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Approach For Autonomous Control Of Intralogistics Considering Deterministic And Probabilistic Material Demand Information In Flexible Production Systems

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Abstract

In today's dynamic production landscape, flexible and resilient production systems are essential to meet the constant changes in internal product and production requirements as well as external market and customer demands. To meet these challenges, various flexible and resilient production system approaches offer the necessary structural, process-related and technological flexibility and resilience. However, the intralogistics material provision within these complex production systems is challenging due to increasing degrees of freedom and uncertainties caused by emerging turbulence, which has even risen very sharply in recent years due to global instability. This makes it difficult to coordinate material demands and material provision in the production system precisely regarding location and quantity. This paper presents a comprehensive approach for determining the material requirements and autonomously executing the corresponding material provision processes in a complex production system, which considers both deterministic and probabilistic information about the material demand's location, quantity, and time. Utilizing autonomous control in intralogistics decentralizes complexity management in flexible production systems by transferring decision-making and process execution tasks to the system elements. For the development and verification of the comprehensive approach, an experimental research study was pursued based on a flexible production system, including simulation and practical experiments. Defining the deterministic and probabilistic material demands is based on the Monte Carlo method for carrying out simulation experiments with parameter variation. The autonomously controlled, target size-optimized execution of material provision to fulfil the determined material demands is based on an agent-based modelling and control approach for manual and automated intralogistics transport resources. The study showed that improved logistics performance (throughput time and adherence to schedules) can be achieved in flexible production systems in the event of turbulences by considering deterministic and probabilistic material demand information together with autonomous control of material provision.

Keywords

Flexible Production; Autonomous Control; Intralogistics; Monte Carlo Method; Agent-based Modelling

1. Introduction

The growing global competition and cost pressure, together with market requirements for increasingly individualized products down to batch size 1, forces companies to make their production more flexible and

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to optimize it continuously to meet changing requirements [1]. Not only during the Covid-19 pandemic, companies were increasingly confronted with internal and external uncertainties and turbulences. Even in the last years, they have risen very sharply due to global instability [2,3]. Turbulences can influence production adversely as internal turbulences, such as resource breakdowns and process delays with an in-house origin, and external turbulences, such as missing or delayed deliveries from suppliers and customer order changes with an external origin [4]. Our investigation with a contract manufacturer revealed a 42 % adherence to schedules over two-and-a-half-years. Within this investigation, late completions of production orders resulted in increased throughput times, mainly due to internal turbulences like process delays, unexpected wait times, and resource shortages, particularly in labour. Following *Erlach et al.* [5], turbulences are short-term fluctuations that require short-term reversible reactions by the production system. This short-term and reversible response to turbulence without structural changes and time-consuming planning and implementation processes can be achieved by the change capability of flexibility [5]. Traditional production systems relying on fixed process and layout structures cannot provide the required flexibility and changeability. Also, major objectives of companies are to reduce throughput times and to increase adherence to schedules (measured based on adherence to a defined schedule tolerance [6]). *Kletti et al.* [7] state that the processing time in manufacturing companies only accounts for 5-10 % of the total throughput time.

Flexible and changeable production system approaches, such as flexible and reconfigurable manufacturing systems [8,9] and matrix production systems [10,11], have been developed to cope with these challenges. Flexible production systems can adapt the production system within defined flexibility boundaries without structural system changes [8,9,12]. Reconfigurable and matrix production systems can surpass predefined flexibility limits by restructuring the production layout to accommodate new product variants [10–12]. In matrix production systems and other flexible and adaptable production systems, each production order moves along its product-specific path through the production system using the process and product flexibility of the production system [10,11,13]. The sequencing of operations and the distribution of orders to production resources are managed ad hoc, relying on the autonomous control features of the cyber-physical elements within the production system [13,14]. Autonomous control of intralogistics has proven to be a major enabler for reducing the negative effects of internal turbulences on throughput time and schedule adherence by using the existing flexibility corridors of flexible production systems [15,16]. If a production resource experiences a breakdown, the flexible production system can address this by reassigning a production order to an alternative production resource. The routing and operational flexibility inherent in the flexible production system and the capabilities of the autonomously controlled intralogistics system facilitate this. In flexible and changeable production systems, a major challenge in material provision arises to match demand and provision of material in terms of time, location, and quantity due to the increasing degrees of freedom in the production control system [14]. Usually, it is not possible to define a fixed order sequence and plan the resources with defined material demands in advance as they arise or become specific (time, location, and quantity) during the actual production operation since they are subject to uncertainties [13,12,14].

2. State of the art and research gap

The core task of the autonomously controlled intralogistics systems is to provide the right material at the right time, quantity and quality at the respective place of demand in the production system [10,13,17]. Emerging turbulences may lead to a time gap between the ad hoc definition of the material demand in terms of time, place, and quantity and the required time for the material handling, picking, and transport for the material provision of the respective material [14]. To deal with this time gap, the material provision system must consider various potential scenarios and the available flexibility corridors regarding time, place, and quantity of material demands to use the flexibility and changeability capabilities of the specific production system. Material demands planned with conventional methods ground on a defined allocation of a production order to a specific production resource using deterministic information about material requirement location, quantity, and time [18]. Probabilistic material requirements, on the other hand, are based on probabilistic information regarding the location, quantity, and time of the material demand [16]. For a target-optimized material provision enabling the use of available flexibility corridors, these probabilistic material demands must be considered in combination with the deterministic material demands. To cope with the rising complexity of deterministic and probabilistic material demands in the intralogistics system, a decentralized, autonomously controlled approach has to be applied to achieve a distributed, flexible management of dynamics and complexity based on intelligent intralogistics entities [6,19].

Existing methods of autonomous control only consider specific (singular) subsystems, e.g., cyber-physical transportation systems [20-22], agent-based production systems [23-25], autonomous/self-organized production planning and control [26–28] or hybrid (centralized and decentralized) control of production or logistics systems [29–32]. They also do not consider forecasted, probabilistic material requirements from possible short-term production program changes (e.g., due to resource failures, process delays, etc.) and thus impair the flexibility of production for a dynamic, target-oriented reaction to short-term turbulences [33,34].

To develop a respective approach, this paper takes up the findings of *Schuhmacher & Bauernhansl* [15] on the data-driven prediction of turbulences. It also includes the research of *Schuhmacher et al.* [16] on the determination of material demands by combining deterministic and probabilistic information. The paper extends the findings by integrating these aspects in the autonomous control of intralogistics in flexible production systems. With reference to these proven possibilities for data-driven turbulence forecasting and determination of material demands involving probabilistic information, this paper presents research for developing a novel approach for autonomous control of intralogistics that considers deterministic and probabilistic material demand information in flexible production systems.

3. Methodology

An experimental research approach combining simulation and practical experiments based on an actual complex production system has been applied to develop and verify the comprehensive approach for autonomous control of intralogistics considering deterministic and probabilistic material demand information [35]. The Information Systems Research Framework of *Hevner et al.* [36] helped to develop and evaluate the research artefacts of the approach. Following this framework, the requirements and characteristics of the production system and the knowledge base regarding existing theories, frameworks, and methods have been analysed and incorporated in the developed approach and evaluated based on simulation runs and practical experiments [36]. The steps for developing the comprehensive approach and the experimental research study conducted for verification are explained in the following chapter.

4. Experimental research study

The developed approach (see Fig. 1) for autonomous control of intralogistics and determination of material demands based on deterministic and probabilistic demand information is aligned with the procedure of VDI 3633 [37] for simulation studies. The method, which consists of *8 main steps*, starts with defining the considered production system, identifying and defining the turbulence attributes and modelling the production system and its turbulence events. In *step 5,* the simulation experiments are conducted using the Monte Carlo simulation method for parameter variation of the random variables. For this simulation-based determination of deterministic and probabilistic material demands, current data from the production system (e.g., status information of resources, process times) and forecasting information on potential turbulence events have to be taken into account. In addition, a defined set of rules considering the global objectives (adherence to schedules and reduction of throughput time) and time restrictions (e.g., for the transition to probabilistic material demands to firmly planned deterministic material demands) has to be considered. In *step 6,* the derived deterministic and probabilistic material demands are transferred into deterministic and probabilistic transport orders that have to be fulfilled by the autonomously controlled material provision system using manual and automated transport systems. In *step 7,* the deterministic and probabilistic transport orders are allocated on the transport systems autonomously considering current data from the production system and defined selection criteria for an agent-based selection of the most suitable, target-size optimized transport system for each transport order. In *step 8,* the autonomously controlled material provision is executed, and the subsequent simulation run for determining and updating material demands in the production system is initiated. The next sections provide further details about the steps of the developed approach.

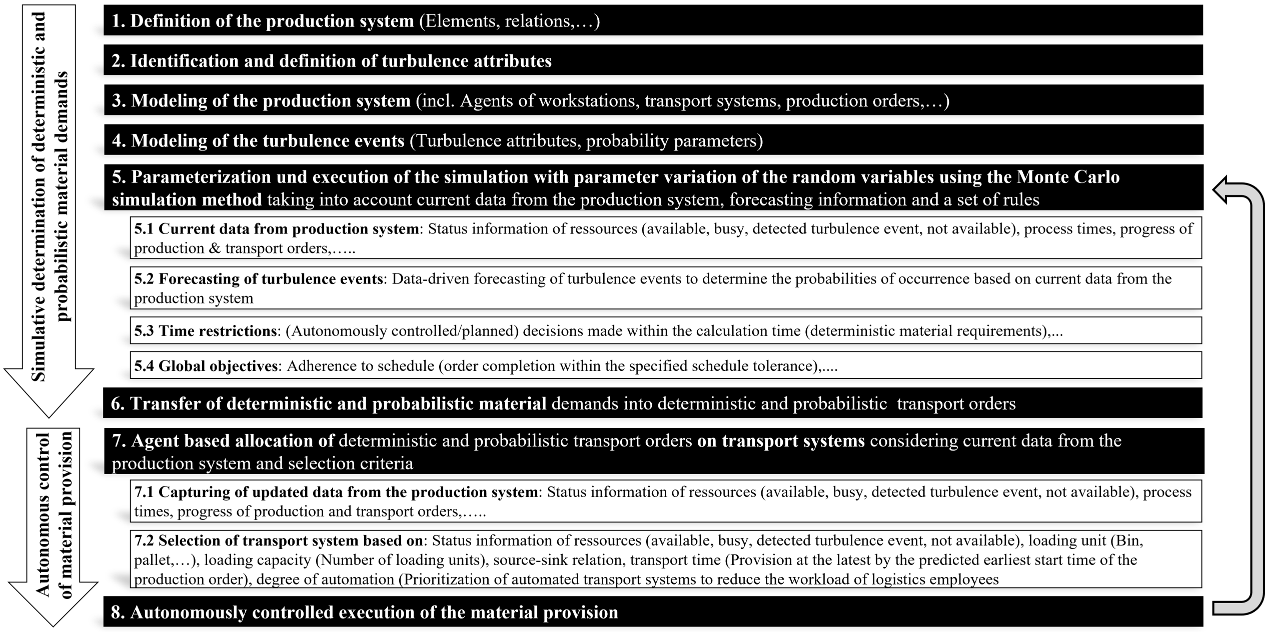

Figure 1: Steps of the developed approach for the autonomous control of intralogistics considering deterministic and probabilistic material demand information in flexible production systems

4.1 Determination of deterministic and probabilistic material demands

Step 1 covers the analysis and definition of the production system with its elements, relations, properties, and parameters. The considered production system is structurally and process-wise based on the flexible work system of the learning and research factory Werk150 at Reutlingen University to assemble customizable scooters (see Fig. 2).

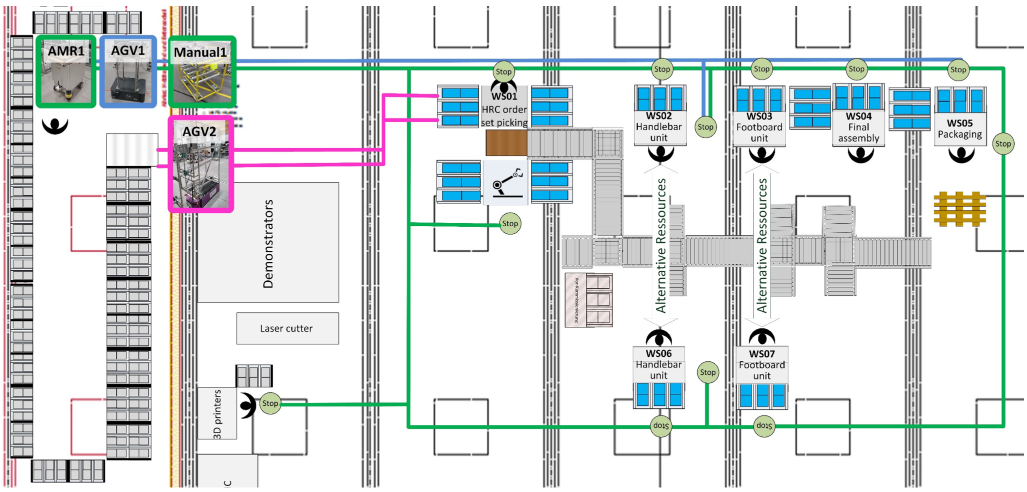

Figure 2: Investigated production system at Werk150

The assembly system consists of an order picking station (WS01) for picking sets of variant-specific standard components (such as handlebars and footboards), two alternative assembly workstations for pre-assembling the handlebar unit (WS02 and WS06) and footboard unit (WS03 and WS07), and a final assembly (WS04) and packaging workstation (WS05). The logistics system comprises a central warehouse and decentralised buffer storages at the workstations for C-parts (such as screws and small standard parts) and at the production resources (3D printing and CNC area) to store raw materials and finished products. Customised components are transported just in time from the central warehouse or buffer storage of the 3D printing and CNC area to the assembly workstation where the customer order is assembled. The material provision to the workstations is autonomously controlled using manual transport resources (Manual1), automated track-guided automated guided vehicles (AGV1, AGV2) and a freely navigating autonomous mobile robot (AMR1).

In *step 2,* the turbulence events have been identified and defined considering the previous work of [15] and common turbulence events in the assembly and logistics system at the Werk150 (see Table 1). Log files of previous production runs have been analysed to identify relevant turbulence events and their turbulence attributes. For the scenario-based investigations, frequently occurring turbulences of different types (such as process delays, resource breakdowns and deviations in the provision of materials) in the assembly (T1-T4) and intralogistics (T5 and T6) system have been selected.

Table 1: Turbulences, turbulence attributes, distributions, and probabilities of the considered production system

Turbulence	**System elements affected**	**Turbulence attributes**	**Initial distribution and probabilities**
T1: Robot collision (breakdown)	WS03	Probability of occurrence Mean time to repair (MTTR)	Probability: 1 % Uniform distribution [38,39]
T2: Jammed screw (delay)	WS02/WS03	Probability of occurrence Process delay	Probability:10 % Triangular distribution [38,40]
T3: Wrong part	WS02	Probability of occurrence Process delay	Probability: 5 % Triangular distribution [38,40]
T4: Excess material	WS06	Probability of occurrence	Probability: 4 %
T5: AGV battery error (breakdown)	AGV1	Probability of occurrence Mean time to repair (MTTR)	Probability: 3 % Uniform distribution [38,39]
T6: Object in way (transport time delay)	AMR1	Probability of occurrence Delay of transport time (AGV)	Probability:10 % Exponential [41,42]

Steps 3 and *4* cover the modelling of the production system and the turbulence events for executing the simulation in *step 5*. The autonomous behaviour of the transport resources was modelled by following an agent-based approach. For the stochastic turbulence events, an event-oriented approach has been applied.

In *step 5,* the simulation model is parameterized and executed for a scenario-based determination of the material demands using the multi-method simulation tool AnyLogic. As described in [16], based on intensive analysis, the Monte Carlo method determined probabilistic material demands scenario-based, including location, quantity, and time. To align the simulation model with the current situation of the production system, the simulation model is parameterised with current data from the production system (e.g., status information of resources, actual process times and progress of production and transport orders). These current data is also used for forecasting potential turbulence events in the production system by applying the selected methods described in [15]. The generated forecasting information (probability of occurrence and possible delay) concerning the considered turbulence events is fed into the simulation model to parameterize the turbulence attributes for the Monte Carlo simulation. For the simulative determination of the deterministic and probabilistic material demands in combination with the autonomous control of intralogistics, a defined set of rules must be considered to ensure that feasible solutions are generated. For example, a probabilistic material demand has to become a deterministic material demand if the (predicted) remaining time is no longer sufficient for a material provision at an alternative workstation. Also, the major intralogistics' objectives to increase performance by reducing lead times and increasing adherence to schedules (compliance with a defined schedule tolerance [43]) are considered in the defined set of rules.

4.2 Autonomous control of material provision

Within *step 6*, the probabilistic material demands are transferred into probabilistic transport orders, and the deterministic material demands are transferred into fixed (deterministic) transport orders, which are to be fulfilled by the autonomously controlled intralogistics system in a performance-optimized manner (considering throughput times and adherence to production schedules).

This agent-based allocation of deterministic and probabilistic transport orders on the transport systems is done at *step 7,* considering updated data from the production system (e.g., progress of orders, availability of resources) and defined selection criteria for an agent-based, autonomously controlled decision on the most favourable transport system. The transport order agents (aiming for a timely provision at the earliest forecasted demand time at the location of demand) and transport system agents selected the system by considering the following criteria for the execution of the material provision (*step 8*):

- **Status of resource**: Available, busy, detected turbulence event, not available
- **Type of loading unit**: Euro container 600 mm x 400 mm / 400 mm x 300mm, small load carrier,…
- **Loading capacity:** Number of loading units
- **Source-sink relation**: Location of material pick-up and drop-off
- **transport time**: Provision at the latest by the predicted earliest start time of the production order
- **Degree of automation**: Prioritization of automated transport systems to reduce the workload of logistics employees

In the next section, the results of the developed approach and conducted study for autonomous control of intralogistics considering deterministic and probabilistic material demand information are elaborated.

5. Results

To test and verify the developed approach a scenario-based simulation study as well as practical experiments have been performed.

5.1 Simulation experiments

Several scenario-based simulation runs were performed by applying the Monte Carlo method to verify the approach before the practical experiments at Werk150. For the turbulence events, the turbulence attributes, distributions, and probabilities described in Table 1 were used. In the following, the detection of the deterministic and probabilistic material demands and the autonomously controlled execution of the resulting transport orders by the intralogistics transport resources will be explained with an exemplary production scenario simulation result (see Fig. 3).

WS01 is the only station where the order sets for the production orders are picked, and a Kanban system is applied to trigger the replenishment. The material demands at WS01 (order set picking station) of 1 euro container of footboards and 1 euro container of rear wheel housings are considered deterministic material demands (see Fig. 3) since there is no uncertainty regarding the material demand's place and quantity. The resulting deterministic transport orders have to be fulfilled by the autonomously controlled intralogistics system by the earliest predicted due time. As these material demands are not tied to specific customers or production orders, the Material Demand (MD) IDs match the respective Transport Order (TO) IDs. Based on the defined criteria and rules, the agent-based transport order allocation combines these deterministic orders into a joint transport executed by AGV2. Decisive reasons for this decision are that this transport system is the only transport system for this source-sink relation capable of performing a fully automated material provision (loading of containers, transport, unloading) due to its shooter rack.

At WS02, a turbulence T2 ("Jammed screw") was registered, resulting in a potential process delay of the current production order 1611. The results of the simulation and forecast for the deterministic and probabilistic material demands and the related transport orders are summarised in Fig. 3.

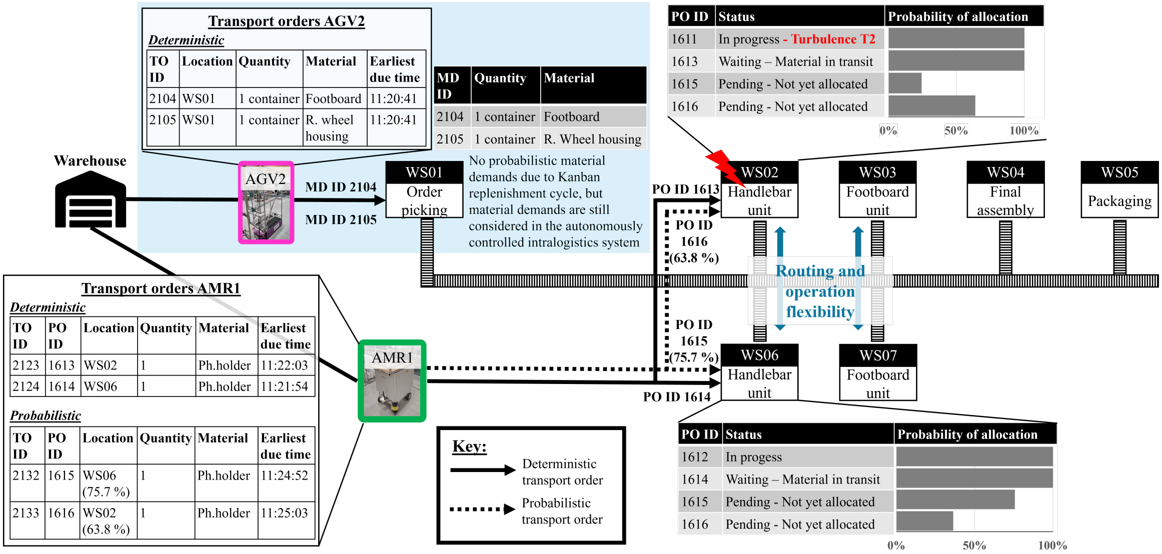

Figure 3: Exemplary simulation experiment

To reduce the negative effects on the throughput time and adherence the schedules for the next production orders, the routing and operational flexibility of the flexible production system is used. The material demands for the customer individual phone holders for the production orders (PO) ID 1615 and 1616, which are mounted on the handle bars on WS02 or WS06, are considered as probabilistic material demands, since the final location of the material demands (next available workstation) is not yet defined. The agent-based decision on the transport system that has to fulfil the transport orders led to the freely navigating AMR1. Major reasons for this decision are that this AMR is capable to reach both alternative sinks within the predicted earliest start times of the production orders, as it can move freely in production allowing a flexible adaption of the material sink. As shown in Fig 3., there is a chance of 75.7 % that TO ID 2132 for PO ID 1615 has to be provided to WS06. In the next Monte Carlo simulation run, initiated upon the completion of PO ID 1611 or 1612 at WS02 or WS06, further specification of their allocation to these workstations occurs, incorporating updated data and forecasting information. Subsequently, probabilistic material demands and transport orders become deterministic based on the final production order allocation. AMR1 delivers the customer-specific phone holders to the designated workstations and the respective handlebar unit order sets picked at WS01 are transported to WS02 or WS06 via the roller conveyor.

5.2 Practical experiments at Werk150

Following the simulation experiments, scenario-based practical experiments gave practical insights into the potential of combining deterministic and probabilistic material demand information with autonomous intralogistics control. They aimed to mitigate the negative effects of potential turbulences on production order throughput time and adherence to schedules. Using the developed approach (see Fig. 1), practical experiments were carried out in the production system of Werk150 with and without the influence of the defined turbulences T1-T6. To determine the corresponding value distributions of the process, turbulence and probability parameters, a sample size of n=30 was used following the central limit theorem [44]. Input data, including assembly process times and notifications of turbulence events, for simulation runs and data-driven prediction were collected from a manufacturing execution system (MES) and stored in a SQL database. For the data-driven turbulence prediction the input parameters and prediction models and methods described in [14] were used. The following describes the actual application of the developed approach on the example of a practical production run.

The assembly of the PO ID 184 at WS03 is subject to a process delay due to a robot collision (turbulence T1) with the footboard unit (see Fig. 4). For the upcoming PO ID 186, which initially was also to be assembled at WS03, WS03 will most likely not be available in time. Therefore, the initially defined throughput time target of PO ID 186 cannot be met.

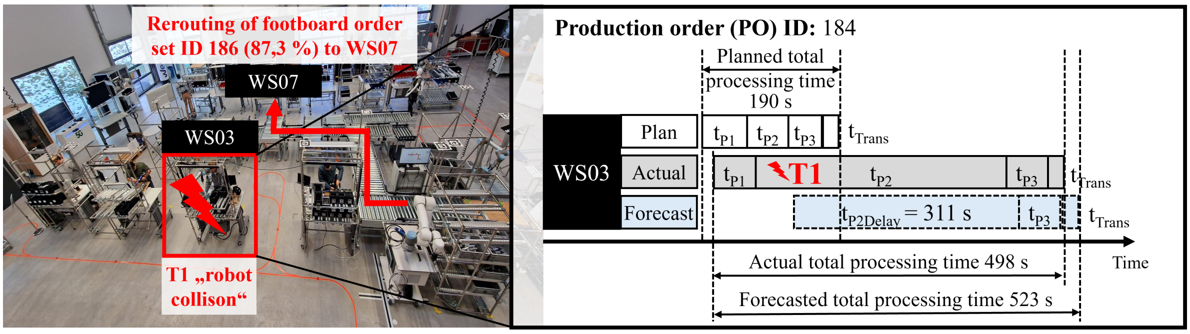

Figure 4: Practical experiment of forecasting a process delay due to a reported turbulence T1

Following the report of turbulence event T1 at WS03 via the MES, a data-driven forecast is initiated using the Generalized Linear Model (GLM). The GLM has been identified in [15] as the most suitable forecasting method for forecasting the influences of this type of turbulence on the process times. The GLM trained with historical process data predicts a delay of process segment 2 at this workstation of 311 seconds and a total process time of 523 seconds. Input information for this predication is the occurrence of T1 and the process time for process segment 1 (t_{P1}) of 58 seconds reported via the MES. This forecast information, as well as the other current process, status and event data for the production, have been transferred into the simulation model to perform a Monte Carlo simulation parallel to the current production in accordance with step 5 (see Fig. 1) of the developed approach. The simulation led to the result that the material demand and transport order for the footboard unit pre-assembly of the upcoming PO ID 186 must be rerouted to WS07 with a probability of 87.3 %. This probabilistic material demand became a deterministic material demand since the turbulence was still there at the next simulation run, which was triggered by the completion of a previous production order. The resulting deterministic transport order was considered in the intralogistics system accordingly by providing the order set picked at WS01 for the footboard to WS07 via the roller conveyor system (steps 6-8 of the developed approach). The employee at WS03 resolved the robot collision faster (289 seconds) than anticipated by the GLM, resulting in an actual total process time of 498 seconds. While the forecasted and actual processing times differed by 25 seconds, the estimated delay information remained valuable for allocating the subsequent PO 186 to the alternative WS07. The throughput time for PO ID 184 increased from 8.0 to 14.2 minutes due to process delays and waiting times at WS04. For PO ID 186, the throughput time slightly rose to 8.9 minutes due to waiting times at WS07 due to the previous PO ID 185 assembled at this workstation. By PO ID 192, the throughput times returned to the planned level without further turbulences. Adherence to schedules (completion on schedule + 10%) was met again from PO ID 191 onwards.

6. Conclusion

This paper introduced a comprehensive approach for the autonomous control of intralogistics in flexible production systems, addressing both deterministic and probabilistic material demand information. A combination of simulation and practical experiments showed the effectiveness of this approach. The simulation experiments and practical experiments demonstrated the feasibility of the approach, showcasing improved target achievement metrics such as throughput time (by up to 28 %) and adherence to schedules (by around 10 %) for subsequent orders after a turbulence event, mitigating the adverse effects of turbulences on production operations. In addition, the significance of autonomous control in intralogistics for enhancing the resilience and adaptability of flexible production systems in response to turbulences has been shown. The next steps involve advancing the developed approach into a comprehensive method for directly coupling of the simulation environment with the actual production system. The comprehensive method will then be validated in a holistic production scenario at Werk150 to prove an improved target achievement (throughput time and adherence to schedules) by considering deterministic and probabilistic material demand information in conjunction with autonomous control of material provision.

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