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Local Digital Twin-based control of a cobot-assisted assembly cell based on Dispatching Rules

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Abstract: In the context of an increasing digitalization of production processes, Digital Twins (DT) are emerging as new simulation paradigm for manufacturing, which leads to potential advances in the production planning and control of production systems. In particular, DT can support production control activities thanks to the bidirectional connection in near real-time with the modeled system. Research on DT for production planning and control of automated systems is already ongoing, but manual and semi-manual systems did not receive the same attention. In this paper, a novel framework focused on a local DT is proposed to control a cobot-assisted assembly cell. The DT replicates the behavior of the cell, providing accurate predictions of its performances in alternative scenarios. Then, building on these predicted estimates, the controller selects, among different dispatching rules, the most appropriate one to pursue different performance objectives. This has been proven beneficial through a simulation assessment of the whole assembly line considered as testbed.

Keywords: Digital Twin, dispatching rules, cobot, control, assembly cell, manual assembly.

1. INTRODUCTION

The convergence of Information and Communication Technologies and Operational Technologies in manufacturing processes is pushing the digital transformation of this industry at an increasing pace. Based on computing and communication capabilities, Cyber-Physical Systems have been introduced to allow the continuous connection of the virtual space with the physical world.

In this field, the concept of Digital Twins (DT) is recognized as a multidisciplinary simulation model synchronized with its physical counterpart (Negri et al., 2017). Indeed, the full potential of DT should be sought in the optimization of production planning and control functions, particularly at the shop-floor level, where prompt decisions could benefit from the near real-time connection of the simulation models with their physical counterparts.

New frameworks are proposed to support the development of DT-based planning and control. Villalonga et al. proposed a distributed DT framework for production scheduling including local and global DTs (A. Villalonga et al., 2020). The local DTs allow the detection of abnormal behaviors, while the global DT supports global decision-making by replicating the behavior of the whole system. A similar framework was developed by Villalonga et al. for improving job scheduling on an automated assembly line (Alberto Villalonga et al., 2021).

Compared with the fully automated systems, only a few DT applications were designed for assembly systems involving manual operations. Firstly, Fera et al. developed a framework for manual production lines, supporting performance improvement through line balancing and corrective actions (Fera et al., 2020). Motion tracking systems collect data coming from the production system in real-time, which are then transferred to the simulation environment. Actions to prevent deviations in the process are taken according to computed cycle times and workers' saturation. The DT developed by (Cohen et al., 2017) is used for reducing the cognitive workload of operators, rather than acting on arising disturbances related to the assembly variabilities. Ling et al. proposed a framework for manual assembly stations in Cyber-Physical Systems inspired by swarm intelligence, allowing to enhance the responsiveness in high-mix low-volume manufacturing (Ling et al., 2020).

New manufacturing scenarios where operators and robots must collaborate are becoming more widespread than ever; thus, the human factor and the relationship with collaborative robots in a factory is gaining much more importance (Segura et al., 2020).

Despite this, few works discuss the application of DT in cobot-assisted production environments. Malik and Brem analyze enhanced human-robot collaboration by means of a DT, considering the different lifecycle phases which can be supported (Malik & Brem, 2021). For the operation phase, they propose the idea of dynamic task allocation, which may allow automating part of the decision-making process by supporting the assignment of tasks either to the robot or to the operator. Bilberg and Malik enhance the cooperation between human and robot by introducing a DT-based method for task allocation in real-time (Bilberg & Malik, 2019). The authors achieved the sequencing and the distribution of tasks to robot and operators for balancing the workload also considering the different skills.

Within the larger research on the role of local and global DTs for production planning and control, this paper contributes to the research on the role of local DTs to support the production control in a cobot-assisted assembly cell, driving the change of

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the dispatching rules as a consequence of the changing performance objectives. In particular, at local level the DT optimizes production within a single assembly, while the support to decisions concerning the whole production system is left for the global level of DT.

The paper is structured as follows: Section 2 discusses the related works and Section 3 clarifies the research design; the proposed model is discussed in Section 4, while Section 5 describes the experimental setup; Section 6 reports and discusses the main results, whereas concluding remarks are presented in Section 7.

2. RELATED WORKS

In manufacturing, dynamic order arrival processes that can be considered stochastic are frequent, and Dispatching Rules (DRs) are often adopted in order to face such complex job scheduling problems (Rajendran & Holthaus, 1999). In fact, DRs offer ease of implementation while having also low computational effort. Thus, they are widely used in complex scheduling environments (Xiong et al., 2017).

Different authors have observed that the most common DRs are scarcely effective in minimizing flowtime, mean tardiness, and variance of tardiness (Holthaus & Rajendran, 1997; Sels et al., 2012).

Defining the most suitable DR, to cope with the stochasticity of manufacturing systems, typically requires using simulation (Frazzon et al., 2018). With the advent of DT, new opportunities in the use of simulation for innovating control systems based on DRs arise.

A distributed architecture for DR setting was proposed by Kouiss et al. in terms of a multi-agent system (Kouiss et al., 1997). The agents' decisions do not rely on any kind of prediction of the future behavior of the work centers, and this represents a gap.

To overcome this gap, Park proposed a production control method based on DT and reinforcement learning to improve efficiency and resilience in the environment of a micro smart factory (Park, Son, et al., 2021). Through the cooperation of DT and artificial intelligence, the authors adjust parameters for DRs. Another reinforcement learning-based framework was also developed in order to set dispatching rules (Park, Jeon, et al., 2021). DRs are able to solve the scheduling problem in a job-shop with re-entrant jobs reducing makespan values.

3. RESEARCH PROBLEM

Previous sections depict the fact that the majority of the works related to DT take a global perspective and only a few deal with machine or station-level control activities. Moreover, although DRs have been studied deeply and are very popular across industry practitioners, the relationships between DT and DRs have been studied only in the mentioned works by Park et al..

For these reasons, this work aims at understanding how a DT may improve scheduling at local level (i.e., cell or machine level). With this purpose, an improvement of local DRs in a cobot-assisted assembly cell is sought.

The overall objective is to design a DT-based framework supporting scheduling at local level by means of DRs. Thus, the problem consists of the dynamic selection of DRs for improving performances of the production system.

4. PROPOSED MODEL

The proposed contribution insists on a local DT-based optimizer of an assembly cell (made of a cobot and some operators), that may be included within a hierarchical local-global architecture of DT of a bigger assembly system including the cell. The DT-based optimizer hosts a DT based on a Discrete-Event Simulation (DES) model of the assembly cell and a near real-time controller which is able to set the DR regulating the functioning of the cell. The main purpose of the DT-based optimizer is in fact to act as a predictive controller of the cell to which it is connected. Figure 1 represents the conceptual flowchart of the proposed DT model.

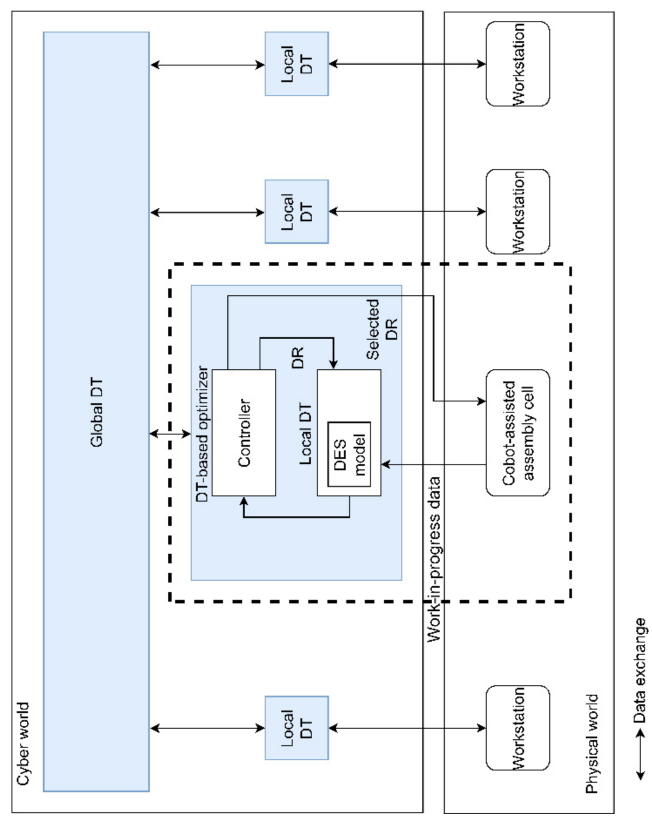

Figure 1. Conceptual flowchart

The unit of analysis of this work consists of the assembly cell and its local DT, which are boxed in a dashed line in figure 1. Information describing the work-in-progress at cell level is streamed in near real-time to the digital space, where it is integrated into the DES model; this allows the synchronization of the DT. The controller tests the DRs provided on the DT to obtain predictions of system performances and, then, it manages the selection of the most appropriate DR. Finally, the controller implements the selected DR on the physical system. It should be noted that, according to the flowchart shown in the figure, field synchronization is done directly through the DT; *alias*, no direct feedback is sent to the controller since the DT is the bridge between controller and physical system.

4.1 DES model

Thanks to the DES model, the DT has the capability to mimic the behavior of the whole assembly cell and to predict its performance under different production control policies. In fact, the simulation model returns the data which allow to compute future values of variables that will enable the control of the assembly cell. Simulation permits to gather data strictly related to cell operational performances, such as throughput in the reference time interval and resource utilization, but also information on production orders.

The model may run on different time horizons, by simulating time intervals of different lengths. It is therefore suggested to identify the best duration of each simulation for the purpose of the production control that needs to be performed. Thus, the duration should be long enough to gather meaningful data for the short-term decision making. However, it should not be excessively long since, otherwise, it would increase the effect of production orders which have not arrived at the cell yet; in this case, if the look ahead in the near future was too long, the local DT would have no visibility, and the orders should be necessarily modeled stochastically, with the drawback of adding variability to the system predictions. To summarize, the controller interacts with the DT to predict system behavior, prior to implementing actions on the real system.

4.2 Controller

The controller is the second essential module of the proposed DT-based framework, and its key capabilities are twofold. Firstly, it sets the DRs which are tested in the digital model, selecting among the available ones. Then, according to the simulated performances, the controller can select a new DR to be set on the real assembly cell; therefore, the controller is capable of analyzing the results of the simulations in order to optimize the selection of the best DR.

At first, the DES model is synchronized to the current state of the cell. Then, the controller evaluates the effects of the different DRs by running simulations in the virtual world employing the DES model. Finally, the decision on the new DR is made and triggered on the real assembly cell. The DR control procedure is shown in Figure 2. Every 60 seconds the controller begins the execution of the outer loop of Figure 2 to grant prompt and stable performances.

According to the sequence diagram, the controller requests the synchronization of the DT to the physical system, from which information related to current work-in-progress (WIP) in the cell is retrieved and used to update the DT. Immediately, the controller is able to test the DRs on the DT, which runs simulations on the underlying DES model. Since the controller only considers a finite set of DRs, those are implemented and tested in the DES model at each control step. Once simulations are completed, the controller must decide on which DR to implement. To achieve this a non-dominated sorting algorithm (Fang et al., 2008) was adopted to analyze results and to automate the selection of the dispatching rule. For this purpose, two variables were considered: flow time and slack. In particular, for each production order, the former represents the time spent within the cell, whereas the latter is computed when the order is leaving the cell and represents the time available for meeting the due date, computed based on the remaining processing times. In case of more than one DR results within the nondominated set, the decision is made according to the DR which maximizes cobot utilization.

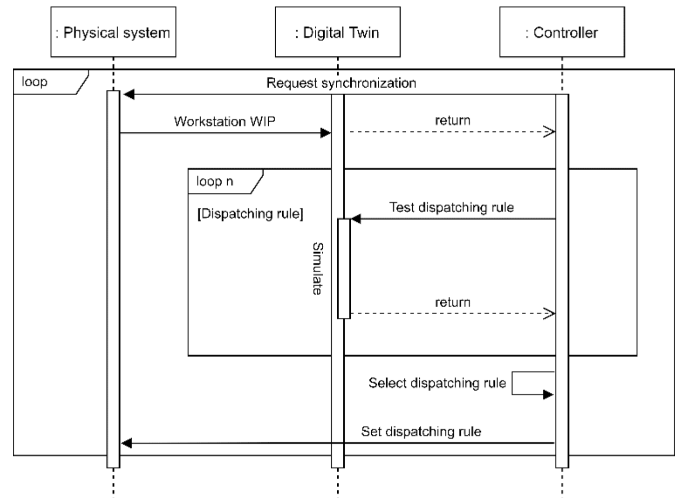

Figure 2. Controller sequence diagram

4.3 Closing the loop to the physical system

The connection between DT and the assembly cell must be bidirectional in order to allow the control of the physical system according to predictions and decisions enabled in the digital space.

To summarize the control loop already figured out with the controller sequence diagram, we could state that:

- the DT must gather information related to the work-in-progress available in the cell (this is essential for a proper field synchronization); in order to achieve this, the synchronization of the DT is done by loading the queue of tasks due to the production orders for which the cobot is required in the DES model;
- the outer control loop is guaranteed by setting the DR to be used in a next period, and the cobot will then be using the DR for the task assignments in an inner control loop (i.e., this control loop is inside the cell at physical level).

It can be noticed that since the DT functions are limited to the cell level, it has no knowledge on the rest of the system beyond the cell boundaries. It does not allow to achieve global optima in the control of the system; on the other hand, it reduces the computational burden and allows to implement the DT "on edge", significantly simplifying connection and integration.

4.4 Dispatching rules

The DRs are made available to the controller which is in charge of setting the active one. According to scientific literature and industrial practice, some DRs have been selected and included in this model:

- First In First Out (FIFO) (Nasiri et al., 2017)

- Last In First Out (LIFO) (Nasiri et al., 2017)
- Earliest Due Date (EDD) (Blackstone et al., 1982)
- Minimum Slack Time (MST) (Blackstone et al., 1982)
- Minimum Slack Time per Operation (MST/OPN) (Blackstone et al., 1982)
- Shortest Processing Time (SPT) (Ruiz & Maroto, 2006)
- Longest Processing Time (LPT) (Ruiz & Maroto, 2006)
- Random (RND) (Ruiz & Maroto, 2006)

4.5 Performance indicators

Three main performance indicators are considered at system level (i.e., for the whole assembly system) to prove the validity of the proposed model: the tardiness, the flow time, the throughput, the cobot utilization. Tardiness is computed as the difference between delivery times and due dates, considering positive values only. Flow time is intended as the time an order spends in the system (i.e., lead time through the cell). Throughput is the number of orders dispatched on average in the time unit (by the cell).

4. EXPERIMENTAL SETUP

The assembly cell of the experimental setup is based on a cobot and two operators and it would replace and enhance the activities currently performed by the robot of the Industry 4.0 Laboratory of the School of Management of Politecnico di Milano, better depicted in the work by Fumagalli et al. (Fumagalli et al., 2016). Material handling operations (e.g., loading and unloading smartphones from conveyors) are performed by the cobot, which also executes a part of the assembly operations. The two operators work in parallel on their workbenches where work-in-progress lays.

The methodology from Ait-alla et al. was adopted for validating the proposed model without establishing a connection with the real system (Ait-Alla et al., 2020). The authors proposed the use of a so-called physical twin, a simulation model which allows to build a DT of a not (or not yet) existing system. A similar solution was proposed by Barbieri et al. for implementing a scheduling framework connecting the DT to a virtual commissioning model (Barbieri et al., 2021).

For the purpose of this work, the duration of each simulation run was set to 600 seconds, which constitutes thus the length of the time interval on which the effect of the different DRs is predicted and evaluated. From preliminary experiments on the system, this value has been identified as sufficient for gathering meaningful data for the short-term decisions which are in the scope of this work.

Figure 3 shows the processes that are performed within the assembly cell and modeled in the DT. The DES model at the basis of the DT has been developed in MATLAB/Simulink® software.

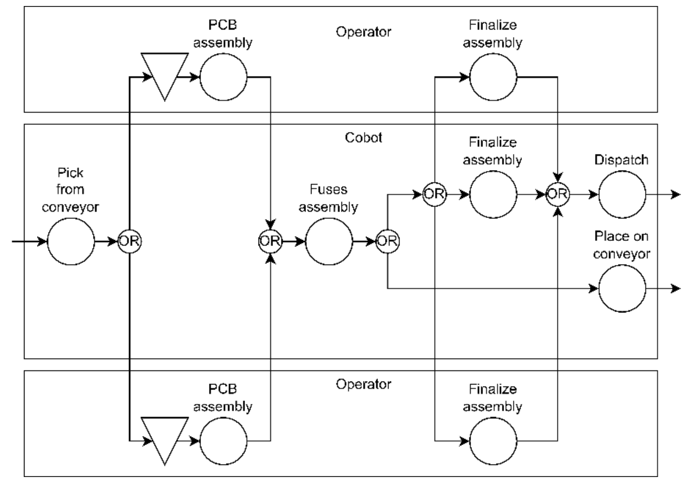

Figure 3. Model of the assembly cell

5. RESULTS

Benchmarking activities were performed to analyze the impact of the proposed model on the whole assembly system. Experiments were conducted without enabling the DT controller at first, in order to obtain tardiness, flowtime, and throughput values for the system controlled with just one DR throughout each simulation run. In addition, cobot utilization was computed at cell level. The DT-based DR control system was then activated and the same KPIs were computed. Table 1 reports main results.

Table 1. Experimental results

Dispatching Rules		T [min]	FT [min]	U [%]	TH [p/h]
FIFO	*Mean*	3.82	14.95	99.4	60.20
	Std.dev.	2.25	3.70	0.2	2.24
LIFO	*Mean*	4.56	15.03	98.7	59.88
	Std.dev.	11.74	24.42	0.3	2.21
EDD	*Mean*	3.34	13.51	99.3	66.62
	Std.dev.	1.07	4.20	0.2	2.47
MST	*Mean*	**2.50**	14.87	99.5	56.49
	Std.dev.	2.33	4.03	0.1	2.10
MST/OPN	*Mean*	2.68	14.36	99.5	58.50
	Std.dev.	1.76	6.15	0.2	2.11
SPT	*Mean*	3.86	**11.39**	99.7	**70.75**
	Std.dev.	3.80	7.26	0.1	2.71
LPT	*Mean*	3.83	15.42	99.6	54.47
	Std.dev.	4.24	12.79	0.1	2.02
RND	*Mean*	4.69	15.23	99.0	59.09
	Std.dev.	8.75	20.93	0.5	2.18

DT-based DR control	*Mean*	**2.08**	**11.20**	99.3	**69.5**
	Std.dev.	2.35	6.14	0.3	1.81

Legend: T = tardiness; FT = flow time; U = cobot utilization; TH = throughput

Ten experiments for each experimental setting (i.e., fixed DR or DT-based DR control) were performed to compute means and standard deviations for the KPIs of interest. Each experiment lasted twelve hours. Production orders are the same for each experiment and their release was adapted to always have products available in the cell in order to avoid performance distortions due to material starvation.

As expected, the measured KPIs show that the selection of a DR affects punctuality and productivity of the system. The table shows that LIFO and FIFO greatly increase the variability of the analyzed performance indicators. Moreover, the results of the experiments prove that they are the least effective for the system under analysis. Although EDD is usually demonstrated useful for minimizing the maximum value of tardiness, the average tardiness achieved is worse than other DRs considered. It can also be noticed that the utilization of the cobot, which is the bottleneck of the system, is scarcely affected by the selected DR. Its value ranges from 98.7% to 99.7%. Overall, the proposed model is able to reduce both tardiness and flowtime with respect to the application of a fixed dispatching rule. In fact, it is slightly better than MST, which was found effective for maximizing the average punctuality. Also, performances achieved are close to the SPT ones in terms of flowtime and throughput.

Figure 4 is an example of how different DRs were changed within an experiment until a certain time instant outlined by the vertical axis (i.e., the synchronization time when the DT simulations are triggered). In fact, the left part of the graph reports the past behavior of the real system for time up to zero seconds, representing the actual dispatching rules applied over time, and the corresponding flowtime results. The right part of the graph represents a prediction of the future performances of the system under a specific DR (the SPT policy in this case, within the prediction time interval between 0 and 600 seconds) in the future. The figure is helpful to understand the two main key points highlighted by this work. Firstly, it shows how the performances of the system under analysis might be affected by the change of different DRs over time. In addition, the figure demonstrates the information to which the controller is exposed, which consists of the predicted values of the reference performance indicators. These values allow the controller to properly select the most effective DR under the current operating scenario. For the sake of clarity, the performance prediction corresponding to a single DR was plotted.

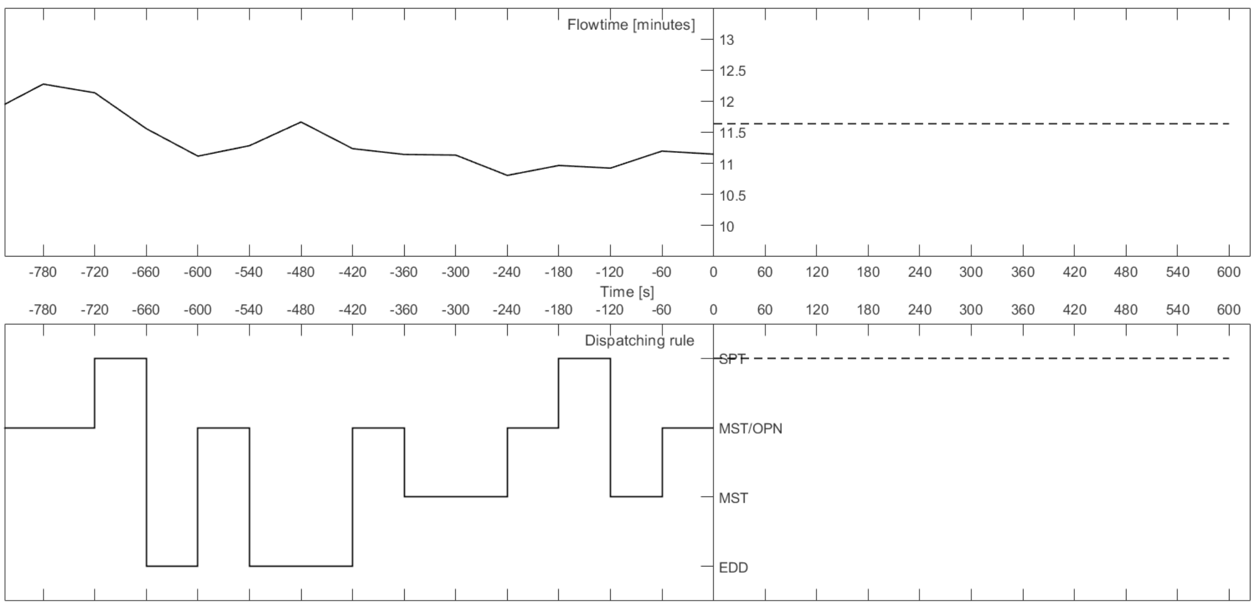

Figure 4. Experimental results

6. CONCLUSIONS

This work aims at showing the capabilities of a local DT which is applied to control the subsystem it models. The DT controls the production in the assembly cell by setting the dispatching rule. Moreover, DT-related studies are almost exclusively concerned with automated systems, while few DT are applied to production activities supported by human operators.

A few limitations of this work can be identified. The dispatching rules considered in this model are rather simple and widespread throughout the manufacturing sector, as this work is intended to contribute to this already well-developed research area through the addition of DT of the assembly cell. Moreover, only static dispatching rules were considered, and no method for improving them was adopted.

To conclude, this work may represent a further development of production control models based on DT. In particular, this works relates to literature on DT supporting the interaction between human operators and cobots by improving work organization in such context. This topic has still to be developed further.

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