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A FRAMEWORK FOR RESCHEDULING A FIXED-LAYOUT ASSEMBLY SYSTEM USING DISCRETE-EVENT SIMULATION

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ABSTRACT

This paper presents a framework for the rescheduling of Fixed-Layout Assembly (FLA) systems. It relies on the automatic generation of a Discrete-Event Simulation (DES) model. FLA systems are used for the assembly of large and bulky products in small volume. Because of their characteristics, they are subject to lots of disturbances and plan deviations throughout the execution stage. Planners currently use their experience to forecast the impact of these changes on the whole assembly system and to imagine new scheduling scenarios. Conventional DES methods are adapted to inflexible and automated manufacturing systems and are often not used for FLA systems. Planners would strongly benefit from a simple and effective solution to quickly forecast the impact of errors and new scheduling scenarios on the whole assembly system. The framework presented in this paper addresses this problem.

1 INTRODUCTION

Factories that assemble large and bulky customer-specific products, such as ships, aircraft, locomotives, and large machinery use Fixed-Layout Assembly (FLA) systems (Guo et al. 2020b). This type of layout requires materials and resources to be moved between assembly islands while the product is stationary (Burggräf and Schuh 2021). Resources of FLA systems such as assembly equipment and tools need to be mobile and universally designed (Mayr 2021). This is due to the fact that products are customer-specific and often only produced once (Lotter and Wiendahl 2012). A common problem for factories using FLA is the amount of disturbances and plan deviations occurring during the execution stage.

Disturbances can be delayed deliveries of components, failures of machinery or equipment and unplanned absence of operators (Matt et al. 2015). This problem is due to many characteristics of FLA systems, such as the small production volume and the high individuality and flexibility they offer to their customers. For FLA planners, it is difficult to predict the precise effects that these disturbances and plan deviations are going to have on the whole assembly. The lack of error identification can cause them to spread in the system (Qian et al. 2020). Planners currently use their experience to forecast the effect of these errors and to find a solution accordingly. The rescheduling of FLA is a complex and manual process that is prone to errors, especially when the impact of the disruptions that caused the need to reschedule cannot be clearly identified. FLA systems therefore need simple and effective methods to facilitate decision-making during the execution stage (Guo et al. 2020b).

This paper analyzes FLA systems and the problems they currently have (section 2), and why classic Discrete-Event Simulation (DES) approaches cannot be applied (section 3). A framework using a new DES modelling technique will then be presented, that could serve as a Decision-Support System (DSS) for the rescheduling of FLA systems (section 4).

2 FIXED-LAYOUT ASSEMBLY SYSTEMS

2.1 Basic Principles

Assembly systems use fabricated components to produce assemblies or products. These components can be manufactured internally or from external suppliers, depending on the business model of the company. Burggräf and Schuh (2021) defined different volume-based production types, from mass production to project production. Automotive assembly systems will typically fall in the category of mass production. To achieve a high productivity, it is common to use automated assembly lines that are based on the product itself. In the case of project production, a low volume of products that require customer-specific engineering are assembled. When assembling large and bulky products in project production, it is common to use Fixed-Layout Assembly (FLA) configurations. This also offers considerable flexibility and operational efficiency when assembling customer-engineered products (Guo et al. 2019). FLA systems use different islands to assemble a whole product without having to move it. Resources such as tools and assembly equipment are mobile and need to be shifted between the islands. These resources are designed to be universally compatible with many assembly configurations and geometries (Lotter and Wiendahl 2012; Mayr 2021). FLA systems typically do not use automation because of the low production volume, high variability, and high space requirement of the assembly islands. This often leads to undocumented processes (Rupprecht et al. 2020).

FLA systems enable manufacturers to assemble highly flexible products and require a low planning and controlling effort. Large and complex products are particularly suitable to FLA systems. On the other hand, they have long processing times, a complex material flow, and require large assembly surfaces. Workers are often highly specialized, resulting in long training periods for new employees. (Lotter and Wiendahl 2012; Burggräf and Schuh 2021).

2.2 Current Problems

The high flexibility of FLA systems leads to constant changes and disruptions occurring during the execution stage (Steinbauer 2012). Common disruptions can be the delayed delivery of components or the unplanned absence of operators (Qian et al. 2020). Assembly processes are also prone to problems because of the lack of verification when designing customer-specific features. In some cases, assembly processes cannot be executed because of reachability problems or collisions. The compatibility of flexible assembly equipment can also cause unexpected errors. This problem typically does not appear during the production of large batches of products, because every assembly process would have been carefully analyzed and verified. For Guo et al. (2020a), the complexity of the product and its sophisticated assembly operation can be prone to lots of errors and disruptions during the execution stage. In addition to these errors, FLA systems often need to react to last-minute customer requirements. Since the product requires customer-specific engineering, it is common for customers to ask for late design changes during the assembly. FLA systems are therefore prone to lots of disruptions and plan deviations. The problem is that the effects of these changes on the assembly system cannot be precisely predicted by decision makers (Qian et al. 2020). Decision makers currently use their experience to predict the impact of an error or a plan deviation. This method is subject to mistakes and could lead to unexpected events.

Modifying an existing schedule to appropriately react to a plan deviation is complex and time-consuming in the case of FLA systems (Steinbauer 2012). This contrasts with the need for decision makers to quickly find a reaction in order to minimize the impact of errors on the whole system. For Qin and Huang (2010), high material dynamics, assembly equipment and manpower flows make the scheduling of FLA systems quite difficult. Commonly used advanced planning and scheduling tools have a limited effectiveness on FLA systems because of the amount of disruptions and plan deviations. Modeling the current situation and the problem in these systems every time an error happens is often too time-consuming for manufacturers (Qian et al. 2020). The large number of tasks and subtasks also make it difficult to reschedule on a global level in short time. Decision makers therefore rely on their management experience rather than on digital tools (Qian et al. 2020). They need simple and effective methods to support rescheduling decision-making during the execution stage (Guo et al. 2020b).

3 DISCRETE EVENT SIMULATION

3.1 Basic Principles

Manufacturing and assembly systems can be analyzed and optimized using simulation models. Bracht et al. (2018) classify simulation methods using their representation of time. In the case of continuous simulation, a continuous time variable enables the analysis of movements, collisions, or ergonomics. A common method to analyze production systems on a global level is the use of Discrete-Event Simulation (DES). This method is used to model a manufacturing system using a distinct sequence of events occurring in time. Each event updates the state of entities such as resources or operations and potentially creates new events (Omogbai and Salonitis 2016). The variable of time is discrete because the simulation clock is only updated on each event, making DES a powerful method to understand the dynamics and behavior of manufacturing and assembly systems (Negahban and Smith 2014). DES is therefore as of today widely used and accepted (Bangsow 2020).

DES is mainly used in the planning phase of a manufacturing or assembly system (Heilala et al. 2010). Different alternatives can be analyzed and compared by predicting performance, bottlenecks, utilization rate and standby times (Bangsow 2020). In literature, this is sometimes referred to as offline-simulation and enables manufacturers to optimize their future factories before they are put into operation.

DES can also be used in the operative phase as a decision support tool (Lugaresi and Matta 2018). This method is referred to as online-simulation, because the simulation model is connected to real-time data concerning the manufacturing or assembly system. It enables manufacturers to test different control alternatives and scheduling strategies for a specific planning horizon (Bergmann et al. 2011). If failures or plan deviations occur, the DES model is used to predict the impact on production and assist decision makers in taking rescheduling decisions (Heilala et al. 2010).

3.2 Usage of DES to Model FLA Systems

DES is very effective for analyzing inflexible and automated systems with lots of standardized movements using elements such as conveyors, buffers, and machine tools. For these systems, the use of DES is widespread and state of the art (Weigert and Henlich 2009). DES for operational scheduling decision-making is commonly used for semi-flexible flow-shops (Azadeh et al. 2015; Xanthopoulos and Koulouriotis 2018; Sobottka et al. 2019). These systems often have standardized movements and product-specific sequencing rules that can easily be implemented in a DES model.

Because of their high flexibility and variability, DES is rarely used for the analysis of FLA systems. FLA systems assemble products with customer-specific engineering in a low production volume without any standardized movements. This makes them difficult to model in a DES software. The workload of these systems is also strongly variable and depends on customer orders, which makes an order forecast difficult. Because FLA systems do not have a specific layout or machine arrangement that could be optimized, manufacturers would not obtain a benefit from using offline-simulation.

Since FLA systems would benefit from a method to support rescheduling decision-making during operations, the use of online-simulation would be appropriate. This would enable manufacturers to analyze the impact of changes and disruptions on the assembly system and to compare and validate rescheduling strategies in reaction to these unexpected events. A drawback to the use of online-simulation for FLA systems is the complexity and time requirement necessary to model the problems in the DES software. Manufacturers would need to constantly change the DES model every time a new product needs to be assembled or every time an experiment would have to be analyzed. This would result in time-consuming modeling tasks for decision makers and simulation experts, that contrasts with their need to make quick and efficient decisions to react accordingly to a problem.

3.3 DES Using Process Modelling

DES commonly models the factory layout. It represents a realistic 2D or 3D-version of the whole manufacturing system (Bergmann et al. 2014). However, it is also possible to create a DES model of a factory using only a symbolic 2D-representation of the manufacturing or assembly processes (Bracht et al. 2018). The simulation will no longer follow the flows of a part between workstations using conveyors, but the processes the part must carry out in order to be manufactured. These processes can be modelled using business process model and notation, flow-charts, AND/OR graphs, or petri nets. These graphs use nodes to represent activities or events, which are interconnected using connecting objects to describe management processes, statistical problems, algorithms, or chemical reactions. More information about process modelling languages is provided by Kunze and Weske (2016). For manufacturers, these methods enable the modelling of parallel, alternative, or optional assembly processes of a product, together with the required time and resources. Compared to using the layout of the factory, the process modelling method is not commonly used because it requires more modelling time and generates a very theoretical simulation model where the optimization of the layout itself (paths, placement of machines, buffer sizes) cannot easily be carried out. However, FLA systems could benefit from it because they strongly rely on the assembly processes and not on the factory layout.

Weigert and Henlich (2009) modelled timed AND/OR graphs in a DES to simulate the scheduling of a FLA system for the assembly of milling machines and presses. This enabled them to validate scheduling experiments by predicting future delivery dates. Baruwa and Piera (2015) presented an approach for finding optimal scheduling solutions for a flexible manufacturing system using petri nets. Qian et al. (2020) also presented a framework for the dynamic scheduling of a FLA system using petri nets and an optimization algorithm.

Process modelling is used to represent every single possibility to assemble a product. The created model is often used as an environment for optimization algorithms to find a good scheduling solution. When integrating them into a DES software, rules need to be specified for the software to decide which path to take during each simulation run. A scheduling agent therefore needs to be integrated inside the DES. Figure 1 highlights these two different approaches. Without a scheduling agent, the simulation model considers a possible sequencing strategy as one simulation experiment.

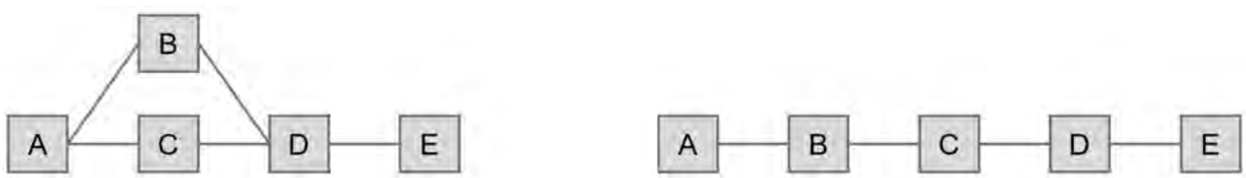

Figure 1: Process modelling.

The Process modelling technique on the left displays every single possible sequencing scenario. It requires an agent, to decide which process is executed after A. On the right, only one sequence of process is possible. It represents a simulation sequencing experiment.

Using a scheduling algorithm often requires a lot of computational effort, especially for large and complex assembly systems (Qian et al. 2020). The created scheduling solution is often not applicable to real-world conditions, especially highly dimensional assembly systems with lots of complex relations between resources and products, that strongly rely on worker know-how and experience. FLA Systems could therefore benefit from a decision support system that enables planners to better understand the consequences of changes and to validate their new scheduling solutions instead of automatically generating them.

Modelling a FLA system in a DES software using process modelling could be a solution for scheduling decision support but is still a time-consuming task that needs to be automated.

4 SOLUTION CONCEPT

4.1 Requirements

FLA systems are prone to lots of disruptions and plan deviations during the execution stage. Planners currently use their experience to analyze how these errors are going to affect the assembly system. This unfortunately often leads to unexpected situations. They would benefit from a tool enabling them to analyze these disruptions and plan deviations in detail from the moment they start the analysis. Planners are not computer scientists or simulation experts, they need a simple and effective tool, that doesn't require deep knowledge of domain-specific notations. Because of the frequency of these events and because of the necessity to react quickly, they need a tool that enables them to rapidly analyze different alternatives without spending too much time modelling the problem and the possible solutions.

Planners therefore need a simple and effective solution to quickly forecast the impact of errors and new scheduling scenarios on the whole assembly system. This paper presents a framework to address these problems.

The presented framework will be adapted to an existing FLA system for the assembly of Large Motors and Converters (LMC) in Berlin. These products are used in many industries such as metals, chemicals, power utilities, renewable energies, and gas. They reach several meters and weigh up to 25 tons. Every assembled product is unique and requires customer-specific engineering.

4.2 Data Architecture

Available data objects concerning the use case of the LMC assembly in Berlin are presented in Figure 2. This enables a better understanding of the typical data architecture of a FLA system.

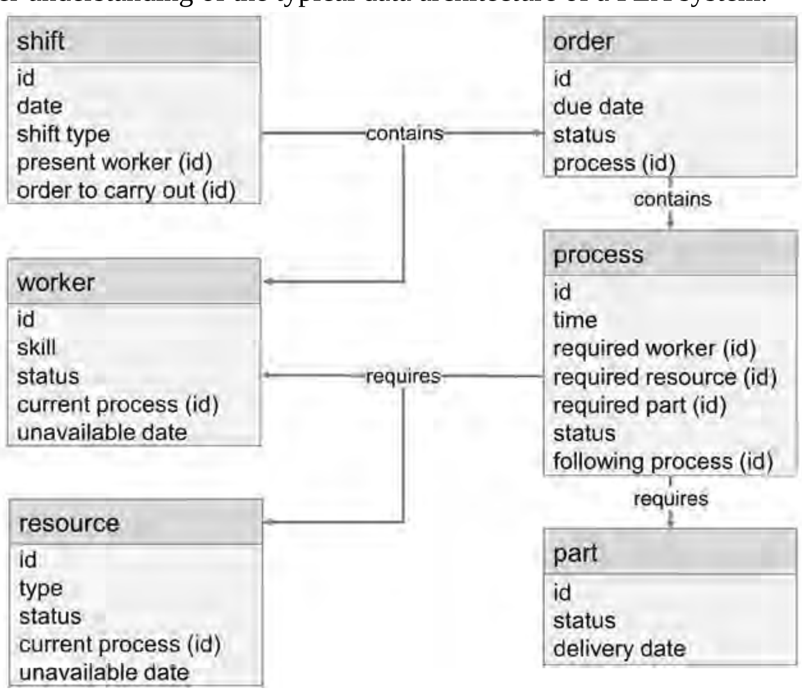

Figure 2: Data models of a FLA system for LMC.

The presented data is spit into six different categories that each represent an object containing several attributes. These objects can often have multiple times the same attribute. For example, an order contains multiple processes that also require multiple resources, parts, and workers. IDs are used to create references to other objects.

The assembly schedule is created by defining upcoming early, late, and night shifts for a planning horizon of around two weeks. Every shift contains a list of orders that need to be processed and a list of workers that will be present. Each assembled product is represented by a unique order, which is linked to a process plan containing every necessary assembly process. These processes require resources such as tools or fixtures, workers and specific parts that are manufactured from suppliers.

The ERP system contains every information concerning shifts, orders, and assembly processes. Data about resources, workers and parts is handled inside a shopfloor management system. This tool also enables the monitoring of the current states of resources, parts, processes, and orders.

4.3 Framework

The proposed solution uses data from the ERP and the shopfloor management systems to enable the automatic generation of a DES model. This model is used to forecast the impact of experiments by predicting the values of specific Key Performance Indicators (KPI). The detailed framework is presented in Figure 3.

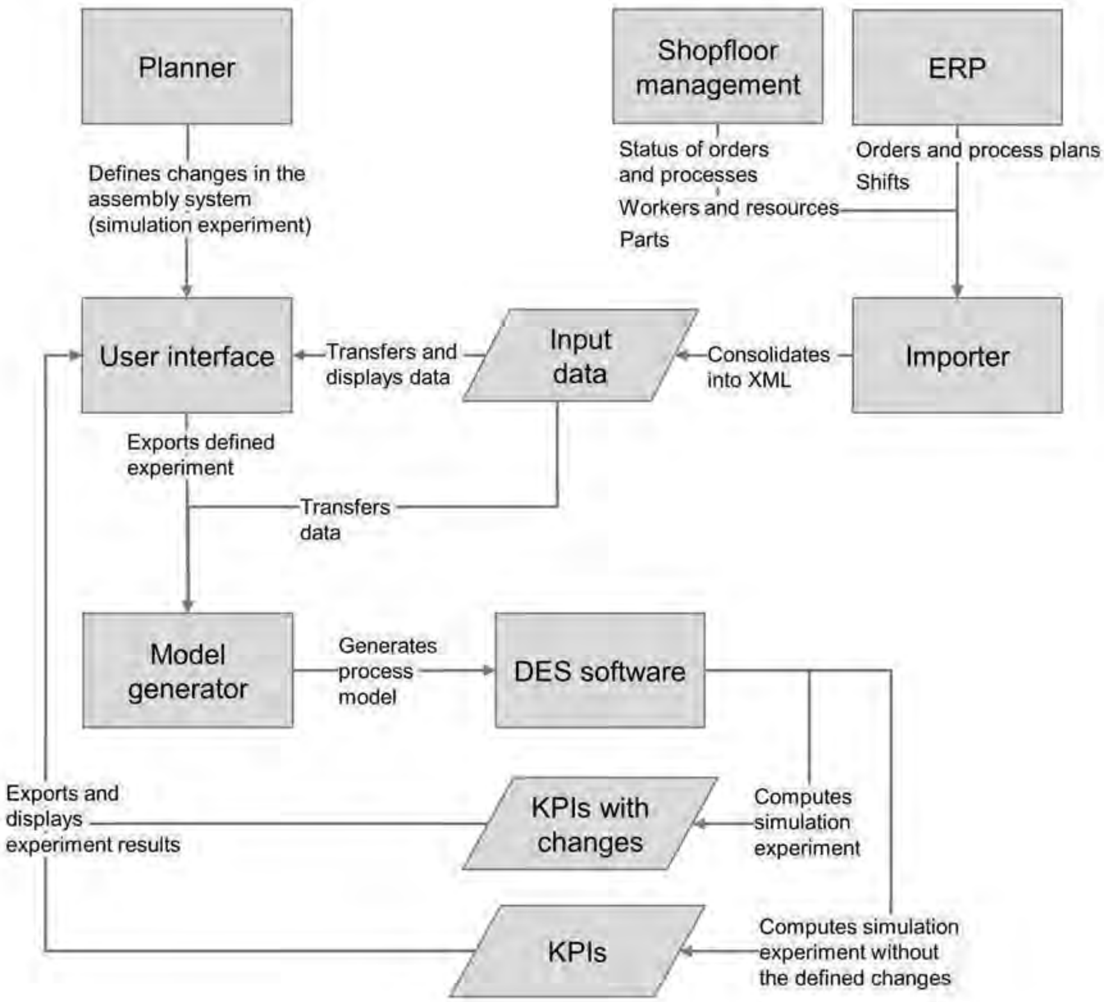

Figure 3: Framework for forecasting the impact of changes in a FLA system for LMC.

A user interface is used to enable planners the configuration of a simulation experiment by defining changes in the assembly system (example: *the delivery of a part is delayed*). These changes are entered by modifying data objects imported into the user interface. An importer is used to bring in relevant data from the ERP and the shopfloor management system (see Figure 3). To facilitate its exchange, the imported data is consolidated into an XML file. This data is then displayed in the user interface to enable the display of the current state of the assembly system and to facilitate the definition of the changes. A model generator is then used to automatically generate a DES in the form of a process model. This is enabled using the imported data and the defined changes from the user interface. The DES model then proceeds to run the experiment by starting the simulation clock on real current time and thus calculates KPIs with and without the defined changes, which are then sent back to the user interface. This framework predicts the effects the simulation experiment is going to have on the whole assembly system and enables planners to quickly forecast the impact of disruptions and scheduling scenarios using a simple user interface.

4.4 Model Generator

The model generator is an algorithm that uses the imported data to generate a DES in the form of a process model, which is able to run experiments and forecast scenarios. Figure 2 displays this imported data, in the case of the assembly system for LMC. Unlike most approaches using process modelling and FLA systems, no scheduling agent is used. This is because the process model is generated in a way that no decisions need to be taken during the simulation run. Alternative process sequences are regarded as single simulation experiments that can be analyzed by the planner (see Figure 1).

A DES in the form of a process model consists of two distinct components. The first one is a 2D environment called a simulation frame, which contains every simulation model element including basic links and rules between them. Objects representing orders, resources, workers, and parts are displayed in the form of elements that contain specific attributes. These model elements are represented in the "Model" part of Figure 4. The model generator uses the input data to create and position these elements on the simulation frame. Every existing order is created as an element on top of a succession of every assembly process, which is part of that order, linked together according to the attribute "following process." Attributes such as the required resources and parts are also included in the created elements. Additional elements representing workers, resources and parts are then generated. Their position and order on the simulation frame is not relevant.

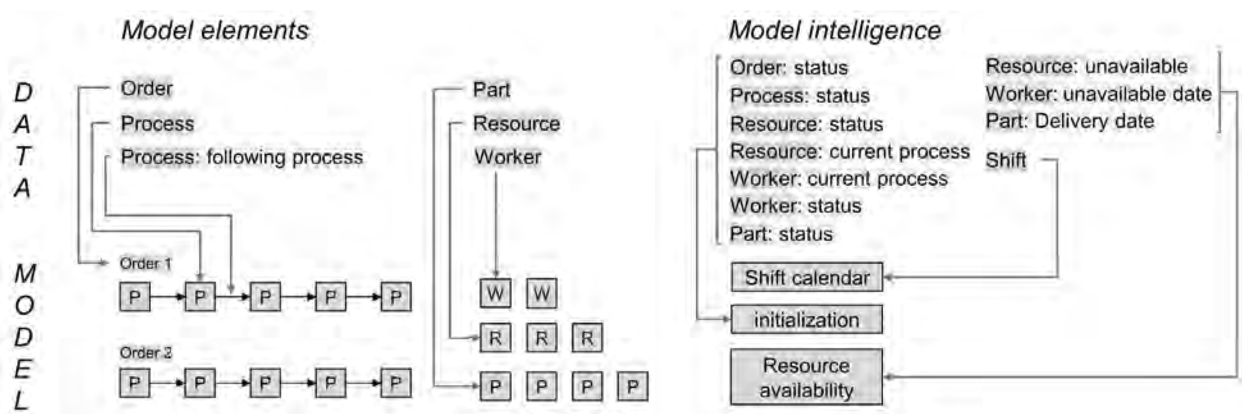

Figure 4: Model generator.

The second component is the model intelligence. It describes rules and relations between elements of the simulation frame. These algorithms specify how the simulation is executed, according to the planned shifts and available resources. Figure 4 displays three different elements that are generated for the model intelligence. A shift calendar is created by using the information contained in the shift objects from the input data. On the beginning of each simulation run, the shift calendar searches for the current day and time of the real FLA system and then cross-references its own shift table to find the current shift that needs to be activated to start the simulation. The next shifts are then automatically triggered during the simulation run. The initialization element uses the current state of resources, workers, and parts in the real assembly system to initialize the corresponding elements in the simulation frame before each simulation run. The current states of processes are also used to make sure that finished assembly processes are not executed again when starting the simulation. The last model intelligence element, resource availability, consists of an algorithm that triggers events throughout the simulation to change the status of resources, workers, and parts according to the attributes “unavailable date” and “delivery date.” Another important aspect that is part of the model intelligence is the resource management system. This is common to all DES using process modelling, which is why it doesn’t need to be generated each time. Its goal is to verify that required resources from starting processes currently are available by observing the status of worker, resources, and parts elements. This status is then modified when they are assigned. The resource management system also stops assembly processes that require unavailable resources.

This model intelligence is specifically built for FLA systems since it only allows processes to be completed once and uses the shift calendar to decide when specific orders need to be executed. Mass production assembly systems would not require such complex model intelligence, since they would be modelled using the layout of the system. In that case, most of the model intelligence aspects would be integrated directly in the model elements.

4.5 Output Data

After each simulation run, an algorithm inside the simulation will gather Key Performance Indicators (KPI) to evaluate how the experiment worked out. Common KPIs for inflexible automated manufacturing systems are throughput or cycle times. Planners of FLA systems need other types of KPIs to evaluate their simulation experiments. A list of relevant KPIs was therefore elaborated in collaboration with planners from the FLA system for the assembly of LMC in Berlin:

- Total personnel costs (€)
- Personnel costs per order (€)
- Total employee workload (%)
- Delivery reliability (%)
- Delivery delay per order (days)

To enable a user-friendly analysis of the KPIs, they will be additionally integrated into a Gantt-chart displaying every order with waiting times, due dates and achieved delivery dates. This will enable planners to quickly identify specific problems when analyzing a simulation experiment.

5 CONCLUSION

This paper presented a theoretical framework for a solution concept, that enables planners of a FLA system for LMC the possibility to predict the effects of changes in their assembly system. The solution automatically generates a DES in the form of a process model, which is then used to forecast relevant KPIs to FLA planners. The presented framework uses input data concerning the upcoming shifts, orders, assembly processes, workers, resources, and parts for the automatic generation. This data is imported from the ERP and shopfloor management systems. Available real-time data, for example concerning the current status of assembly processes, is used to initialize the simulation on the current state of the manufacturing system. The generated simulation model is then used to run an experiment, which analyzes the impact of changes on the assembly system. Specific KPIs are therefore calculated and presented into a user interface back to the planner.

Planners will no longer need to use their experience to forecast the impact of changes in the assembly system, thus preventing the emergence of unexpected situations. This framework will also save them considerable time compared to having to model the entire state of the assembly system before each experiment, without requiring any simulation knowledge.

The theoretical framework presented in this paper is currently being implemented using an existing DES software and a web-based user interface. This implementation will then be evaluated in collaboration with planners from the assembly system for LMC.

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