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Additional Information

Smart Digital Twin for ZDM-based job-shop scheduling

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Abstract—The growing digitization of manufacturing processes is revolutionizing the production job-shop by leading it toward the Smart Manufacturing (SM) paradigm. For a process to be smart, it is necessary to combine a given blend of data technologies, information and knowledge that enable it to perceive its environment and to autonomously perform actions that maximize its success possibilities in its assigned tasks. Of all the different ways leading to this transformation, both the generation of virtual replicas of processes and applying artificial intelligence (AI) techniques provide a wide range of possibilities whose exploration is today a far from negligible sources of opportunities to increase industrial companies' competitiveness. As a complex manufacturing process, production order scheduling in the job-shop is a necessary scenario to act by implementing these technologies. This research work considers an initial conceptual smart digital twin (SDT) framework for scheduling job-shop orders in a zero-defect manufacturing (ZDM) environment. The SDT virtually replicates the job-shop scheduling issue to simulate it and, based on the deep reinforcement learning (DRL) methodology, trains a prescriber agent and a process monitor. This simulation and training setting will facilitate analyses, optimization, defect and failure avoidance and, in short, decision making, to improve job-shop scheduling.

Keywords—Smart Manufacturing, job-shop, scheduling, smart digital twin, zero-defect manufacturing

I. INTRODUCTION

In today's highly competitive and globalized industrial environment, maximizing performance demands improving the traditional ways of dealing with production processes. An ever-changing industrial environment requires more flexibility and acting as a smart network; a more dynamic and reliable supply chain requires tracking, traceability, and interoperability capacities, and incorporating commercial partners into its own strategy; a smart manufacturing (SM) process requires the capacity to adapt in real time to sudden changes in production volumes, products or their scheduling delivery, and to adapt to customer quality requirements; increasingly more demanding and well-informed customers need to be integrated into the value chain, with greater production personalization; a professionalized occupational context requires more digitization, training and ergonomics; an increasingly deteriorated natural environment requires more efficient resources use, among others. The SM paradigm arises to respond to conventional formulas' incapacity to meet the requirements of today's competitive environment in the industrial sector.

SM is the core in the fourth industrial revolution [1]. With the development of SM, more and more new information and communication technologies (ICT), such as

Internet of Things (IoT), cloud computing, big data and artificial intelligence (AI), have been used in manufacturing to improve production efficiency and flexibility [2]. The manufacturing sector is currently reinventing itself by embracing the opportunities offered by digital transformation, industrial internet, automation, machine learning (ML), among other innovations [3]. Digitalization in manufacturing can lead to significant productivity and effectiveness improvements in complex systems [4].

Driving a production job shop toward SM entails the challenge of deploying, at least partially, the aforementioned ICT in all the different manufacturing stages from supplying raw materials or components to distributing products, and in all manufacturing areas from quality areas or plant engineering to maintenance or logistics, and operations planning and control (OPC), and at any of its decision-making levels. In the operational decisions area, specifically scheduling as a decision-making process that is followed on a regular basis in many manufacturing and services industries deals with resource allocation to tasks over given time periods in order to optimize one objective or more [5]. So supporting this specific decision-making process with new ICT is necessary to provide the process with speed in order to delay the results as minimally as possible, and to obtain accurate [6] and robust [7] results which ensure that set objectives are optimized.

In the zero-defect manufacturing (ZDM) environment, it is necessary to underline that speed, accuracy and robustness are critical factors for optimizing order scheduling because the central objective of the ZDM strategy is to achieve things by the first attempt [8]. This is an ambitious purpose, and the difficulty in fulfilling it can be overcome by this second reading: doing things properly the first time in a real environment after having simulated, analyzed and optimized them in the virtual world; in other words, replicating them in the virtual world to optimally solve them. This way of ensuring accurate, robust and faultless results in the real environment requires ICT if we aspire to achieve suitable speed to obtain results in real time, since it is the only way to contemplate a flexible production job shop given that it allows being able to rely on the valuable possibility of resequencing production, even in ongoing production, by minimizing the negative effects of such action, provided its positive effects render it advisable [9].

Therefore, taking SM to the production order scheduling process level involves considering whether it is worthwhile to virtually replicate it by ensuring an optimum interaction and integrating the physical and virtual space, and the SM response to this worthwhile endeavor is a digital twin (DT)

[10]. However, the potential of a DT-based approach may substantially vary depending on the services it incorporates after it has been implemented. Visualization, modeling, simulation, analyzing “what-if” scenarios, forecasting, alternative management scenarios, learning or optimization are, among others [11][12], the most habitual possibilities. However, firstly prescription, and secondly decision making, are the services that enable both the process and tool to be classified as smart, namely production order scheduling and the DT, respectively. These services also allow the process to be conceived as being either semi-autonomous if it is capable of prescribing, or autonomous if it is capable of deciding, and lead SM to be completely implemented into short-term job-shop planning.

Characteristics of the production order scheduling problem allow an AI-based solution approach by ML techniques to be considered. The objective of this work is to present an overview of the considered problem, and to propose a preliminary conceptual framework for semi-automatic production order scheduling in a job-shop with a ZDM strategy by implementing a smart DT (SDT) with a prescriptor role.

The remaining of this paper is organized as follows. Section 2 presents a brief overview of the related literature. Section 3 describes the proposal in short. Section 4 discusses the primary results and contributions. Finally, Section 5 provides the conclusions and further research.

II. LITERATURE REVIEW

Increased manufacturing efficiency has been a constant challenge since the first industrial revolution [13]. According to this more up-to-date and defined perspective, the purpose of production order scheduling also faces an increased efficiency challenge because inefficiency in this task contributes to overall manufacturing inefficiency. Therefore, job-shop scheduling efficiency outlines directly and positively affect not only the production cycle, but also costs and competitiveness [14]. Optimum resource use, where resources include time that is of utmost importance, and minimizing associated costs, are two relevant questions about order scheduling research and are fundamental objectives for OPC in operational decision making. As this is one of the most typical and complex production scheduling problems [15], many varied strategies are found in the literature to fulfill this double objective in order scheduling in the job-shop scheduling problem (JSSP). We now go on to indicate some literature works related to the JSSP lines herein defined.

A. Applying machine-learning (ML) to solve the JSSP

Although the resource most widely resorted to in the literature about problem solving is to present new modeling approaches based on metaheuristic algorithms, it is worth stating that the use of AI techniques to solve the JSSP is progressively gaining ground. A recent literature review about applying ML algorithms to solve the JSSP is provided by Pérez-Cubero and Poler in [16], where these authors offer an overview of the current research status by characterizing the employed algorithms and presenting future research lines. Their study examines the predominance of each algorithm, and concludes that reinforcement learning (RL), Q-type learning and the deep Q network (DQN) currently predominate with 36% of cases each, followed by the deep neural network (DNN) with 14%, and finally by the recurrent

neural network (RNN) type and deep reinforcement learning (DRL) with 7% each. One of the conclusions drawn by that study is that the first future research line to derive from this consists in building simulation environments. By an original approach, in 1997 Lee et al. considered in [17] that empirical research results pointed out that using ML in the job shop was a promising field and proposed combining the strong points of genetic algorithms and induced decision trees as the ML technique to develop a production order scheduling system. This shows the researchers’ long-since dated interest in this matter. Since then, scientific production has advanced at the rate that increasing computing power has allowed it, and the dimension of study object problems has sustainably grown in parallel with it. This has been increasingly evidenced in recent years by the generalized presence of computers with Core i5 or i7 Intel processors, or similar ones, and RAM exceeding 8 Gb in production environments. Wei et al. [18] propose an intelligent job scheduling framework for suppliers with applications using a JSSP configuration and a method in which DRL is the key framework component. Applying the DQN algorithm from Google DeepMind for RL in the production scheduling of a flexible job-shop is the study object for Waschneck et al. in [19]. Zang et al. [20] propose a hybrid DNN scheduler to solve the JSSP by first dividing it into subproblems, and then using a deep learning (DL) framework to solve the subproblems by applying the convolution two-dimensional transformation method to transform irregular scheduling information into regular functions so that the convolution DL operation can be introduced into JSSP processing. The dynamic JSSP with jobs and machine breakdowns randomly arriving is dealt with by Shahrabi et al. in [21] by means of RL and implementing a Q-factor algorithm (Q-Learning) based on the variable neighborhood search.

B. Virtual JSSP replication by implementing the DT

This is a recent research line whose first main contributions to the literature date back to 2018. Zhang et al. [22] performed a review of research into job-shop scheduling and its new perspective from the SM. They place the DT in the group of novel and emerging technologies in 4.0 settings and contemplate the importance that the simulation models built with virtual simulation technology have so that smart agents can forecast results themselves, build their own multi-objective optimization models and solve them to better schedule with available algorithms. Within the framework of proposals of DT models acting as a tool to enable the production order scheduling function in the job-shop, Feng et al. [23] study the problem of deploying and adjusting reconfigurable machines in a job-shop with several products. This problem requires a solution before being able to make online adjustments to reconfigurable machines. The online simulation control system they contemplate is based on the DT and includes follow-up, decision-making and control tasks. Zhang et al. [24] propose a DT-based dynamic job-shop scheduling methodology from the perspective of its more frequent bottlenecks: i) forecasting machine availability; ii) detecting disturbances; iii) evaluating performance and investigating how, when introducing the DT, greater convergence between job shops’ physical and virtual spaces can be achieved by facilitating dynamic scheduling to a great extent as, respectively: i) the DT merges both real and simulated data to the DT helps to detect disturbances by comparing the physical machine to its digital counterpart, which is continuously updated in real

time, and which activates appropriate scheduling whenever necessary; iii) the DT enables integral performance assessments for rescheduling purposes using multidimensional models that can describe geometric properties, physical parameters and machine performance. Fang et al. [2] propose a production order scheduling method in a flexible DT-based job-shop to reduce deviations in schedules as a result of uncertain events, information asymmetry or abnormal disturbances, whose effect reduces both scheduling efficiency and quality. According to these authors, the DT allows the possibility of virtually interacting with reality, provides process mapping in real time, and shows its symbiotic evolution as a quality when referring to the capacity to virtually associate different types of job-shop entities. An example of applying commercial software that plays the DT role as a discrete events simulator to generate a simulation environment in which to compare or assess different scenarios in job-shops is provided by Zupan et al. [25]. These authors consider multistart local search heuristics algorithm “remove and reinsert”, which they implement into the simulation software of Siemens Tecnomatix Plant Simulation plants, and they compare it to the incorporated genetic algorithm. Using discrete events simulation or the DT is an efficient tool for analyzing “what-if” scenarios in all types of production systems [26].

C. The ZDM strategy in the job-shop environment

This research area remains practically unexplored with very few contributions. Psarommatis et al. [27] recognize production order rescheduling in contemporary job shops as an inevitable and critical phenomenon, and center their study on identifying the critical reaction time for the events that trigger it so that productivity and costs remain within acceptable ranges by considering that four related factors may lead to confusion and loss of productivity: on the one hand, new order events, faulty parts and machine breakdown; on the other hand, the number of daily re-schedulings. Psarommatis et al. [28] base their research on the more frequent need to reschedule the job-shop in ZDM because this strategy imposes that all events during production have their counteraction to mitigate these events and focus their research on improving the quality of the solution in line with this in flexible JSSP by a metaheuristic method, namely Tabu search.

D. On the combined SDT approach for a ZDM-based JSSP

No works in the literature were found that completely coincide with this combination of conceptual sets. However, two close considerations appear in the OPC context, which are not included in previous sections, but are relevant: i) SDT models for production order scheduling; ii) DT models for ZDM-based production order scheduling. Although these works do not center specifically on solving or improving the JSSP, they potentially offer some valuable keys. The literature search related to the first approach gave some articles that associate the DT, intelligence and production scheduling in which the intelligence attribute stems from referring to the SM paradigm, and not from employing AI algorithms or systems. It is worth citing Hu et al. [29], who resort to a DQN to solve the dynamic scheduling problem of flexible manufacturing systems (FMS), which involves shared resources, route flexibility and stochastic arrivals of raw materials, and they model the system by taking into account both manufacturing efficiency and avoiding deadlocks using a type of Petri networks that combine time-

place Petri networks, and a simple sequential processes system with resources that the authors call timed S3PR. Liu et al. [30] integrate the advantages of the DT and a supernetwork to develop a smart production order scheduling method so that the job-shop quickly and efficiently devises process plans. By establishing a supernetwork model based on feature-process-machine similarities in the DT job-shop, it allows the centralized and classified management of many data types. Production order scheduling outlines are formulated by doing similarity calculations of decomposed features and the supernetwork mapping relations. Negri et al. [31] propose a framework to include equipment status forecasts into scheduling activities by embedding a field-synchronized equipment health indicator module into DT simulation. The production order scheduling optimization approach is metaheuristics performed by a genetic algorithm, but it is connected to a DT simulator and provides several generations of scheduling alternatives, which are assessed by simulation with the help of an equipment health indicator module that calculates the equipment health status and is included in the assessment.

No literature works were found that completely coincide with DT models for ZDM-based production order scheduling. However, the literature search for DT models used in ZDM environments without contemplating scheduling gave two works that are worth considering. Lindström et al. [32] propose an initial model for ZDM that employs a cost function, which they employ to reflect the production process situation and product/process qualities by means of the DT to virtually represent the process, its control system, and possible interconnections among different unit processes. Papacharalampopoulos et al. [33] consider that the optimization and control of manufacturing processes are key approaches for efficient manufacturing and zero defects. Thus it is important to study hypothetical scenarios in relation to changes in process parameters. These authors state the need to design and implement DTs to study these hypothetical scenarios in real time. For this purpose, they review a specific methodology deriving from process physics as a candidate technology for the DT process level.

E. Synthesizing the state of the art

The following can be concluded from the literature review: (i) applying AI to the JSSP depends directly on the available computing power; (ii) Q-learning and DQN algorithms concentrate 70% of the ML solutions considered for the JSSP in recent years; (iii) building simulation environments as part of using ML algorithms is the first future research line for some authors; (iv) the possibilities of applying DTs to the JSSP field are very diverse: simulation, analysis, evaluation or forecasting, among others. However, their prescriptor or decision-maker role has barely been explored; (v) no research exists on the specific JSSP case in ZDM environments; (vi) no scientific works completely coincide with the conceptual framework herein proposed. Nevertheless, those that have employed similar approaches with the DT assisted by AI in ZDM environments for other planning subjects that differ to the JSSP report promising results in the area corresponding to these subjects.

III. PROPOSAL

The proposal herein set out is based on the DRL methodology and uses a DT scheme to delimit virtual and physical spaces and actions.

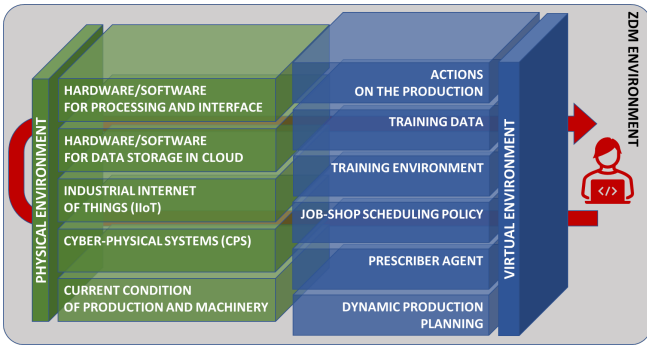


Fig. 1. General SDT-based manufacturing environment

The general job-shop manufacturing environment within the conceptual framework herein proposed is arranged as a series of clearly interrelated and overlapping layers, in which each layer delimits a defined subenvironment (Fig. 1).

According to the characteristics of the roles played in the DT body, all these layers act as a generator and/or processor and/or receiver of data and information. In the physical environment, the following are set up: (i) the current production and equipment status; (ii) the cyber physical systems (CPS) associated with both; (iii) the system defined for implementing the industrial Internet of things (IIoT); (iv) the hardware and software that support cloud data storage; (v) the hardware and software that support the SDT's interface process. The group of subenvironments that belong to the virtual environment is made up of: (i) the current production planning, which is dynamically updated in real time; (ii) the DRL-based smart agent; (iii) the job-scheduling policy in the job-shop, the basis of the reward strategy for the agent; (iv) the simulation subenvironment in which agent undertakes their training activity for learning; (v) the data from the learning that are accumulated while agent trains; (vi) the resulting actions to be applied to job-shop scheduling tasks.

The SDT merges all these subsets by making them converge in the human agent's interface as a single cohesioned environment composed of synchronized elements. It not only informs about production in real time, but also autonomously manages scheduling based on its perceptive and cognitive capacities. This environment structure makes the whole set visible and consistent.

When configuring the system (Fig. 2), three activities are considered: (i) training; (ii) prescribing; (iii) monitoring. These activities are performed by a DRL-based algorithmic framework. The reason for choosing this methodology lies in: on the one hand, the circumstance that the literature on this matter indicates that RL improves the results obtained by using DL in the JSSP solution [16]; on the other hand, the limitations of pure RL algorithms, as regards the solution's reproducibility and robustness, prevailing [16], which allows considerations based on pure RL or DL algorithms to be ruled out to favor DRL algorithms.

As part of the training activity, the training environment integrated into the SDT acts as a space in which the prescriber agent performs its action. This space is, in turn, made up of two subspaces and two functions: (i) the observation space; (ii) the action space; (iii) the reset function; (iv) the action function. The observation space is delimited by all the variables defining job-shop scheduling and its possible range of variation. The action space

determines what the agent can do inside the observation space and within which range of variation. The reset function determines the initial predetermined scheduling state from which all training must begin. The action function, on the one hand, simulates the result of the prescriber agent's individual action on the environment, which leads it to a new state and, on the other hand, analyzes how this new state helps the fulfillment of the objectives set by the job-shop scheduling policy to be approached and, accordingly, assigns a reward to the prescriber agent. The association of the assigned reward with a new state, as a result of the action performed by the agent, can be considered a cognition process, albeit on a very simple scale, which provides the agent with a smart attribute.

This process is successively repeated until all the periods that are set out in the job-shop scheduling horizon are covered, with which a training series is completed. Training series are, in turn, repeated as many times as necessary to cover a sufficiently representative part of the observation space so that the successive scheduling proposals that the agent puts forward from one same state start converging toward a preset acceptance level. In this way, the agent indicates that learning has ended. The training is valid while no production process reconfiguration takes place, which would require a new learning process. The SDT's capacity to adapt to changes confers job-shop scheduling flexibility and fulfills the ZDM strategy parameters.

When training is completed, the SDT is ready to prescribe job-shop scheduling solutions semi-autonomously. With: (i) dynamic production planning from the tactical decision-making level that is updated in real time in the cloud, (ii) a preset scheduling policy; (iii) the current production inventories state and production resources capacities, collected in real time by the CPS set, the SDT selects the suitable action and schedules the start of job-shop scheduling, or reschedules it in real time if any event requiring this occurs during the production process. The human agent confirms any rescheduling. However, training does not end. The SDT activity, once it is considered sufficiently trained and ready to start prescribing real solutions intended for the physical production environment, adds additional training. Therefore, with more learning, the SDT's performance level tends to improve.

While no changes occur in the job-shop setting, the SDT does not intervene and, while no new actions are performed, the production process advances according to the last rescheduling.

So between one change and another, the SDT merely monitors how production advances until a new event of the following kinds occurs: (i) changes in production scheduling when new orders arrive or due dates change; (ii) changes in production scheduling because orders are cancelled; (iii) changes in processing times; (iv) failing to supply materials, such as delays or temporary stockouts of a given material, component or subproduct; (v) predictive maintenance operations; (vi) faulty tools; (vii) breakdowns; (viii) deconfigurations of production resources that enable faulty products or breakdowns to be forecast; (ix) failed energy supplies; (x) faulty products detected. Any one of these events triggers the SDT to follow the same previously indicated process by prescribing job-shop rescheduling in real time and, thus, fulfilling the ZDM strategy parameters.

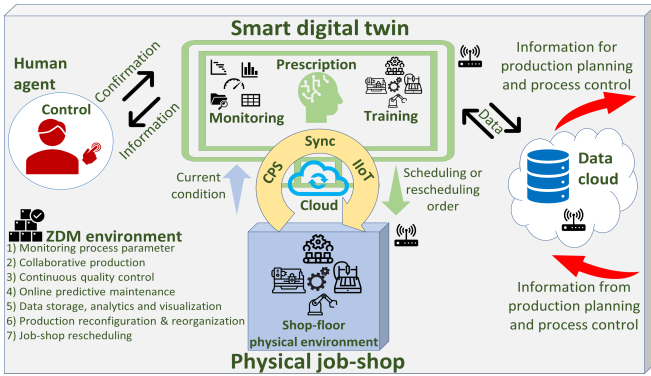


Fig. 2. Setup of the SDT for ZDM-based job-shop scheduling

In an initial phase, the SDT semi-autonomously manages job-shop scheduling; that is, it prescribes the human agent its scheduling or rescheduling, who finally confirms this and decides to apply it. Nevertheless, if the SDT's prescriptor function is sufficiently robust, the next step consists in autonomous management with no human intervention. This implies automated job-shop scheduling, which would meet all the objectives indicated by the SM paradigm.

IV. DISCUSSION

Scheduling is the heart of a production floor and optimized scheduling is a major enabler of improvements in production capability [34]. Unexpected events (i.e. machine breakdowns, late or new job arrivals, product defects, job cancellation, change in processing times, faulty tools, etc.) disrupt normal manufacturing system operations and, subsequently, impose risks, extra costs and less efficient systems. Thus, changes are made to the current schedule and, therefore, re-scheduling is required to include correction actions and to allow manufacturing systems to optimally run in its optimal way [27]. By introducing the DT, further convergence between the physical and virtual spaces of job-shop scheduling can be achieved, which enables dynamic scheduling by triggering timely rescheduling whenever needed [24].

Moreover, introducing AI as a central part of the DT is a natural step to take because: (i) its rapid performance on problems in which their large size implies unacceptable calculation times by using other solution approaches [16] makes it a useful tool for overcoming the real-time data synchronization challenge, which is fundamental for optimum DT operation and (ii) it enables the decision-making process to become the center of smart capacities by conferring it knowledge of job-shop scheduling operation patterns [35] so that once the introduced AI is trained, it allows the system to more quickly identify errors, act on these errors more accurately to, therefore, make quicker and more efficient decisions. Moreover, AI allows ways to adapt to environmental conditions, such as breakdowns or equipment maintenance, which reduces idle time costs [35].

In addition, when the JSSP is tackled from the perspective of these different combined conceptual subsets, the job-shop scheduling setting acquires the ideal capacities to successfully adopt a ZDM strategy [32]. These job-shop scheduling capacities for ZDM are: (i) facilitate monitoring process parameters through the SDT; (ii) enable collaborative production by virtually replicating job-shop scheduling and, thus, enabling its visualization and remote operation; (iii) enable continuous quality control by

preparing the system to face reschedulings from ruling out faulty materials, components or products; (iv) make the system compatible with a hypothetical predictive online maintenance [34]; (v) promote the job-shop scheduling data/information storage, analysis and visualization performed by operators; (vi) favor the adaptation of job-shop scheduling to the contingencies related to the need to reconfigure or reorganize the production process given the virtual system's flexibility; (vii) empower job-shop scheduling for real-time rescheduling. The proposed framework considers all these characteristic ZDMs, and is modeled and adapted to reschedule production orders, which contributes to cushion risks related to disturbances, e.g., saving costs and increasing production system efficiency. With such characteristics, job-shop scheduling shares the principles that define the SM paradigm and address its digital transformation.

V. CONCLUSIONS

This article has set out an initial DT-based conceptual framework driven by AI to model the JSSP with a ZDM characteristic. This framework has focused on generating JSSP optimization algorithms in the specifically described environment, which are based on applying RL techniques with which to enable the DT's training, prescription, and monitoring, and to confer it the intelligence attribute.

The present article describes: (i) the very structure of the general job-shop SDT manufacturing environment, provided to enhance the visibility of all the set's elements and confer it consistency; (ii) the SDT configuration for job-shop scheduling with a ZDM strategy designed so that the specific decision-making process is quick, accurate, robust and faultless. The environment's structure and the SDT's configuration are considered the main contributions of this research. Managerial implications are oriented to favor mitigating risks related to disturbances, saving costs and making the production system efficient.

In the model, the SDT layer that supports cloud manufacturing services will enable access to data outside the environment. While it is developed, a reversible configuration of this layer will allow agents outside the environment to access the SDT and, therefore, to access the virtual job-shop scheduling environment. This will allow synchronized data and information to be shared with higher OPC decision-making levels; that is, with tactical and operational decision-making levels, and with other manufacturing areas, or also with other supply chain links, such as supplier partners, logistic partners or distributor partners, to orientate the job-shop management towards collaborative production planning. It can also allow access to customers, which will be oriented to customization.

Moreover, the results of training in simulated environments cannot always be directly extrapolated to the real world. The strategy followed to extend the learning dataset to the physical job-shop space is also a challenge which depends on the fidelity of replication that is intended for the SDT to a great extent. Regarding fidelity, the model considers 10 types of events with a potential disturbance for JSSP, which are controlled during monitoring to trigger rescheduling as necessary. The consideration of all these types of events improves the SDT's fidelity by approaching the generated virtual entity to the replicated one, though this markedly increases the dimension of the problem, which has

been a previous limitation for other researchers [16]. Incorporating this capacity into the model is challenging; is also a limiting factor, and one that requires further research. Finally, this research has focused on the JSSP. Research into knowing whether the proposed conceptual work framework, which is based on the SDT in a ZDM setting, is applicable to other problems like flow-shop, or even to some of the characteristic ones of other decision-making levels of the OPC, such as master production scheduling (MPS) or materials resources planning (MRP), represents a new future research line.

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REFERENCES

- [1] H. Zhang, G. Zhang, and Q. Yan, “Digital twin-driven cyber-physical production system towards smart shop-floor,” in *Journal of Ambient Intelligence and Humanized Computing*, 2019, 10, 4439-4453.
- [2] Y. Fang, C. Peng, P. Lou, Z. Zhou, J. Hu, and J. Yan, “Digital-twin-based job shop scheduling toward smart manufacturing,” in *IEEE Transactions on Industrial Informatics*, IEEE Computer Society, 2019, 15, 6425-6435.
- [3] K. Xia, C. Sacco, M. Kirkpatrick, C. Saidy, L. Nguyen, A. Kircaliali and R. Harik, “A digital twin to train deep reinforcement learning agent for smart manufacturing plants: Environment, interfaces and intelligence,” in *Journal of Manufacturing Systems*, Elsevier, 2020.
- [4] S. M. Bazaz, M. Lohtander, and J. Varis, “5-Dimensional definition for a manufacturing digital twin,” in *Procedia Manufacturing*, 2019, 38, 1705 – 1712.
- [5] M. L. Pinedo, “Scheduling: Theory, algorithms, and systems,” in 5th edition Springer Science+Business Media, 2016.
- [6] G. Schuh, C. Thomas, A. Hauptvogel, F. Brambring and K. Windt, “Achieving higher scheduling accuracy in production control by implementing integrity rules for production feedback data,” in *Procedia CIRP*, Elsevier B.V., 2014, 19, 142-147.
- [7] J. Billaut, A. Moukrim, and E. Sanlaville, “Flexibility and robustness in scheduling,” in *Flexibility and Robustness in Scheduling*, 2010.
- [8] G. Angione, C. Crisalli, J. Barbosa and P. Leitão, “Integration challenges for the deployment of a multi-stage zero-defect manufacturing architecture,” in *Int. Conf. Ind. Informatics (INDIN)*, Institute Electrical and Electronics Engineers Inc., 2019, 1615-1620.
- [9] M. Souier, Z. Sari and A. Hassam, “Real-time rescheduling metaheuristic algorithms applied to FMS with routing flexibility,” in *Int. Journal of Advanced Manufacturing Tech.*, 2013, 64, 145-164.
- [10] Y. Lu, X. Xu, R. Y. Zhong, M. I. Dessouky and X. Xu, “A digital twin reference model for smart manufacturing,” in *Proceedings of Int. Conf. on Computers and Industrial Engineering*, 2018.
- [11] D. Jones, C. Snider, A. Nassehi, J. Yon and B. Hicks, “Characterising the digital twin: A systematic literature review,” in *CIRP Journal of Manufacturing Science and Technology*, 2020, 29, 36-52.
- [12] W. Kritzing, M. Kärner, G. Traar, J. Henjes and W. Sihn, “Digital twin in manufacturing: A categorical literature review and classification,” in *IFAC-PapersOnLine*, 2018, 51, 1016-1022.
- [13] P. H. De Modesti, E. Carvalhar, M. Borsato, K. Safsten and F. Elgh, “Production planning and scheduling using machine learning and data science processes,” in *Adv. Transdiscipl. Eng.*, 2020, 13, 155-166.
- [14] Z. Liu, W. Chen, C. Zhang, C. Yang and Q. Cheng, “Intelligent scheduling of a feature-process-machine tool supernetwork based on digital twin workshop,” in *Journal of Manufacturing Systems*, 2020.
- [15] P. Sharma and A. Jain, “A review on job shop scheduling with setup times,” in *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 2016, 230(3), 517–533.
- [16] E. Pérez-Cubero, R. Poler, “Application of machine learning algorithms to job shop scheduling of production orders: A review of recent literature,” in *Dirección y Organización*, Universidad Politécnica de Madrid, 2021, 82-94.
- [17] C.-Y. Lee, S. Piramuthu and Y.-K. Tsai, “Job shop scheduling with a genetic algorithm and machine learning,” in *International Journal of Production Research*, 1997, 35, 1171-1191.
- [18] Y. Wei, L. Pan, S. Liu, L. Wu and X. Meng, “DRL-Scheduling: An intelligent QoS-Aware job scheduling framework for applications in clouds,” in *IEEE Access*, Institute of Electrical and Electronics Engineers Inc., 2018, 6, 55112-55125.
- [19] B. Waschneck, A. Reichstaller, L. Belzner, T. Altenmüller, T. Bauernhansl, A. Knapp and A. Kyek, “Optimization of global production scheduling with deep reinforcement learning,” in *Procedia CIRP*, 2018, 72, 1264-1269.
- [20] Z. Zang, W. Wang, Y. Song, L. Lu, W. Li, Y. Wang, Y. Zhao, “Hybrid deep neural network scheduler for job-shop problem based on convolution two-dimensional transformation”, in *Computational Intelligence and Neuroscience*, vol. 2019, article ID 7172842, 19 pages, 2019.
- [21] J. Shahrahi, M. A. Adibi and M. Mahootchi, “A reinforcement learning approach to parameter estimation in dynamic job shop scheduling,” in *Computers & Industrial Eng.* 2017, 110, 75-82.
- [22] J. Zhang, G. Ding, Y. Zou, S. Qin, and J. Fu, “Review of job shop scheduling research and its new perspectives under Industry 4.0,” in *Journal of Intelligent Manufacturing*, Springer New York LLC, 2019, 30, 1809-1830.
- [23] X. Feng, Z. Zhao and C. Zhang, “Simulation optimization framework for online deployment and adjustment of reconfigurable machines in job shops,” in *IEEE Int. Conf. Ind. Eng. Eng. Manage.*, IEEE Computer Society, 2020, 731-735.
- [24] M. Zhang, F. Tao and A. Y. C. Nee, “Digital twin enhanced dynamic job-shop scheduling,” in *Journal of Manufacturing Systems*, 2020.
- [25] H. Zupan, J. Žerovnik, N. Herakovič, T. Borangiu, A. Thomas, O. Cardin and D. Trentesaux, “Local search with discrete event simulation for the job shop scheduling problem,” in *Stud. Comput. Intell.*, Springer Verlag, 2018, 762, 371-380.
- [26] J. Siderska, “Application of tecnomatix plant simulation for modeling production and logistics processes,” in *Business, Management and Education*, 2016, 14, 64-73.
- [27] F. Psarommatis, A. Gharaei and D. Kiritsis, “Identification of the critical reaction times for re-scheduling flexible job shops for different types of unexpected events,” *Procedia CIRP*, 2020, 93, 908.
- [28] F. Psarommatis, M. Vuichard and D. Kiritsis, “Improved heuristics algorithms for re-scheduling flexible job shops in the era of Zero Defect manufacturing,” in *Procedia Manufacturing*, 2020, 51, 1485.
- [29] L. Hu, Z. Liu, W. Hu, Y. Wang, J. Tan and F. Wu, “Petri-net-based dynamic scheduling of flexible manufacturing system via deep reinforcement learning with graph convolutional network,” in *Journal of Manufacturing Systems*, Elsevier B.V., 2020, 55, 1-14.
- [30] Z. Liu, W. Chen, C. Zhang, C. Yang and Q. Cheng, “Intelligent scheduling of a feature-process-machine tool supernetwork based on digital twin workshop,” in *Journal of Manufacturing Systems*, Elsevier B.V., 2020.
- [31] E. Negri, H. D. Ardakani, L. Cattaneo, J. Singh, M. MacChi, J. Lee and A. Barari, “A digital twin-based scheduling framework including equipment health index and genetic algorithms,” in *IFAC-PapersOnLine*, Elsevier B.V., 2019, 52, 43-48.
- [32] J. Lindström, P. Kyösti, W. Birk and E. Lejon, “An initial model for zero defect manufacturing,” in *Applied Sciences*, MDPI AG, 2020, 10.
- [33] A. Papacharalampopoulos, P. Stavropoulos, D. Petrides, R. Teti and D. M. D’Addona, “Towards a digital twin for manufacturing processes: Applicability on laser welding,” in *Procedia CIRP*, Elsevier B.V., 2020, 88, 110-115.
- [34] P.-A. Dreyfus and D. Kyritsis, “A framework based on predictive maintenance, zero-defect manufacturing and scheduling under uncertainty tools, to optimize production capacities of high-end quality products,” in *IFIP Advances in Inf. and Communication Technology*, Springer New York LLC, 2018, 536, 296-303.