and the product, are subject to uncertainty. A learning approach can contribute to conquer these uncertainties. [29] present an approach to control in disassembly based on reinforcement learning. The competencies as well as aspects such as human fatigue are considered in a model-based, analytical way. External factors such as uncertainties regarding the arrival of components as well as machine failures are also considered. With a task allocation based on reinforcement learning employee fatigue and average lead time can be reduced. However, product-related uncertainties are currently not considered and no (human) digital twin is built to simulate the system. [30] consider the assignment problem between human and task in assembly. Based on historical data, they predict how long a specific worker will take to complete a given task based on skill, gender, and age, and thus determine the task execution time. The focus is on the selection of workers for specific tasks, focusing on task complexity. Fatigue is highlighted as essential aspect, but not implemented so far. The methodology allows job rotation to be performed in real time. [31] present a modelling approach to map the learning behavior of both, human workers and autonomous robots in a simulation model to incorporate and predict productivity increases in the decision-making process on a production planning and control level. However, their approach is based on a learning curve model, which is not coupled and updated by actual production data. However, product related uncertainties and simulation are not elaborated. In another approach, [9] use a learning approach to identify a critical fatigue level based on variables such as task repetitiveness and complexity, human-specific variables (skill, BMI, stress, gender, age) and workload. For this purpose, a so-called fatigue classifier is used, based on which a job rotation can be triggered. For validation, a simulation is used, whereby the simulation only refers to the detection of fatigue in one use case, but it is not clear to what extent this is a sequence simulation over several periods. In other work, the optimal time given to an employee for a specific task was systematically investigated [32].

2.5. Identification of research gap

Reflecting the listed, representative approaches it is found that there is no approach addressing all aspects, product and human-related uncertainty to further enhance the quality of a simulation to increase the performance of a production system on the long term and create the basis for a (human) digital twin and simulative evaluation. Therefore, a structured approach is needed to build such system and thereby improve planning and control within a production system.

3. Methodology

In this section a framework for a conceptual methodology for task assignment in production planning considering product and worker related uncertainties is described. An overview in which the different elements are listed is given in Figure 1. In addition, reference is made to the chapters in which the elements are discussed.

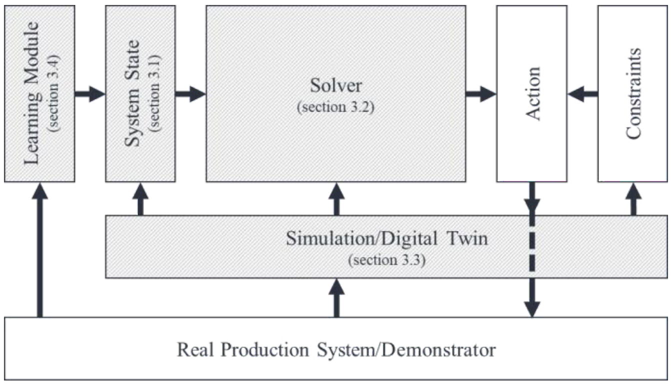

Figure 1 Overview of conceptual approach

The proposed methodology allows linking different areas. First, the state of the production system is mapped. However, the state of the system is learned and continuously improved in another loop via a learning module focusing humans. Based on a solver, an action is to be executed to further change the system. The action space is thereby limited by constraints. Actions are distinct into short-term decisions (control) resulting from optimization and long-term suggestions (planning) from simulation results. This is underpinned by a process simulation in which the characteristics of people are considered and thus a human digital twin is realized. Data is exchanged between the real production system and the digital twin as well as between the real production system and the learning module. In the following, the individual sub-areas will be presented and thus the approach is clarified.

3.1. System State

In the suggested approach the system state is characterized by three elements: The human, the product and the production system. For all elements, an extendable data model must be defined.

In the model, analogous to previous publication [30], each human has a dynamic set of skills and knowledge based on experience. At the same time, it is assumed that each human in the system has a specific stress level. In addition to stress, different types of fatigue (cognitive, physical) are to be captured. To model these, reference should also be made to appropriate sources, which has been used elsewhere ([29]). It is assumed that the current position of each human (example assignment to the machine) is known from shift schedules or sensors. Thus, simulation, sensory and questionnaires are used to determine the factors listed in Table 1. Based on this data, a human digital twin for each worker is built.

Each product that becomes part of the system has a specific input state that requires a different treatment in the disassembly system [33]. This results in a specific set of tasks that are required to complete the job. It is also a subject of research to investigate which data has an influence on the processing time by human workers.

The production system is characterized by the existing stations, their capabilities, possible buffers and availabilities of these. The data for mapping the production system are collected based on a real use case. An overview of the data aimed to be collected is provided in Table 1.

Table 1. Data captured for state description

	Human	Product	Production System
Type of data	Skills Competencies Stress Fatigue Position	Initial state Target state Degree of disassembly	Availability Capabilities Assistance Systems Machine Scheduling Buffers
Data capturing	Sensors Simulation	Tracking Analysis	Sensors Simulation

3.2. Solver

The problem is characterized as a task assignment problem. The objective function of the assignment can be described in terms of cost or time minimization but also worker well-being, creating a multi-objective optimization problem. The decision variable can thus be characterized in terms of whether a specific employee performs a particular task (exemplary notation in [7]). The problem is subject to a set of constraints, regardless of how the solution is found. The constraints are influenced from within the simulation, so that a certain action (i.e. solution of the optimization problem) is not possible or only possible with restrictions over a certain period of time. The action space or the control levers of the system can be distinct with regard to task allocation, changes to the production system or changes with regard to the human being. In terms of task allocation, for example, the sequence of components to be processed can be adjusted, thus enabling a change within the possible tolerance that is determined by the demand. In the production system itself, different material movements could be made.

The behavior or the condition of the human being can only be influenced indirectly. At this point, the use of assistance systems for targeted human support [34] or breaks are considered as control levers. Alongside with the change in task assignment, there is the possibility that the variety of tasks that an employee is given to work on increases or decreases in order to regulate the cognitive load [35]. The cognitive load is individually different and it is necessary to find an optimum for a specific person [35].

3.3. Simulation

The decisions for a specific action made by the solver are then examined with a discrete event simulation. The simulation therefore fulfills two functions: first, actions chosen by the optimization can be validated under the consideration of the future development of the system. Second, measures for improvement of the overall system (e.g. automation, use of assistance systems) can be derived. Here, it is important to represent the components analogously to the system state: Product, human and machine. The product is subject to uncertainty and, analogous to [24], standard times for the execution of each task are used at first which are then incrementally improved. After execution of the task by a certain employee in a certain state, the information about the actual processing time is passed on to the learning module (cf. section 3.4). In order to enable a better estimation of the processing time of future, unknown task execution times based on product similarity.

The machines and station are mapped so that capacities but also disturbances are modeled. Here, common models for process simulation are to be used.

The basis for the initial human model is given by analytical models how the execution of a certain task changes the state of the human being (e.g. [29]) and thus also to be able to make a statement with regard to the fulfillment of future tasks. In the course of the analysis, this modeling will be enriched with real data and thus tailored to the individual.

Product-related uncertainties are to be included at this point as well. For each employee a zone should be defined in which a task can be performed depending on the current state. This should ensure that even after the task has been completed, any tasks that arise in the further course of disassembly can be completed satisfactorily from the system's point of view. If this is not the case, further solutions are to be investigated simulative. A conceptual visualization is provided in Figure 2.

Here, task 1 would be fine to executed, but with task 2, the acceptable fatigue would be surpassed.

Long term modifications suggested based on simulative results could comprise the use of assistance systems to for example reduce the cognitive load of an employee or the automation of a repetitive, simple process. Thereby, it is distinct between process and people related modifications.

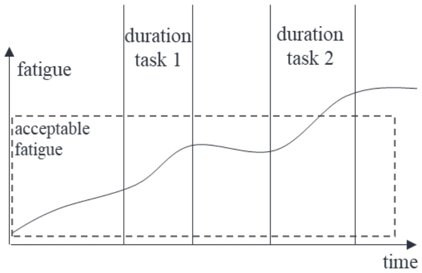

Figure 2 Impact of task execution on fatigue

3.4. Learning Module

The learning module is used to "get to know" the person on the assembly or disassembly line and thus continuously approximate to the real representation of the person and thereby a real human digital twin. Thus, the aim is to successively improve the models mentioned in section 3.1 on an individual level.

For this purpose, the human worker's abilities, physical and cognitive fatigue and stress are included. At this point, learning methods shall be used. As a further input, the product is considered with its variation of the product state, the time planning given by external factors such as demand, the tasks on the product and the target states. Thus, it is to be determined data-based, how much time a specific employee needs for a certain task. At this point, the acquisition of the relevant data and the creation of a data model are identified as a major challenge. In addition, product-related uncertainties are assessed and mapped to employee skills.

3.5. Implications for Production Planning and Control

The approach considered has implications for both planning and control. Based on the close coupling between simulation (i.e. digital twin), decision and real system, a targeted control of the products in the (dis-) assembly system can take place as a short-term reaction to changes in the (dis-) assembly system including for example a reallocation of tasks.

At the same time, possible results, especially those leading to entries of "forbidden" actions determined by constraints, can be used to derive implications for a possible change with regard to capacity in a further step. In particular, for planning the aspects of the development of competencies of the employees can be considered at this point, as well as the possible provision of assistance for the execution of certain tasks.

4. Use Case Implementation

The results will be validated using a demonstrator in the Global Production Learning Factory of the wbk Institute of Production Technology. Especially in the context of electromobility, an increase in production volume is to be expected. It is therefore necessary to develop EOL strategies for these products.

The component of interest is the axis of an electric vehicle or a part of it, so that the handling of the component is facilitated. It is planned to build a complete workstation that can be used to demonstrate the application. The key questions to be answered in the course of the implementation are the type of information that is beneficial in terms of improving planning and control for the employees and what added value can be achieved with it. At the same time, it will be investigated how a human digital twin can be usefully integrated into a discrete event simulation. Thereby, the focus is on the sensor-based capturing of the human being.

5. Conclusion and Future Work

In this paper, a conceptual approach to disassembly control and planning was presented. Humans are the most flexible resource in the production system, but at the same time are subject to the highest uncertainty. In addition, there is a high level of product-related uncertainty in disassembly. With the presented approach both aspects shall be analyzed equally and linked via a learning approach. Thus, an improvement of planning and control under a high amount of uncertainties shall be enabled. Using a universal data model, the current system state shall be modeled, which acts as input for an optimization problem. Promising approaches are thereby mathematical optimization or reinforcement learning (e.g. [36]). A simulation-based evaluation of the selected action is then performed, in the course of which a digital twin is extended to include the human worker and product-related uncertainties. The model of the human being is continuously improved with data from reality via learning approaches, thus also ensuring that the individual is fully considered so that real-time control can be generated. For future planning of the system, measures such as the inclusion of assistance systems or automation are derived.

The validation of the approach is planned using an example from electromobility performing a case study in the learning factory Global Production at wbk Institute of Production Science.

In addition to the practical realization of the approach, it may also be of interest to investigate it in combination with, for example, adaptive automation. Furthermore, it seems promising to investigate which methods can be used for learning on small amounts of data. In a large number of approaches, collaboration between humans and machines is in focus, and the suggested approach could also be for this field, where an accurate prediction of human performance is essential. Questions arising on the data and employee protection must be treated with care.

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