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A methodology for simulation production systems considering the degree of autonomy

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Abstract

The increasing number of product varieties and declining product life cycles combined with individualised customer behaviour demand flexible and efficient production systems. A proper solution approach can be the use of intelligent technologies, capable of autonomous processing in order to react rapidly to changing requirements. However, production planners need a profound planning approach for the implementation of such technologies in production systems due to their cost intense investments. Therefore, simulation studies are suitable means for the analysis of a proper degree of autonomy in production systems. An appropriate methodology for the simulation of such systems is presented in this paper. The methodology is aligned with common guidelines on simulation studies and focuses on system analysis, formalisation and simulation. It is based on consistent methods – fact sheets and Value Stream Design for system analysis, Unified Modelling Language (UML) diagrams for formalisation and agent-based simulation. A central contribution to current research is the modular modelling of intelligence skills in production resources and parts in a simulation environment. Consequently, the developed methodology provides a basis for the implementation of simulation experiments in order to facilitate the evaluation of the economically efficient use of intelligent objects in production systems.

Keywords

Simulation Modelling Methodology; Autonomous Production Systems; Agent-based Simulation; Production System Planning

1. Introduction

Market developments like globalisation, mass customisation, declining product and technology life cycles are putting high demands on production [1]. It no longer suffices to produce solely large batch sizes cost efficiently. Moreover, high flexibility and changeability of production structures are necessary in order to cope with these trends and meet fluctuating demands [2]. Therefore, production systems need to be capable of reacting rapidly to external factors, e.g. demand fluctuations regarding product variants, as well as internal factors, e.g. machine capacities and breakdowns – and in the best case even anticipate them. The complexity of planning and scheduling production systems increases with these factors as efficient and at the same time flexible production chains are required [3]. The industry faces this challenge by introducing intelligent technologies such as automated guided vehicles to attain autonomous processes in production systems. Instead of using central planning and scheduling systems, self-reliant entities are applied, which resolve problems locally and thus contribute to the overall solutions [4].

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Production planners can apply simulation studies in order to validate the efficient use of autonomous processes. Nevertheless, various factors, such as the individual behaviour of objects, have to be considered. This leads to an increased planning effort in implementation of simulation studies. Therefore, a modelling procedure is presented for simulation of production systems containing different degrees of autonomy in production processes. Beforehand, the paper gives an introduction to autonomous processes in production systems and existing procedures for simulation studies.

2. Autonomous processes in production systems

Within the context of production systems, a manufacturing or assembly system is subdivided into independent subsystems and modules with standardised interfaces. Thereby, it can have a given degree of autonomy to respond flexibly to changes by themselves and adapt to new requirements. Besides the independence from neighbour systems and its environment, it must also be fulfilled the ability of the system to control itself. Thus, it is capable of using these autonomous decision-making and action-performing processes. This self-control ability demands the decentralisation of the control system corresponding to the level of detail of the subsystems and modules. Hence, the degree of autonomy of the system elements depends on two characteristics. First, the given freedom of action by the superior system and second, the capability of the element to make use of this given freedom of action. [5]

The interlinking of these system elements can lead to autonomous processes, e.g. transport or assembly processes in the production system. For this, the objects like parts and resources as system elements "should be able to identify and locate themselves, to sense their environment, to communicate with other resources and parts […] and to control themselves autonomously by using their integrated control system" [5]. Approaches for such intelligent objects are, e.g., parts with integrated RFID devices, automated guided vehicles, intelligent robots or intelligent grippers [5]. Based on the independency and autonomous behaviour of such intelligent objects, flexibility increases in the production system. This can lead to higher capacity utilisation of installed equipment, less personnel costs or shorter throughput times.

Nevertheless, the increased degree of autonomy in the production system can imply higher overall costs. On the one hand, the investments in intelligent objects for autonomous processes requires higher initial costs [6,7]. On the other hand, a high degree of autonomy can lead to higher operating costs [8,9]. Therefore, a certain degree of autonomy has to be determined during the planning process of manufacturing systems in order to select appropriate production resources for the dimensioning of production systems.

3. Methods for simulation studies

3.1 General approach for simulation studies and simulation methods

In order to plan the introduction of intelligent objects on economic grounds, simulations can examine their behaviour and effects. However, there is a wide range of approaches for the simulation of production processes in production systems using different kinds of simulation methods or combining them. Two of the most commonly used simulation methods are discrete-event simulation (DES) and agent-based simulation (ABS). In DES, the system is modelled as a sequence of events, which occur at discrete points in time [10]. Hence, system changes are discontinuous. In comparison to DES, ABS is not an independent simulation type. It is based on existing types as parallel and distributed discrete-event simulation, object-oriented simulation and dynamic micro simulation [11]. It was established in order to study the unique behaviours of individual actors, map their decision-making processes, respectively resulting actions and make valid statements on the emerging global system [12,13]. Therefore, it is the preferred way of simulating autonomous processes as it has strengths regarding the representation of flexibility and autonomy [14].

However, there are a number of steps involved in simulation studies. A generally applicable approach for carrying out simulation studies gives the German guideline VDI 3633. The guideline only differs insignificantly from other procedures (cf. [15–17]). The general phase-oriented approach can be summarised in the phases: task definition, system analysis, model formalisation, implementation, experiments and analysis as well as the parallel-running phase's data acquisition and data preparation. The steps and their outputs are depicted in Figure 1. The following capture outlines specialised methodologies for simulation of autonomous processes.

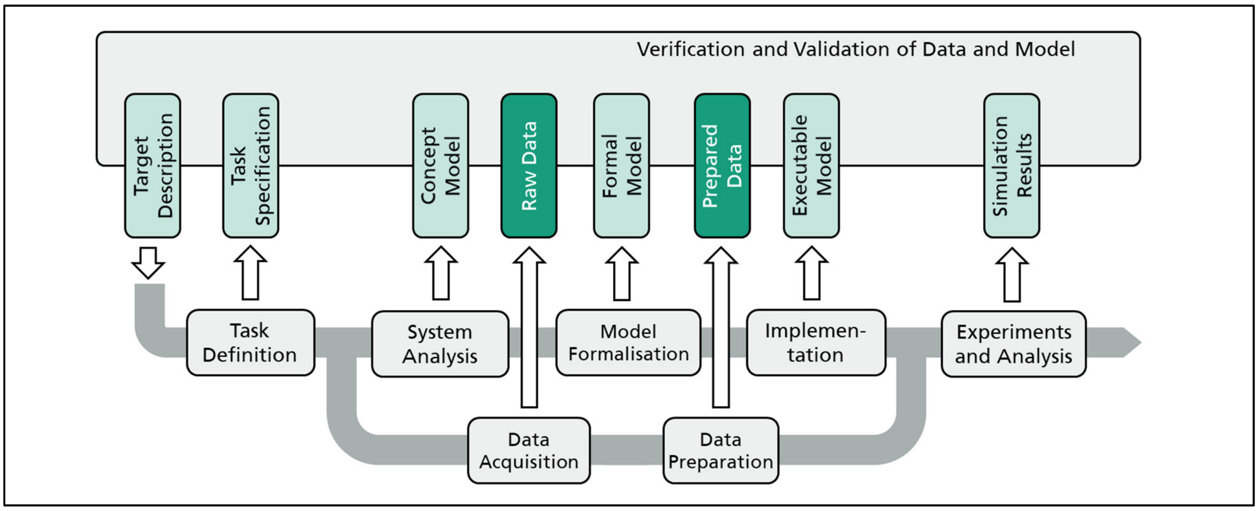

Figure 1: General approach for simulation studies [18]

3.2 Approaches for simulation studies of autonomous processes

There is a wide range of approaches for the simulation of autonomous processes in production systems. In this context, simulations are mainly used for the investigation of control methods (cf. [4,19]) rather than in the context of planning production systems. Nevertheless, there are also appreciable simulation modelling approaches. In the following, an excerpt of relevant approaches is given.

For example, Scholz-Reiter et al. [20] present a modelling method for autonomous logistic processes. It contains a requirement analysis by specification of the system as well as methods for business processes and simulation modelling. Another approach delivers Köchling [21]. The presented solution contains a three-step methodology. It is used for integrative planning of self-optimisation behaviour in production systems. Based on the structuring and creation of the simulation model, the operative implementation of self-optimising behaviour is facilitated. Besides both methodologies, the procedure of Lass can also be mentioned [22]. The methodology uses a hybrid simulation approach in the form of a model factory. It consists of virtual and real elements. Thus, it is possible to model cyber-physical production systems and implement a scenario. Thereby, the scenario can be individually tested in the simulator to adapt cyber-physical systems.

From the reviewed simulation approaches, further potential can be identified. Existing methodologies do not suffice to replicate the characteristics of autonomous behaviour. Thus, it is difficult to draw conclusions on the system as a whole. Additionally, the approaches are economically inefficient in the early planning stage as their development is highly time consuming or an expensive investment is necessary for model factories. Therefore, the objective is to develop a simple yet effective method of simulating autonomous behaviour in the context of production system planning. Thus, it should provide a basis to facilitate the evaluation of the economically efficient use of intelligent objects in production. Furthermore, it should ensure a consistent combination with methods for describing and formalising production systems.

4. Simulation modelling methodology

4.1 Concept of the modelling methodology

The developed methodology focuses on the main steps of simulation studies according to the mentioned German guideline VDI 3633. It incorporates extended approaches regarding the modelling and simulation of production systems considering the degree of autonomy. Figure 2 assigns these specific methods to the respective steps in the simulation study approach.

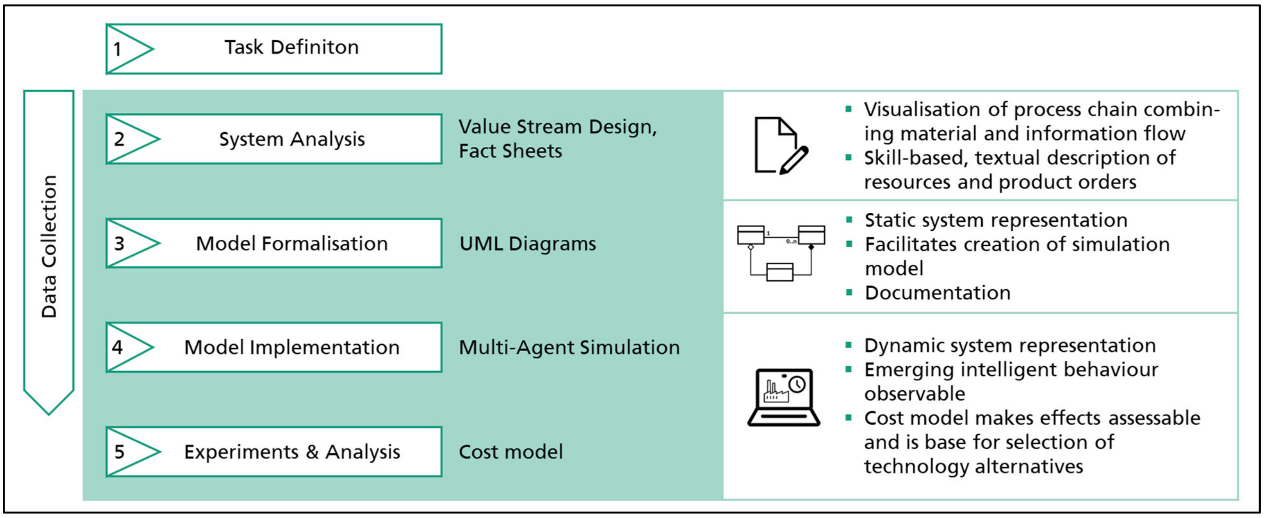

Figure 2: Developed Methods - allocated to the steps of a simulation study

Based on the task definition, which defines the tasks suitable to attain the goals regarding the planning of autonomous processes in production systems, the *system analysis* can be started. This analysis step comprises the definition of system boarders, the structure, relationships and characteristics of its elements, and the description of the process structure as well as its basic principles. For this purpose, the methods of Value Stream Design and fact sheets are used to describe the characteristics of production systems objects (resources and parts). The next step is the *model formalisation* by displaying the system elements and relationships in a formal representation. In this context, Unified Modelling Language (UML) diagrams as a static representation of the production system, its objects and relationships are used. Afterwards, the formalised model can be transformed into an executable simulation model as part of the *model implementation* phase. A multi-agent simulation serves as a simulation platform in order to represent the dynamic and autonomous behaviour of the production system and its elements. Finally, parameters and variable values can be implemented into the simulation model for purposes of *experiments and analysis*. The experiments can be executed with varying parameter values or structural adaptations of the model before the individual experiment can be analysed regarding economical aspects. In the following, the individual methods to the respective steps are presented and required extensions for autonomous processes are discussed.

4.2 System analysis

Based on the initial task definition, the production system planner can conduct the analysis of the production system. The system analysis consists of both: Value Stream Design and fact sheets. The method of the Value Stream Design can be used in order to visualise the process chains of the production system. The defined symbolism of the method helps to represent the logistical interactions of the system elements like inventory, supplier, customer, production processes as well as material and information flows [23]. However, the information flows are just demonstrated on an aggregated level. Therefore, an extension of the Value Stream Design is necessary to describe production systems containing different degrees of autonomy in processes.

Such a modified Value Stream Design is demonstrated by Theuer (cf. [23]). Next to Value Stream Design, fact sheets are applied for the textual, skill-based description of objects (resources and parts) in the production system. Thereby, it is possible to carry out the object´s ability to participate in autonomous processes based on their intelligence level.

Figure 3 depicts an exemplary resource fact sheet. It describes an intelligent cleaning machine for the powder removal of metal laser-melted parts. The fact sheets for resources contain basic information and a list of operating and intelligence skills. The characterisations of the operating skills are founded on guidelines like VDI 2860 or DIN 8580, whereas the seven intelligence skills are defined on the aggregation of existing classifications describing intelligent objects (cf. [24]). The classification is carried out according to an allocation matrix connecting the possession of certain architecture elements with feasible intelligence skills. Exemplarily, the skill taking Action requires the architecture elements energy supply, communication interface, data storage and processor, as well as actuator. Analogous to the fact sheets for resources, those for product orders comprise product features and intelligence skills. However, products do not possess actuators that are necessary for intelligence level 6 and 7. Hence, only intelligence level 1 to 5 can be attained.

ORGANIZATIONAL INFORMATION

Producer: Solukon
Name: SFM-AT800S
Communication: OPC-UA
Dimensions: 3 x 3 x 3 m³

ECONOMIC INFORMATION

Investment cost: 140,000€
Useful life: 10 yrs
Maintenance rate: 2 Percent

ENVIRONMENTAL FACTORS

Power consumption: 0.4 kW

BRIEF DESCRIPTION

Autonomous cleaning system with 2 programable axis for cleaning highly complex parts. Optimized movement based on digital twin is determined independently.

OPERATING SKILL

Process	Architecture element
Swivel	Swivel arm
Turn	Rotary plate
Vibrate	Rotary plate
Fixate	Pneumatic rapid clamping system
Manual cleaning	Pneumatic connections, glove ports

INTELLIGENCE SKILL

Intelligence level	Skill
1	Identifiability
2	Localizability
3	Saving object information
4	Data processing
5	Interaction/Communication
6	Automatic transaction
7	**Action**

SOURCE

Solukon

Figure 3: Fact sheet of an intelligent cleaning machine for powder removal

4.3 Model formalisation

After the production system analysis, the system elements and their connections together can be structured into a formal model. This model forms the basis for the implementation of the system into an executable simulation model. The most commonly used formalisation methods for production systems are petri-nets and Unified Modelling Language (UML) diagrams. Both are suitable in the context of production systems planning [25,26]. They have a graphical presentation, formal notation and are capable of mapping hierarchies, (de)compositing elements and illustrating dynamic time behaviour. In addition to petri-nets, UML diagrams allow demonstrating the modular structure of production systems. Thereby, it facilitates the transformation of the structure model into an executable simulation model [27]. Therefore, UML is the preferred method to illustrate and analyse the objects, their structure and relationships in the production system graphically and formally.

Figure 4 shows the UML diagram for intelligent resources in general. Based on the fact sheets, the diagram comprises basic information, the basic structure as well as further architecture elements related to carrying out skills. Organisational, environmental and economic information contain data for the parameters and variables of the simulation. The basic structure possibly in combination with energy supply, sensors and actuators enables operating skills. Furthermore, intelligence skills are enabled by the energy supply, identifier, information storage, information processor, communication interface, sensors and actuators. The more kinds of these architecture elements are given and intelligence skills are enabled, the higher is the intelligence level. The fact sheet for parts is similarly structured but doesn't contain operating skills and actuators.

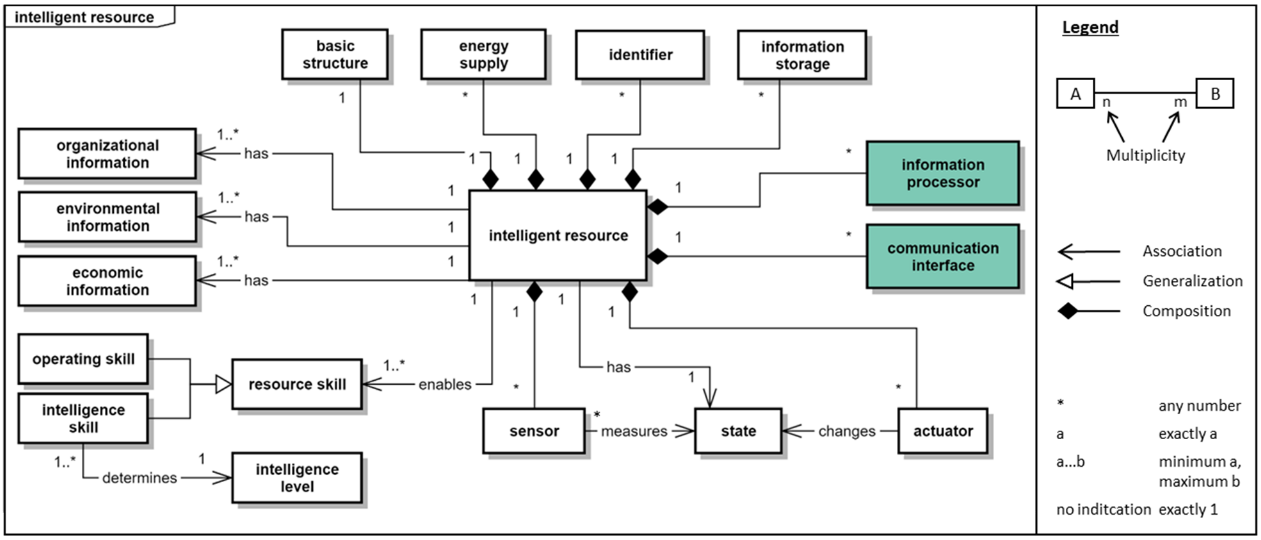

Figure 4: UML class diagram of the generic architecture of an intelligent resource based on [28]

Besides the formalisation model of objects, a formal model of the entire system has to be developed as only the interlinking of multiple objects enables autonomous processes in the production system. Hence, the UML class diagram of the production system demands process functions, besides objects and relations. The function are necessary to represent the autonomous processes which are enabled by the resource skills. Moreover, the resulting production costs can be allocated to the produced products and their features. The first figure in chapter 5 illustrated an exemplary formal model of a production system.

4.4 Model implementation and experiments

After the model formalisation, the model can be implemented into an agent-based simulation model for purposes of experiments and analysis (cf. chapter 3.1). Figure 5 illustrates exemplarily the schematic structure of such a simulation model for the software environment AnyLogic. The model is divided into three interconnected levels: the main, the database and the agent. The main level represents the process chains containing the process costs and the corresponding resource pools. In comparison, the database comprises the relevant parameters of the orders and their product features as well as the resources and their skills. The level agent is used to model different agent types of objects - orders and resources - including their specific behaviour realising autonomous processes.

In order to implement the objects' behaviour based on their *intelligence skills*, the following modules of the software AnyLogic have to be used alone, in combination or extended:

- **Parameters** are used for agent (or system) information, which is constant during simulation time, e.g. resource capacities or hourly rates.
- **Variables** should be used for information that changes over time, e.g. an agent's location.
- **State charts** allow the agent to monitor its current state by itself. State changes are triggered by message exchanges between levels or agents. Furthermore, state changes can cause another message exchanges initiating further state changes.

- **Statistic objects** monitor and save data on the system's or the element's behaviour. Therefore, it can be used for KPIs and represent the basis for decision-making processes, e.g. throughput.
- **Database** interfaces for example in form of the Excel spreadsheets serve as an external data storage similar to cloud solutions in real life.
- **Functions** enable modelling of complex agent-based decision-making processes by inserting customised code blocks and assigning them to certain agent types.

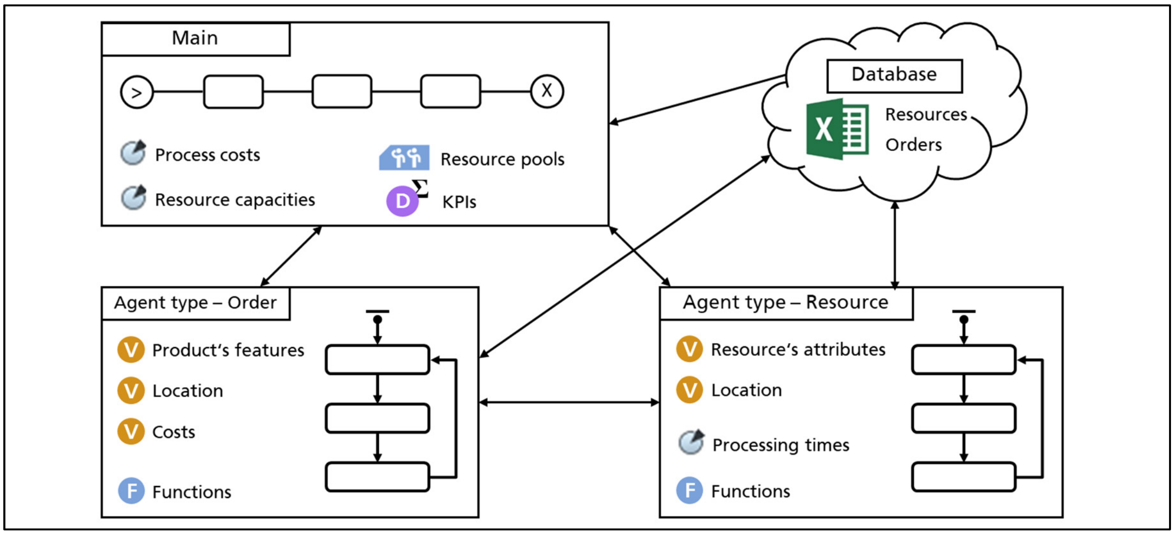

Figure 5: Structure of an agent-based simulation model with the main level, agent level and database

5. Exemplary application of simulation modelling methodology

The developed simulation modelling methodology was applied for the use case of a powder removal process for metal laser-melted parts. The simulation study had the goal to evaluate different degrees of autonomy in the powder removal processes. Therefore, several production resources were firstly investigated regarding their intelligence level as well as their interlinking with each other. Based on this system analysis, the production process was formalised into a UML class diagram (Figure 6). The cleaning machines (cf. Figure 3), AGVs and robots containing different intelligent skills are linked to an *autonomous production system* and interact via communication *interfaces*. The intelligent products also interact via communication with the system. Furthermore, workers can communicate with resources and products via the user interface. Therefore, a stationary terminal exists for the cleaning system and a mobile terminal is used for AGVs, robots and products. The post-process in the context of additive manufacturing uses the operating skills *swivel*, *position* and *convey* enabling the functions *cleaning*, *handling* or *transporting*. These functions change the *product's state* regarding location or production status as well as allocate the incurring *costs* to the relevant order. The *parts' features* determine the required operation skills of the resources.

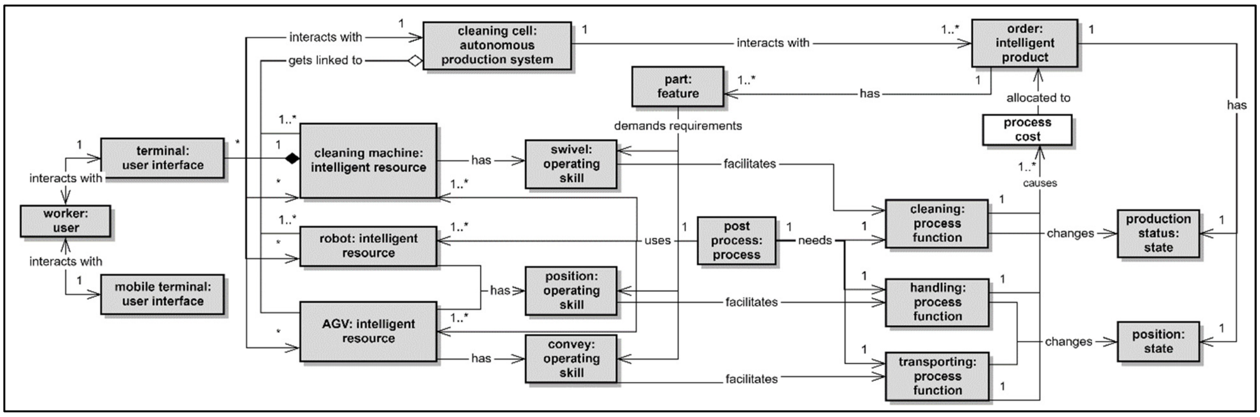

Figure 6: UML class diagram of an autonomous powder removal process for metal laser-melted parts

In the next step, the UML diagram was implemented into the simulation environment AnyLogic. Figure 7 shows the visual representation of the simulation model. The cleaning process contains the machines for cleaning, transportation and handling as well as workers operating for manual tasks. In this context, experiments were applied by using parameter variation. Thus, different degrees of autonomy in the cleaning process could be examined in order to determine the optimal mix of intelligent resources. The evaluation of the experiments is based on average cost per unit considering the restriction of maximum throughput time.

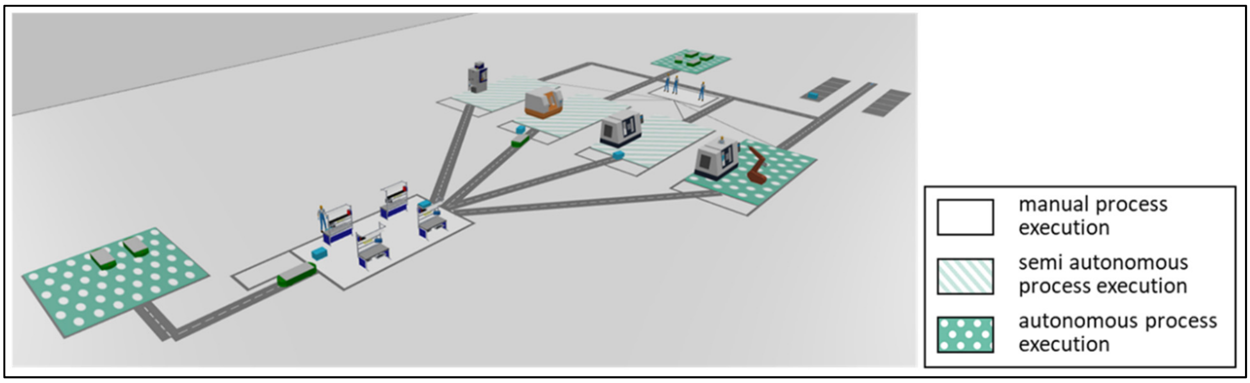

Figure 7: Simulation model of an exemplary powder removal process for metal laser-melted parts

6. Summary and Outlook

Production planners can apply simulation studies to validate the efficient use of autonomous processes. However, different aspects have to be considered in the studies implementation phase as the degree of autonomy depends on two factors: First, the given freedom of action by the system and second, the objects' intelligence skills enabling the use of this freedom. In order to reduce the implementation effort, the paper presents an adequate methodology for the simulation of (semi-) autonomous production systems.

The methodology is based on the German guideline VDI 3633 and contains the four main steps: System analysis, model formalization, model implementation and experiments. At first, the method of Value Stream Design and fact sheets are used to analyse the system and its objects. Afterwards, the analysed production system should be formalized in UML diagrams. Thus, the resulting formalized model can be transformed into an agent-based simulation model, which is applied to evaluate the autonomous system behaviour.

In addition, further potential was identified. On the one hand, the focus on flexibility and changeability could be increased by including scenario analysis in order to investigate stochastically alternate developments and events. On the other hand, production scheduling has a high impact on the system's performance. Therefore, researchers are advised to analyse the impact of differing scheduling methods.

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