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Towards Human Digital Twins to enhance workers' safety and production system resilience

Nicola Berti, Serena Finco, Mattia Guidolin, Daria Battini

Department of Management and Engineering, University of Padua, Stradella San Nicola 3, 36100 Vicenza, Italy (e-mail: nicola.berti@unipd.it)

Abstract: Industry 5.0 complements Industry 4.0 aiming to create a sustainable, human-centered, and resilient industry. In this context, enabling technologies, such as artificial intelligence, internet of everything, and digital twins, can be used to monitor and enhance the workforce to improve the efficiency and resilience of the entire manufacturing system. By developing socio-technical digital twin architectures, companies will be able in the short future to monitor machines, products, and workers' real-time states as a whole ecosystem. In this study, the authors focus their attention on human digital twin solutions for manufacturing systems, enabling dynamic scheduling of jobs by minimizing the makespan and considering a set of workers' parameters that are continuously monitored through an ergonomic digital platform. This paper proposes the architecture of a real-time monitoring system and how it can help detect awkward postural behavior or unbalanced workload among workers, according to their individual features. At the same time, the system interacts with the human digital twin system which proposes a rescheduling of the jobs whenever it is necessary. Finally, a discussion on the practical limitations of human digital twin implementations in industrial environments is provided.

Keywords: Human Digital Twin, Operator 4.0, Smart manufacturing, Real-time monitoring and control

1. INTRODUCTION

In smart manufacturing and cyber-physical production systems (CPPS), several information technologies and tools such as cloud computing, big data, artificial intelligence, augmented reality, smart sensors, and assistive devices are used to improve efficiency and flexibility (Fang et al., 2019). They represent the core of the Industry 4.0 concept since they lead to making intelligent decisions through real-time communication and enable flexible production of highly customized products (Xu et al., 2021). The new Industry 5.0 paradigm promotes the development of more human-oriented production systems, also considering the adoption of wearable sensors enabling workers' well-being monitoring during task execution to eventually trigger changes to the schedule of activities (Maddikunta et al., 2022).

The human-centric perspective fostered by Industry 5.0 has also contributed to shaping an evolution of the classical concept of the Digital Twin (DT) system toward specific applications for human operator's risk monitoring (Breque et al., 2021). Considered such an extension of the classical concept of the DT system, "Human-Digital Twin" (HDT) or "Digital Twin of the Person" opens new possibilities and challenges for human motion analysis for safety and well-being purposes (Löcklin et al., 2021). Research perspectives are currently not focused only on the integration of the DT system with the ergonomic design of workplaces (Caputo et al., 2019), but also on real-time monitoring of worker movements and behaviors during daily work activities to get data allowing updating the digital models of the system, and triggering a prompt feedback intervention to real physical shop floor with the most profitable solution (Peruzzini et al., 2020).

Real-time information on worker risk levels and system performance can be used to improve the efficiency of planning and scheduling activities due to their importance in production process decisions. The scheduling process represents an operational activity covering a short-term period, aiming to allocate tasks to workers or machines (Negri et al., 2020). Furthermore, it guarantees a reduction in production time and improves production efficiency. In smart manufacturing systems, real-time data availability gives new connotations to production scheduling. Productivity and flexibility are the main goals of such types of systems, and they can be achieved by applying dynamic scheduling to perform prompt changes in the current workplans to enhance the resilience of the production system to any kind of disturbances. In such a way, uncertain events can be included while performing scheduling or assignment tasks to workers or machines activities.

This paper aims to propose an HDT-driven methodological framework to integrate a dynamic scheduling model that processes in real-time postural data collected via the WEM-platform (Battini et al., 2022), urgent jobs for customers, and processing time changes, by minimizing the total makespan. The remainder of this paper is structured as follows. Section 2 provides an overview of the literature concerning HDT, particularly focusing on the human factors integration on real-time task scheduling decisions in the manufacturing field. Section 3 reports the methodological framework of this work, the mathematical model, and the possible adoptions based on different work contexts. In Section 4, the architecture of the HDT-based scheduling model is illustrated, focusing on how data flow progresses between the different nodes of the system. Finally, Section 5 discusses the conclusions and limitations of this work.

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2. LITERATURE REVIEW

The first adoptions of Human Digital Twin systems refer to the health and medical sector (Löcklin et al., 2021); however, they have quickly gained interest in the manufacturing field, offering the chance for real-time monitoring machines, products, and workers' states as a whole ecosystem (Greco et al., 2020). The literature has recently proposed novel methods to integrate models of human behavior into the DT system, allowing the development of dynamic scheduling approaches for the optimization and resilience of the factories of the future (Bécue et al., 2020). Contributions in this field are mainly devoted to human-robot collaboration, where dynamic task assignments may vary according to the capabilities or health conditions of the workers. Dimitropoulos et al. (2021) proposed an AI-based system able to capture the operator, the environment and the state of the process, identifying the tasks that the operator performs to provide customized support to the worker from the robot side, automatically adapting to the operator's needs and preferences. Zhu et al. (2022) created a dynamic configuration to suggest workers' rotations based on their previous performance during a scheduled shift in human-robot collaboration manufacturing systems. In the work presented by Maruyama et al. (2021), digital human technology was integrated in a DT-driven human-robot collaboration (HRC) system for human modelling and simulation of ergonomic assessments, during work activities. Finally, Kim et al. (2022) implemented an HDT system to support decision-making about safety management and operator work management.They monitored operators with a motion capture system and adopted ergonomic indexes for fatigue level detection.
In all the previously mentioned works, the adoption of DT allowed the possibility of considering the diversity in computational decision-making processes, customizing the scheduling decision based on their current schedule, preferences, skills, experience, and risk propensity (Graessler and Poehler, 2017). The literature review proposed by Cimino et al. (2019) on the application of autonomous integrated DT with control systems in production environments confirmed that DT can be helpful for safety reasons, such as collision avoidance in human-robot interactions or in monitoring operators' health through smart wearable equipment and garments. Therefore, the integration of real-time data collection with the Manufacturing Execution System (MES) may be beneficial to quickly provide a prompt reaction to uncertain disturbances (Negri et al., 2020). However, previous research has not sufficiently considered human factors for DT and the possible benefits that sensors and IoT can have on workforce safety and well-being (Berti & Finco, 2022). Therefore, real-time analysis and simulation can be performed with HDT for safety monitoring and production management. Furthermore, it is interesting to highlight that, based on the literature on dynamic job scheduling models based on HDT real-time data collection, none of the above-mentioned works has effectively quantified the implications that rescheduling decisions can have on the productivity of the whole system and the level of safety of workers. To the best of the authors' knowledge, the impact of HDT-driven dynamic scheduling decisions has been mainly investigated for collaborative workstations. Hence, the literature lacks architectures able to integrate real-time health state data collection, and in particular the detection of hazardous safety and health conditions, as events that can trigger dynamic job rescheduling and workforce job assignment to reduce occupational risks.

3. FRAMEWORK & MATHEMATICAL MODEL

3.1 Methodological framework

The objective of the proposed HDT-driven dynamic job scheduling architecture is to understand, predict and optimize workforce health conditions and shop floor resilience to deal with unexpected disturbances. Similarly to predictive maintenance policies, which benefit from real-time machine monitoring for failure prediction, postural data collection with cameras and sensors can help prevent prolonged hazardous work conditions for operators.
In predictive maintenance, smart sensors are adopted to warn the system when there is a deviation between nominal and actual working conditions, which can trigger DT simulations to detect the optimal time to intervene to prevent machine failure and product quality degradation. Similarly, the workforce health state can deviate from the safe working conditions described by ergonomic indexes and international standards. The possibility of monitoring in real-time the health conditions of workers and their occupational risk enables the opportunity to dynamically intervene in the EMS and generate new job schedules based on the available resources of the company. Figure 1 reports a possible data flow, specifically its collection from the field, and how the generated information on resource availability and workforce health state can be used to take actions to address disruptive events.
Initially, the information coming from the supply of raw materials and those related to the market demand for upcoming or urgent orders are integrated into the EMS (1). Then, the MPS (2) is created accordingly, based the availability of machine and resource. Therefore, the production plan is delivered to the working field to be processed. Real-time data collection (3), operated with smart sensors on workforce and machines, constantly updates the ergonomic platform that computes the occupational risk index scores with the latest data captured from the field (4). The refresh rate of the ergonomic indexes depends on the technology used for data collection. Once the HDT is updated with the latest data and the WEM-Platform progresses the ergonomic indexes in real-time, warning signals (5) can be generated when dangerous risk zones are approached according to the worker's time-weighted risk index score. Furthermore, simulations (8) run in the HDT system to determine the risk related to the current job assignment initially designed by the MPS (2) and propose to the company management alternative solutions for each worker, based on their characteristics and skills. The nature of disturbances can vary depending on the source of the disruptive events, and among them, awkward postures maintained for a prolonged time, corresponding to a high-risk score of the corresponding ergonomic index, are considered in this work as a source of disturbance. Once the impact of the abnormal event has been determined and quantified (6), the company must take counteractions to react to the occurrence.

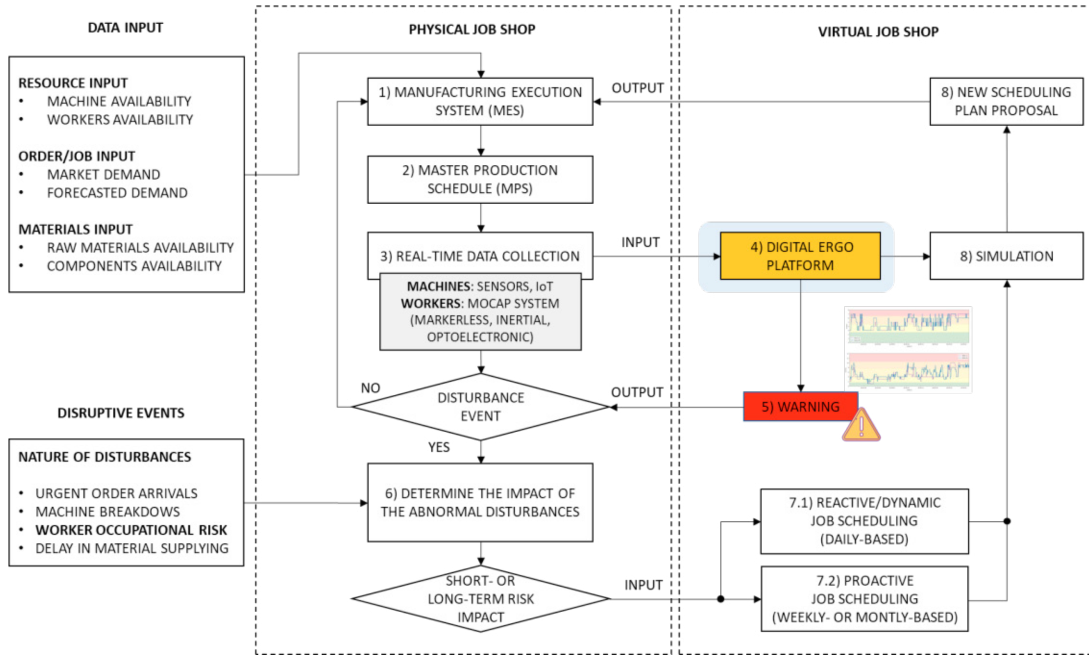

Figure 1: Human Digital Twin architecture for real-time risk evaluation and job rescheduling strategy

This research considers two different strategies that a company can pursue based on the collected real-time information: Reactive job scheduling (7.1) or proactive job scheduling (7.2).

In reactive, or dynamic, job scheduling (7.1), a warning message can alert the company production planner whenever dangerous postures and/or high levels of occupational risk characterize one or more workstations. To immediately react and avoid excessive risk, or unbalanced risk exposures, real-time data of worker movements and information on the overall risk level performed in previous job progression are used to simulate the daily workload of the current job assignment (i.e., knowing the orders to be progressed in the shop floor, the average occupational risk of the workstations and workers' individual features) and eventually suggest modifications to the original job assignment with a reactive job rescheduling workplan that can find through simulations the best solution to lower the overall safety risk level (Figure 1).

Since warning messages may be triggered multiple times during the workday and frequent rescheduling activity is most likely unfeasible in most industrial applications, this scenario results more suitable in uncertain contexts, where the market demand is highly fluctuating, and the arrival rate of urgent orders does not allow for a long-term job scheduling plan. Moreover, the high variability of raw materials and component availability requires more frequent job rescheduling. In this case, whenever job rescheduling is triggered to deal with unforeseeable disturbances (e.g., machine breakdown, urgent order arrival), workforce rescheduling can also be triggered for safety purposes, following the job shop rescheduling model presented in Subsection 3.2.

In proactive job scheduling (7.2), the dynamic rescheduling based on daily events represents a strategy that does not easily suit all industrial applications. In contexts where disruptive events may occur with less frequency, and hence can affect less the stability of the production job scheduling routine, proactive job rescheduling represents a more efficient strategy. This alternative scenario adopts time-weighed occupational risk scores to periodically monitor, simulate, and predict the risk level of the following days, based on incoming and forecasted orders. The frozen and rescheduling intervals for planning the Master Production Schedule (MPS) can shift from one day up to several days, defining a customizable rolling-horizon, based on the probability of disturbances occurring. Job rescheduling suggestions can then be generated and triggered based on the values of time-weighted occupational risk index scores that are monitored and computed for customizable medium- or long-horizon time. The postural data collection performed in previous weeks is adopted to determine the current level of occupational risk of the available set of workers and predict, through the adoption of simulations, the forecast of risk scores based on the upcoming jobs that need to be executed.

Once job scheduling strategy has been established and streamlined to the production work field (8), the HDT system continuously keeps track of the deviation events and adopts the most suitable strategy to adjust and react to external and internal disturbances.

3.2. Mathematical model

Dynamic job-shop scheduling consists of defining a scheduling plan to assign m jobs to n shops (both machines and workers are present) for processing. Each job requires a set of tasks, O_{ik}, requiring a processing time, P_{ik}. However, due to the limited availability of workers and real-time disturbances, the initial plan needs to be revised dynamically to adapt to the actual conditions, thus generating a rescheduling. The unavailability of workers and, thus, the necessity for rescheduling are mainly caused by excessive fatigue levels or wrong postures that are continuously monitored with an ergonomic platform (Battini et al., 2022). Other disturbances (e.g., changes in processing time, urgent job arrival, and machine failures) would also affect the initial scheduling.

Since frequent schedule regeneration would bring the scheduling process nervousness or instability, efficiency and stability should be considered at each rescheduling point. Moreover, the following assumptions are included in our model: 1) All workers, machines, and jobs are available at starting time; 2) Each job must be assigned to a machine or a worker; 3) Each worker and machine can process one job at a time; 4) One operation of a job cannot be processed until its preceding operations are completed; 5) Once a job is processed by a worker or a machine, it cannot be interrupted except in case of fatigue threshold value achievement or machine unavailability; 6) The processing time is known in advance but it can change during the processing; 7) The time duration required to recover fatigue is known; 8) A rescheduling can be done also in case the postural indexes are not equally balanced among workers. Table 2 reports the notation.

Table 2: Notations for the rescheduling problem.

Notation	Description
i = 1,.., m	Index for jobs
j = 1,.., n	Index for workers
k = 1,.., l_i	Index for tasks related to a job *i*
C_{ik}	Completion time for operation O_{ik}
P_{ikj}	Processing time of operation O_{ik}
E_j	Postural risk of worker j
PF_j	Physical fatigue of worker j
E_{max}	Upper bound of postural risk
PF_{max}	Upper bound of physical fatigue
x_{ikj}	1 if operation O_{ik} is assigned to worker j, 0 otherwise
y_{ikghj}	1 if operation O_{ik} is preceded by operation O_{gh}, 0 otherwise
C_{max}	Makespan

The mathematical model aims to minimize the makespan, which is defined as follows:

$$\text{Min } C_{max} \tag{1}$$

Subject to the following constraints:

$$C_{ik} \leq C_{max} \quad \forall\, i = 1,..,m;\ k = 1,\dots,l_i \tag{2}$$

$$C_{i(k-1)} + P_{ikj}x_{ikj} \leq C_{ik} \quad \forall\, i = 1,..,m;\ k = 2,\dots,l_i \tag{3}$$

$$\sum_j x_{ikj} = 1\ \forall\, i = 1,..,m; k = 1,\dots,l_i \tag{4}$$

$$C_{ik} - C_{gh} + UB\left(1 - x_{ikj}\right) + UB(1 - x_{ghj}) + UBy_{ikghj} \geq P_{ikj} \quad \forall\, i = 1,..,m;\ k = 1,\dots,l_i; j = 1,..,n \tag{5}$$

$$C_{gh} - C_{ik} + UB\left(1 - x_{ikj}\right) + UB\left(1 - x_{ghj}\right) + UB(1 - y_{ikghj}) \geq P_{ghj} \quad \forall\, i = 1,..,m;\ k = 1,\dots,l_i; j = 1,..,n \tag{6}$$

$$E_j \leq E_{max} \forall\, j = 1,..,n \tag{7}$$

$$PF_j \leq PF_{max} \forall\, j = 1,..,n \tag{8}$$

Where constraint (2) defines the makespan; constraint (3) sets the completion time; constraint (4) guarantees that a task O_{ik} of a job can be assigned to exactly one worker. Constraints (5) and (6) set the completion time order, while constraints (7) and (8) guarantee the respect of the maximum postural risk and physical fatigue. Furthermore, for constraints (7) and (8), data related to each worker are collected and processed in real-time.

4. HUMAN DIGITAL TWIN ARCHITECTURE

Real-time data describing human motion can be obtained by exploiting different motion capture (MoCap) technologies. Optoelectronic MoCap relies on a series of retroreflective markers applied on the body of the analyzed subject to estimate the body motion. A set of high-frequency infrared cameras then estimates the 3D marker positions via triangulation. These systems require delicate calibration of the relative camera positions and precise applications of the markers in specific body landmarks. As a result, its usability in the industry is limited. Inertial MoCap, on the other hand, exploits a series of inertial measurement units (IMUs) worn by the subject, without requiring any external camera.
The positioning of the sensors on the body is less strict than the markers required by optoelectronic MoCap. As a result, the setup is quick and convenient. However, operators still need to wear multiple sensors on the body. Finally, markerless MoCap allows estimating a subject's movement without requiring any sensor or physical marker on the body, granting maximum dexterity. It relies on one (or more) cameras to extract a series of body key point positions based on deep learning techniques. Although intrusiveness is minimal, the achievable accuracy is still lower than that of optoelectronic and inertial MoCap. Despite the specific characteristics and hardware manufacturer, all systems allow representing the pose of a person through a series of 3D keypoints describing the joint center positions and/or joint angles describing the relative orientations between pairs of joints (Wu et al., 2002).
To allow the use of such data for DT-driven dynamic rescheduling models, support different MoCap systems, and grant stability and long-lasting support, the authors propose the use of the Robot Operating System (ROS) (Quigley et al., 2009). ROS is considered the de-facto standard for the development of robotics applications and provides a set of open-source libraries and tools enabling fast and reliable communication among distributed software and hardware components. A typical ROS-based system is made up of a series of nodes communicating via messages sent through topics based on a publisher/subscriber model. The first step of the digital twin process refers to the integration of the specific MoCap technology used within ROS, as depicted in Figure 2.

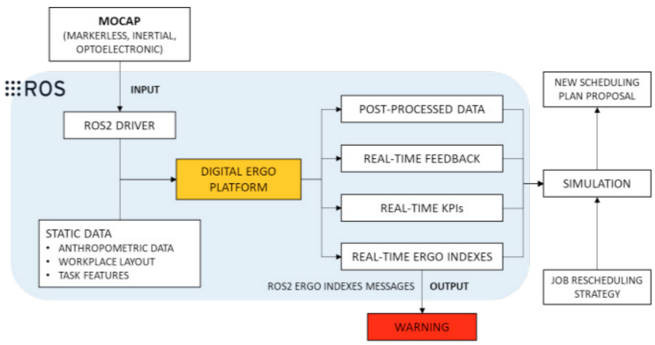

Figure 2: Real-time occupational risk feedback architecture

This consists of developing (if not already available) a driver able to publish the estimated body poses as a series of ROS messages that can be accessed at runtime by anyROS node in the network. In this way, different MoCap systems can be used interchangeably, as long as they publish the same typology of data. Once real-time body poses data are available, ergonomic indexes can be calculated using the software presented in Battini et al. (2022). Postural risk index scores assess static postures; therefore, time-weighted values are used to trigger warning messages to the job production plan.

The software, namely the WEM-Platform, requires real-time body captures and a series of offline parameters describing anthropometric data of the operator, task features, etc. as input and computes a series of ergonomic indexes, i.e., Rapid Upper Limb Assessment (RULA; McAtamney & Corlett, 1993), Rapid Entire Body Assessment (REBA; Hignett & McAtamney, 2000), Ovako Working posture Assessment System (OWAS; Karhu et al., 1977) and Postural Ergonomic Risk Assessment (PERA; Chander & Cavatorta, 2017). Such postural risk indexes can be used to provide real-time feedback to single or multiple operators, compute a series of online productive key performance indexes (KPIs) and provide post-processed information at the end of the acquisition, allowing further analyses on workload and risk balancing (Berti et al., 2022). Since the software is based on ROS, all computed data are available at runtime as custom-defined ROS messages. This allows the integration of different software with the WEM-Platform, supporting real-time communication. To this end, the next step will be to integrate a simulation process or a metaheuristic algorithm with ergonomic assessment tools. Since ROS exposes both the C++ and Python message interfaces, enabling real-time communication with any algorithm or simulation program is straightforward.

5. DISCUSSION AND CONCLUSION

In this paper, we want to highlight the achievable benefits that real-time monitoring analysis of the workforce movements can have on preventing prolonged hazardous situations, by producing a new concept of performing dynamic job rescheduling considering human workforce dynamic disturbances for safety purposes. The Human Digital Twin structure presented in the previous paragraphs reflects that DTs could be expanded from a conceptual idea to applications in many industries in the future. Managers and workers could realize the full potential of an HDT in terms of improved worker wellbeing and safety.

Despite the benefits would be clearly recognized, currently, there are several limitations and concerns about tracking and recording physical parameters of employees using IoT and sensors. Employee monitoring and biomonitoring are not new (Cardillo et al., 2021), especially smart personal protective equipment with IoT (Kanan et al., 2018), which is on the rise since the pandemic outbreak. With that rise comes an increase in discussions about trust, employee rights, privacy, and trade unions. Complaints could arise if the human tracking system also performs time tracking by recording employee attendance and absences from the production workstation. In the same way, tracking by collecting data on how employees spend their time during a work shift could also limit the workers' privacy. Finally, biological and physical data tracking could open the company to legal concerns with the General Data Protection Regulation 2016 (Regulation EU on GDPR, 2016), which governs the processing of personal data. Violating regulations could open the door to HR complaints and lawsuits.

Finally, monitoring every moment of an employee's workday can damage employee morale. Employees may be resentful of intrusion and lack of trust, which could cause stress and burnout. There are several limitations in the implementation of complete HDT in real manufacturing contexts, even if the technologies and the methodological approaches are ready. However, by correctly understanding the benefits on workers' wellbeing and safety of such systems, it is possible to work towards a faster transition from traditional DT to socio-technical DT, according to the different industrial contexts, employment contracts, and labour relationships.

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