Dependable Cyber-Physical Matrix Production Systems utilizing Holonic Multi-Agent Systems

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Abstract. In the domain of reconfigurable production systems, Cyber-Physical Matrix Production Systems (CPMPS) are recognized for their advanced levels of operational flexibility. Given the inherent flexible material flow, these loosely coupled systems are characterized by dynamic interdependencies and rapid changes in order sequencing and allocation. This leads to major challenges in production flow control including the emergence of instable behaviors decreasing robustness and threatening overall performance.

Traditional methodologies for assessing and enhancing the reliability and ensuring the robustness of the system do not tackle the dynamic behavior of reconfigurable production systems. Due to rigid probabilistic assumptions, efficiency decreases and reasoning in fault propagation is not apparent. For this reason, dependable systems engineering embraces formal descriptions of the systems' dynamical behaviors and continuous monitoring of system properties.

This paper proposes the application of distributed artificial intelligences in the form of holonic multi-agent system (MAS) that integrate the concepts of dependability as part of the system design. Multi-level monitoring of state properties and fault-tolerant control mechanisms are used to minimize deviation between the modelled and observed behavior, therefore ensuring robustness and securing the system's intended operation. The presented framework demonstrates feasibility by first implementations of dynamic interaction mechanisms for subsidiary decision improving makespan while remaining flexible.

Keywords: reconfigurable production systems, fault-tolerant production flow control, holonic multi-agent systems, dependable systems engineering.

1 Introduction

In the rapidly evolving landscape of manufacturing technologies, reconfigurable production systems stand out for their ability to adapt to changing product demands and production conditions rapidly. Rigid linear assembly systems struggle to adapt to the current demand for flexibility and can only be reconfigured with significant down-time.

Therefore, service-oriented and reconfigurable production systems emerge as suitable alternatives to existing production systems [1]. In the case of Cyber-Physical Matrix Production System (CPMPS), the inherent modular structure and flexible transportation between production entities leverages the ability to anticipate any deviations dynamically through reconfiguration and therefore minimizing throughput loss caused by the linkage of failure rates [2, 3].

The high degree of freedom in CPMPS introduces significant complexity, making it challenging for traditional centralized control approaches to calculate optimal solutions in a reasonable timeframe [4]. Instead, agent-based control systems, which utilize multiple distributed autonomous agents, have emerged as suitable solutions and been successfully implemented in various domains [5, 6]. These Multi-Agent Systems (MAS) can divide and conquer planning, scheduling, and control problems through negotiation and learning mechanisms [6, 7].

Nonetheless, as highlighted by [7–9] complex networks of loosely coupled systems such as MAS, confront new threats through unpredictability and dynamic interdependencies. The newly acquired degrees of freedom and flexibility lead to new complexities with unknown effects on the systems behavior. Purely data-driven approaches such as reward-based deep reinforcement learning (DRL) may solve the problem of complexity, yet leave the effect of unknown emerging system behaviors due to possible nonlinear feedback and local minima. This threatens reliability of the system exposing the gap of combining this emerging technology with more reliable control methods [8–10].

Therefore, the main objective of this research is based on MAS based production control of CPMPS and the integration of the principles of robustness and resilience, which are closely tied to the fundamentals of dependability [10]. This leads to the central research question: How can MAS be designed to integrate mechanisms that asses and enhance the dependability of CPMPS? This addresses the gap in the understanding of flexible agent-based control in combination with required formal assessment of dependability. To address these issues, the state of the art is examined for dependable agent-based solutions. Then, a generic methodology for applying principles of dependability is utilized and adapted to design a holonic multi-agent systems (HMAS). Lastly, components and interactions are designed to enhance the overall robustness against failures and resilience of CPMPS and validated in experiments.

2 State of the Art for Dependable MAS

This section will introduce the fundamentals of MAS and the connection to the principles of the discipline of Dependable Systems Engineering. The final sub-section will provide an overview of existing approaches and their advantages as well as possible limitations to the system application.

2.1 Multi-Agent Systems for Planning, Scheduling and Control

MAS consist of multiple interacting agents, each with distinct behaviors, collectively working towards defined objectives. MAS offer a flexible and scalable approach for control and coordination, essential for handling the high degrees of freedom and dynamic nature of systems such as CPMPS [11]. While MAS are generally effective for managing complex systems, the choice of control mechanisms significantly impacts scalability and system performance [7, 12]. MAS can be organized in centralized, decentralized, or hybrid forms representing entities in the production. Centralized MAS feature hierarchical agents overseeing the entire system, making global decisions. While providing optimal solutions, they suffer from scalability issues and single points of failure, making them less suitable for dynamic environments like CPMPS. Decentralized MAS allow to operate autonomously with local context, enhancing scalability and response-time but potentially resulting in suboptimal global performance due to instable behavior. Hybrid MAS balance global optimization with local autonomy, where agents operate independently but are coordinated by higher-level agents [12].

However, when considering the integration of agent systems into industrial multi-level environments, the robust and resilient control of the intended operation of the system is of uppermost priority [7, 8]. To achieve this goal, the HMAS approach of encapsulated systems of systems is suitable as it can solve a certain degree of global optimization combined with fast-responding local interaction [10, 13]. Nonetheless, despite the flexibility offered by MAS, independent from the control paradigm, their perceived intransparency and potential unreliability raise concerns about their dependability [8]. As environments such as production systems are safety-critical, they demand full consideration of attributes like safety, reliability, maintainability and availability – dimensions that are essential for a system to be considered dependable [14].

2.2 Dependable Systems Engineering

The discipline of Dependable Systems Engineering includes the Design and Implementation of highly-robust and resilient systems. The concept of dependability emerged as part of the need for a methodological approach of assessing a systems property and evaluate it's intended and actual behavior. The focus is on model-based systems engineering to enable a formal and safe integration [14]. This differs fundamentally from reliability as depicted in the comparison in Table 1.

In order to maintain the aforementioned system attributes threatened by faults, errors and failures, several measures are employed. According to the general taxonomy by Laprie [14], fault prevention aims to prevent the occurrence of faults; fault tolerance ensures that the system continues to operate correctly despite faults; fault removal involves reducing the number of existing faults; and fault forecasting estimates and predicts future faults and assesses their potential impact. Implementing these mechanisms is crucial for preventing fault propagation, thereby maintaining an acceptable level of performance and safety [14, 15]

Traditional risk assessment methodologies in reliability engineering rely on probabilistic assumptions to generate fault rates, leading to extensive experimentation, leaving Boolean fault modeling inadequate for unexpected changes. Similarly, Markov Chains, which use probabilistic features to predict future system states, can lead to a combinatorial explosion of states when dealing with high degrees of freedom, thus contradicting the dynamic nature of reconfigurable production systems [15].

Table 1. Difference between Reliability and Dependability [15]

Subject	Reliability	Dependability
Modelling	Probabilistic, based on random processes	Deterministic, based on dynamical behavior
Assessment	Function of failure probabilities	Functional in the state deviation
Means	Decrease of failure probability by redundancies and diversity	Decrease of state deviation by fault-tolerant control

2.3 Related Work for Dependability with MAS

When looking at the concept of reliability and dependability within production control with MAS, often the concept of holonic systems is found. One of the most prominent approaches tackling the challenge of chaotic behavior is found in the ADACOR[2] system by Barbosa et al. [16]. Here, the holonic approach is used and an advanced PID controller for stabilization in the production control is integrated. Inspired by classical control theory this leverages adaptive self-organization of the holons, yet does not fully examine the dimensions of dependability as such. In contrast, this leaves room for research on the design and training of controllers to enhance system dependability.

Similarly, Heid et al. [17] shows a significant step forward in dependable production systems by incorporating flexibility to manage evolving risk assessment effectively. Here the multi-level design is suggested introducing a safety agent with pre-configured hazard rules for strategical, tactical and operational levels. Nonetheless, the focus is on control device level and lacks fault-tolerant implementation for other levels. Komesker et al. [4] developed a hybrid planning, scheduling and control architecture which serves as an enabler for multi-level mechanisms due to its fractal approach. Yet, it is noted that there is need for further exploration of fault tolerance mechanisms as the approach predominantly focused on the underlying system architecture. With a similar focus Bayanifar [18] developed an Failure Mode and Effects Analysis (FMEA) method. Nonetheless, uncategorized errors are neglected which especially in multi-level environments is dangerous as emerging behavior can't all be categorized beforehand.

Wannagat and Vogel-Heuser [19] apply Fault Tree Analysis (FTA) to enhance fault diagnosis, offering a structured method to assess and manage system failures. Here, especially the dependability requirements are examined and results show stabilization effects on the systems behavior in case of a physical fault. This approach focuses on control device level only and does not consider predictive dimension since it is based on predefined faults in FTA. Rehberger et al. [20] emphasizes the dimension of dependability by aiming to improve planning processes and ensuring right timing for real-time scheduling, yet does not consider the runtime control and emerging behaviors.

As [8–10, 21] come to the conclusion that when it comes to complex networks of units, most existing safety-related approaches are not dynamic enough. They emphasize the need for safety-focused strategies for the control design. While this can set limitations on the flexibility, they have to be balanced out to enable dependable control. This comes together with the need for concepts to tackle emerging behaviors and not just categorized faults to make these systems applicable for large-scale modular production systems [21]. The related work reveals possibilities and requirements for a combination of adaptive control through MAS considering principles of dependability. However, generic holonic structures and formal methods for dependability assessment as well as unified reconfiguration are still not fully integrated.

3 Approach for Integrating Principles of Dependable Systems Engineering into MAS for CPMPS

One approach to cope with complexity and flexibility at the same time is the combination of model-based techniques for accessing the deterministic behavior attributes of the controlled system and the integration of data-driven methods for more flexibility and automatic model generation. While the latter can be used to quickly find new solutions such as production order reconfigurations, these solutions can be checked for feasibility and predictability by deterministic models. A generic system architecture (GSA) for the assessment of dependability in continuous and discrete systems has been developed in [15] which is based on the recursive-nested behavior control (RNBC) introduced in [22]. This formal model-based methodology aims at controlling complex systems through behavior-based models, and therefore will be used in this work and examined for applicability to HMAS with Active Fault-Tolerant Control (AFTC).

To enable the developed system for large-scale CPMPS, this framework is based on the holonic architecture by [4, 23] and will be extended to assess and leverage dependability by using model-based behavior control while also enable data-driven flexibility inside the holons. Based on the GSA, the methodology starts with a Behavior-Based System Decomposition and Description, to assess system properties and composition, ensuring scalability by decomposing the system into controllable subsystems. Defining system behavior is crucial for dependability, allowing deviation assessment and ensuring intended behavior. The System Architecture is then designed for control of the production system, deriving a generic fractal architecture by matching components with the HMAS. In the subsequent sections, the Interaction Design for Multi-Level Monitoring and AFTC for dependable control by minimizing deviations is derived.

3.1 Behavior-based System Decomposition and Description

Since the ISA 95 layered architecture for automation systems struggles with the flexibility accompanied by new modular production systems, the Reference Architecture Model Industry 4.0 (RAMI 4.0) is proposed for modern production systems [11, 24]. It has been demonstrated before that the nested behavior-based control structure, original developed for autonomous mobile robots, can be applied to other types of semi-autonomous systems such as rehabilitation systems, medical robots and unmanned air vehicles. In the case of RAMI 4.0, it is possible to use different adopted model types for every hierarchy level, e.g. continuous state space models on the motion levels, hybrid models on the machine level and discrete event systems on the planning and scheduling levels as the environment in this work. These can be trajectories for robotics or composite Key Performance Indicators as defined in ISO 22400-1 such as ratios, utilization ratios, efficiency, effectiveness or rates. Examples for behavioral information and time increments for state updates can be cycle times for control devices in ms, makespan of products in hours or supply chain metrics on factory level, formed as sets of trajectories.

Therefore, it is proposed to define the mission of a system, which represents the intended behavior of the system in a limited set of reference trajectories. Such trajectories are common practice in many engineering fields and similar forms such as trust vectors exist, yet mainly on control device level not discrete event levels [15, 17]. In the case of CPMPS these missions can be represented as trajectories of production metrics over time derived from production plans and orders. Defined as part of the production planning the responsible planner will get a future state estimation of the expected intended behavior, by solving methods such as heuristics. Sub-missions can then be derived for further granularity and be used for dependability assessment on lower levels. Plans will be formulated at top level and then divided and conquered defining the intended behavior of the system [4]. According to Wagner [15], the deviation from this intended behavior b_{ref} / mission can be defined as Dynamic Performance δ_p as depicted in Fig.1. The deviation from the pre-defined safety margins $s_{high/low}$ can be defined as Dynamic Safety δ_s.

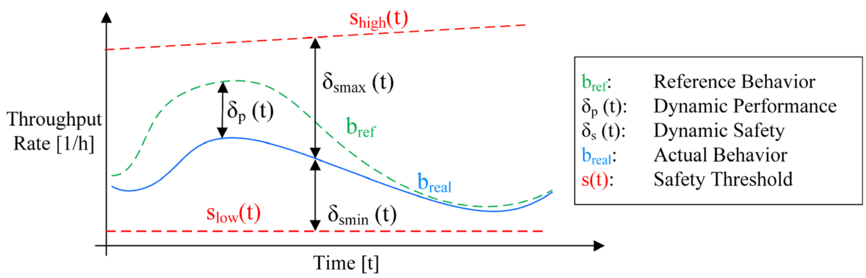

Fig. 1. Exemplary Schematic Overview of Behavior Metrics adapted from [15]

This integrated approach to describe the behavior and define thresholds to use for evaluation functions and triggers accordingly. The corresponding metrics can be combined to serve as a unified measure for dependability depicted in equation 1. This allows to compare control designs regarding a combined normalized measure of integrated dependability measure (IDM). Given the discrete event-based updates in the production environment, the time-discrete version of the IDM over n samples can be defined as follows.

$$D(n) = 1 - \frac{1}{m} \sum_{k=1}^{n} \sum_{j=1}^{d} a_j \left[1 - A_j\left(u(k), y_r(k), y(k), \theta_j\right)\right] mit \sum_{j=1}^{d} a_j = 1. \quad (1)$$

The IDM $D(n)$ shows the weighted discrepancy between the wanted and the actual behavior in terms of Dynamic Performance and Dynamic Safety. The IDM coefficients (acceptance functions) A_j(k) in the integral are time dependent functions of defined dynamic properties, which are normalized in the interval [0, 1] and weighted by the constant factors a_j, while the sum over all j = 1…d factors is unity. Further variables are the mission input trajectory $u(k)$, the reference output trajectory $y_r(k)$, and actual system output $y(k)$. The vector θ_j includes performance parameters [15].

3.2 Dependable System Architecture utilizing HMAS

As the examination of the state of the art and the related work suggests, the holonic system architecture is suitable for being established over several production layers. The system decomposition as suggested by the generic methodology, matches the system decomposition from the level specific control in the HMAS by [23], as it done according to RAMI 4.0. The generic system architecture based on RNBC by Wagner is adapted to the principles of HMAS and depicted in the following architecture model in Figure 2. The RNBC of a system requires monitoring and reconfiguration components. If we match these controller elements with the agents from [23], the functionalities can be found in the Data Agent (DA), the Deviation Agent (DevA), the Process Orchestration Agent (POA) and the Production Flow Agent (PFA) which are extended by services. Corresponding to the RNBC and the HMAS, the following generic component diagram results with their respective levels for Holon_{Ln} and two Holon_{Ln-1}.

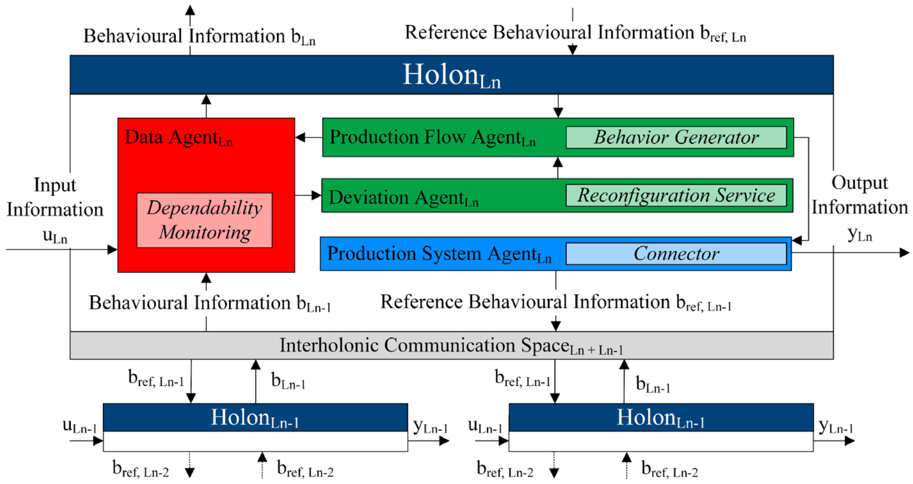

Fig. 2. Components of the HMAS for dependability integration: Monitoring (red), Reconfiguration (green) and Control (blue)

In the initial step the intended behavior $b_{ref, Ln}$ is defined. According to the definition of missions and sub-mission, these are distributed over the several layers of the architecture. The PFA_{Ln} is used to split an assigned mission as part of the reference behavior $b_{ref,Ln}$ to the holon and a reference $b_{ref,Ln-1}$ into several sub-reference behaviors. These are passed on to the corresponding holon via the POA_{Ln} and are further processed according to the fractal concept. The corresponding sub-mission $b_{ref, Ln-1}$ are forwarded to sub-holons or same-level commands send as output information y_{Ln}. The sampling rates for monitoring correspond to the levels and thus lead to fast inner feedback control loops and superordinate slower control loops as depicted in the following section.

The DA_{Ln} is subscribed to the Interholonic Communication Space with subordinate holons and thus takes over the monitoring task by receiving externally sensed input information u_{Ln} from the same level and behavioral information $b_{ref, Ln-1}$ from sub-holons. Here, the DA_{Ln} receives all information on the production and transportation entities of the subordinate level. The events contain formatted information and are preprocessed and used for metrics calculation such as the Dynamic Performance and Dynamic Safety for IDM and state estimations. Following the GSA and HMAS concept, the information is evaluated by the $DevA_{Ln}$ with the help of its Reconfigurations $Service_{Ln}$ for minimizing behavior deviation to restore the measurable dependability.

4 System Design for Dependable Control of CPMPS

The following section provides an overview over the production use case and the general task to be fulfilled. Based on the problem description the interactions and signals for the agents are defined, implemented and validated in a simulation in section 5.

4.1 Use Case Description

The reconfigurable production system consists of a large-scale CPMPS with skill-based resources, grouped into stations and lane-based AGV for inter-station and smaller free-roaming AGV for intra-station transfer of parts. Each resource includes multiple skills for production orders and has defined failure rates. According to the system architecture, the developed HMAS utilizes services for solving the production mission which is the daily production program provided by the ERP and preceding planning. The subsequent problem for the factory and the system of interest is defined as an np-hard flexible job shop scheduling (FJSS) problem which optimizes order allocation to resources and sequencing on multiple levels for makespan. The primary goal is to secure the overall production mission by the heuristic method and the metrics defined within. To achieve this, the system will divide the initial reference plan from the ERP System to generate sub-missions for station and resource level and will use reconfiguration such as level-specific order reallocation and sequencing to adapt to deviations locally.

4.2 Interaction Concept for Multi-Level Monitoring and Active Fault-Tolerant Control

As previously mentioned, the interaction mechanisms are the heart of MAS and predominantly influence the performance of the overall system [25]. The resulting signal diagram depicted in Figure 3 illustrates the coordination among different agents in a holonic multi-agent system for controlling the CPMPS. This system consists of the Process Orchestration Agent (POA) for control, the Data Agent (DA) for monitoring and the Deviation Agent (DevA) plus Production Flow Agent (PFA) for reconfiguration of the system. Moreover, the exemplary Holonic Levels are now matched to the RAMI 4.0 resource, station and factory for the use case problem from the previous section 4.1. and are shown encapsulating the introduced agents.

The sequence begins with the daily production plan ERP Data$_{L1, ref}$ of the ERP System being send to the Holon$_{Factory}$ transmitting the first reference information. The metric of products for the day is provided by a higher hierarchy of the ERP system that is not observed in the system but provides the production mission for the overall factory.

Using the skill-based decomposition the PFA will generate suborders which will serve as production missions for lower levels as part of a Backlog$_{L2, ref}$ for multiple Holon$_{Station}$. As this is the first reference, the PFA will generate sub-behaviors by using a heuristic service to solve the FJSS problem optimizing the overall makespan and get a first estimation of the model behavior. The DA of the Holon$_{Factory}$ will store the corresponding Trajectories$_{L1, ref}$ in form of aggregated metrics over time and scheduled orders for continuous monitoring. The sub-orders are sent as a command collection of orders O$_{L2, ref}$ via the POA controller and the Interholonic Communication Space to its loosely coupled child-holons. This down-stream information flow is continued inside the station level where the sub-orders of the orders are allocated and sequenced to the resources which will then executed the corresponding Process$_{L3, ref}$.

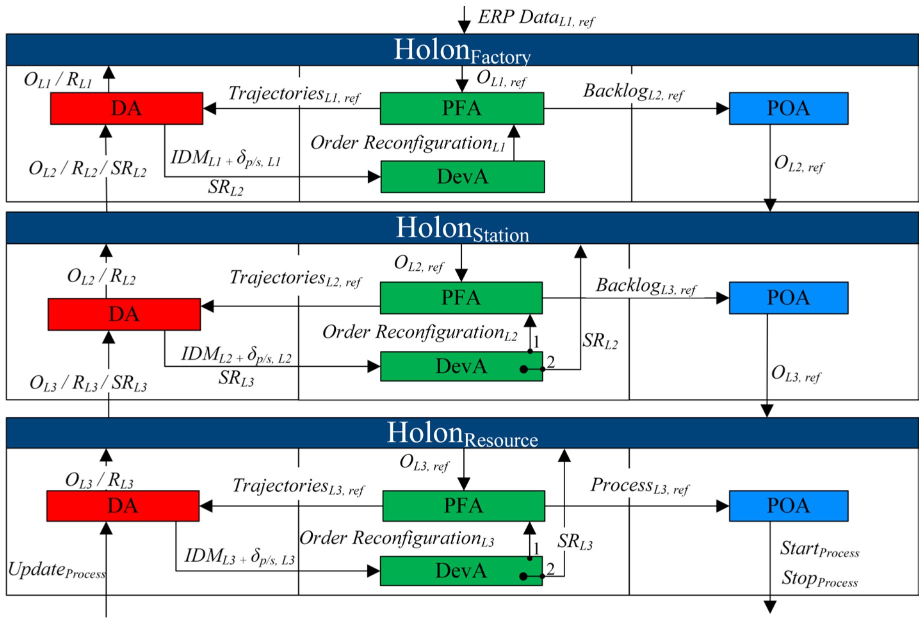

Fig. 3. Signal schemata for fast inner feedback control loops and slower outside feedback control loops with Monitoring (red), Reconfiguration (green) and Control (blue)

Given that the RNBC is a feedback control, the process values Update$_{Process}$ are collected from the field devices to the resource level and forwarded bottom-up. The relevant information for orders O$_{L3}$ and resource states R$_{L3}$ are processed by the DA$_{L3}$ of the Holon$_{Resource}$. After pre-processing and monitoring the relevant information such as the IDM, these are forwarded to the internal DevA for reconfiguration activities which is a resequencing of orders O$_{L3}$ as part of the internal Backlog$_{L3, ref}$ based on the evaluation of the Dynamic Performance and Dynamic Safety. If another sub-level below would be integrated an order reallocation to multiple field devices would be a suitable action here as well. State deviations occur in case of machine break-downs, late orders or full buffers due to uncertainties in the planning or non-linear feedback as part of emerging system behavior.

The $DevA_{Ln}$ on every level plays a crucial role by assessing the behavior information to determine the necessary actions to reestablish reference behavior. Based on decision rules regarding the IDM including the Dynamic Performance and Dynamic Safety three potential outcomes can arise from the $DevA_{Ln}$ evaluation on every level: (1) Additional support is required beyond the local capabilities of the holon as the local production mission is not retrievable and no reconfiguration is feasible, a support request $SR_{L2/L3}$ is sent to a higher-level holon. (2) If the system decides for a feasible internal order reconfiguration to minimize deviation to the intended behavior, this information is forwarded to the appropriate decision support services on the level for reconfiguration such as DRL agents or heuristics. (3) No action is taken as the deviation is in acceptable boundaries. Each reconfiguration service is provided with information about the local context of the system. The services for order allocation and sequencing differ in their horizon, speed and performance corresponding to the slow outer and fast inner control loops and will be presented in section 5.1

5 Simulation Study

The developed HMAS is connected to a discrete-event simulation for multi-method simulation to test the mechanisms in cooperation with the services. The setup for proving the feasibility is described in section 5.1 and the results are discussed after.

5.1 Setup

The simulation framework consists of the industrial-grade discrete event simulation tool *Plant Simulation* connected to the MAS framework *Janus* [26]. The connection is established via asynchronous OPC UA to account for delay in the subscription interval. Containerized and pre-trained DRL agents are spawned for each production entity reconfiguration commands and are continuously trained during simulation.

For the simulation three different scenarios were compared: (1) Central: Fulfilling strictly the central reference schedule with minimum deadlock-avoidance techniques, (2) Active DRL: Using station-level reconfiguration for resource allocation and sequencing with higher-priority than initial schedule, (3) Passive DRL: Using station-level reconfiguration for resource allocation and sequencing with lower priority than initial schedule. Each scenario works with same initial schedule and will have the same failure profiles for machines given the individual technical availability of 95 %. The ERP Data provides the initial daily plan for 200 products. The reconfiguration services in the DRL scenarios are configured with the same decision rules and allowed deviation of 30min per order when it comes to tardiness. The overall schema for the HMAS and DES integration are depicted in Figure 4 showing the system boundaries for an example on each level.

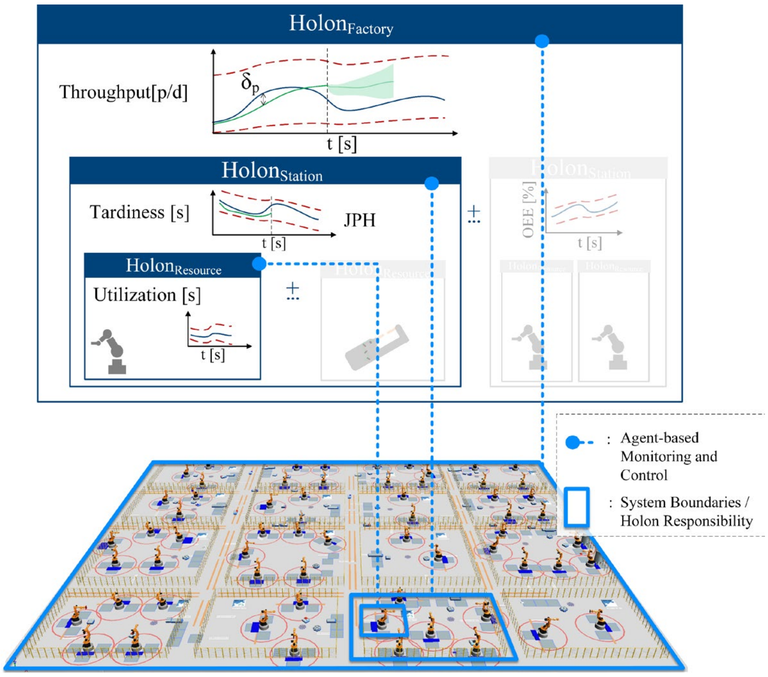

Fig. 4. Schematic overview of the developed HMAS (top) and DES (bottom)

On the outer slower loop of the $Holon_{Factory}$ the overall throughput is continuously compared to the initial reference. In case of large deviations as the systems runs empty, the reconfiguration is triggered releasing new orders from its backlog into the systems and optimizing the allocation and sequence to achieve the intended production mission of a number of products. For the reconfiguration for $Holon_{Station}$ an existing approach called auction-based online scheduling with reinforcement learning (ABOS RL) from [27] is used to manage local deviations. The ABOS RL is pre-trained on optimizing the makespan and minimizing tardiness within individual stations, ensuring the throughput is maintained even if there are disruptions. The DevA of the lower $Holon_{Station}$ will gain access to local products and orders as well as neighboring products that are within feasible reach of the station both timely and spatially allowing the $Holon_{Station}$ to reconfigure in its system boundaries with little horizontal overlap. For $Holon_{Resource}$ mechanisms according to FIFO decision rules are used to reconfigure its own $Backlog_{L3, ref}$ and therefore sequence locally to improve local utilization for the intended production mission as long as the $Holon_{Station}$ is not intervening. The IDM for evaluation and triggering the reconfigurations is solely evaluated based on the difference in performance in a one-dimensional trajectory as of current implementations.

5.2 Results & Discussion

The results as depicted Table 2 show a clear picture when it comes to overall makespan. The initial plan with no alternative paths has a throughput time of 13710 seconds for the set number of products. The Active DRL can produce the same number of products in 12877 seconds and therefore needs more than 6% less than without any deviation detection. The Passive DRL has a more restrictive operation area and will have lower priorities then heuristic based orders showing negative effects in the makespan.

Table 2. Simulation results for different deviation strategies

Metric	Central	Active DRL	Passive DRL
Makespan [s]	13710	12877	13757
Average throughput time [s]	6033.7	5748	5804.4
Average tardiness [s]	1524	916.3	906.9
AGV utilization (lane-based) [s]	419325	612134	666099
σ of orders per resource [pc.]	234.7	175.3	157.3

Average tardiness, describing the delay of orders is a factor to be evaluated and served as the main reference trajectory in the framework. Therefore, it shows the difference between the planned finish timestamp provided by a heuristic and the actual timestamp for order and its suborders accordingly. The results are to be expected as the Active DRL can catch up on the delays and reduce tardiness through reconfiguration, as illustrated in the left graph of Figure 5. This can help for short-term tardiness but can also eventually have negative consequences in the long term, as seen in the overall makespan for the Passive DRL. Other metrics related to transportation via AGV usage show increased activity for the DRL strategies. These strategies show a lane-based AGV utilization significantly higher than the central control strategy increasing transportation effort but also leveraging makespan in the long-term.

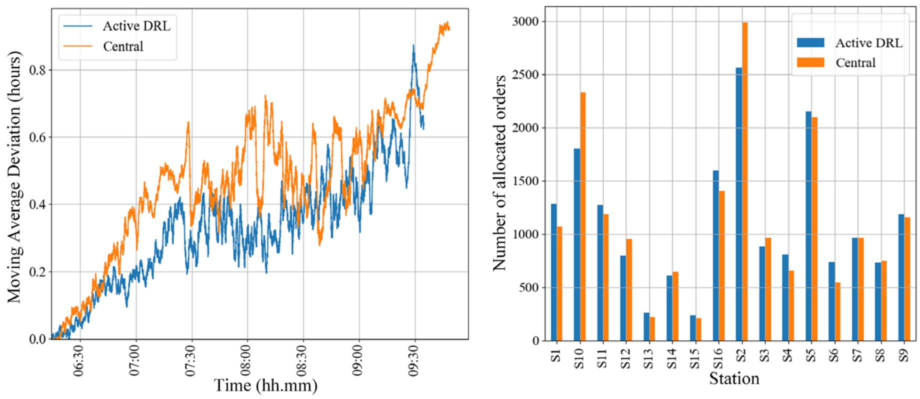

Fig. 5. Dynamic Performance on factory level for throughput (a) effects of order reconfiguration on station-level between Active DRL (blue) and Central strategy (orange)

Figure 5 shows the average deviation of the orders collected over all stations for the factory for the two main strategies of the Central FIFO and Active DRL. Since all machines are equipped with availabilities of over 95% and the initial plan is optimized for an ideal production, the loss is inevitable and increases over the time. As it is evident, the Active DRL manages to minimize the deviation of the individual orders from their intended start. The Central FIFO shows a much higher variance in the tardiness of individual orders due to higher vulnerability due to minimum deviation strategies and being unable to dodge any failures.

The standard deviation in order allocation per resource indicates workload distribution balance and reconfiguration activities. The central control strategy has the highest deviation at 234.7 per resource which was the initial global optimum for a failure free production for the overall makespan of 200 products. The Active DRL reduces it significantly, demonstrating more efficient workload distribution necessary as part of the deviations. This is also shown in Figure 5 (right) aggregated to stations for clarity.

In conclusion, it is evident that the DRL strategies successfully minimize deviations to predicted performance for the observed period. This indicates that the combination of model-based behavior generation and evaluation with data-driven flexibility and speed can minimize delays, maintaining performance within acceptable limits even under varying conditions and potential disruptions over multiple-levels. The implemented DRL strategies enhance the system's ability to adapt to changing conditions, ensuring that the performance remains within limits defined by configurable reference behaviors.

6 Conclusion & Further Research

In conclusion, the approach presented in this paper offers a promising solution to addressing the challenges faced in reconfigurable production systems, giving transparency and accessibility to the dimensions of dependability. By establishing a holonic control design, a nested control over the system dynamics is achieved, serving the multi-level CPMPS control. The fusion of HMAS with dependability principles creates a fault-tolerant system architecture, enhancing the overall performance. The developed interactions allow continuous IDM monitoring and control of the corresponding holonic systems and also allowing future extensive analysis on combinations of reference trajectories and reconfiguration services. Divided in fast inner loops and slow outer loops, this enables quick adjustments to deviations while also handling slower trends operating on larger time increments. Furthermore, the integration of self-similar components ensures reusability within the system with reconfiguration services to minimize different aspects as part of the IDM in the future. Using the heuristic for reference behaviors grants transparency and therefore control over the system's operations.

Future research should explore the multi-dimensional description of trajectory sets instead of a single trajectory. This will provide a more comprehensive understanding of the system behavior and fault-propagation across different levels. Another main focus in future work will be the existing trade-off between model-based restrictions and data-driven actions provided by DRL shown in the two different DRL configurations in this work. Balancing these aspects is essential to maximize the system's performance while maintaining flexibility, yet always assuring the dependability. This will benefit from a more extensive integration of the IDM which can be used to optimize the DRL policy according to dependability and evaluate different actions while maintain model-based formalism for transparency.

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