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A meta-model for modular composition of tailored human digital twins in production

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Abstract

Multiple and diverse factory digital twins have been proposed in the literature. However, despite the recognized growing importance of workers in smart and autonomous industrial settings, such models still lack or oversimplify human representation.
Human digital twins must include human monitoring and behavioural data and models based on psychophysical status, knowledge, skills, and personal needs to manage production systems that aim, at the same time, to achieve process performance and workers' wellbeing. This paper proposes a meta-model based on data, events, and connectors that supports the modular composition of tailored human digital twins. This work also addresses an industrial application of the meta-model for preliminary validation.

Keywords: Type your keywords here, separated by semicolons ;

1. Introduction

Industry 4.0 introduced the idea that production system control and decision-making can be realised, even automatically, by relying on Cyber Physical Systems (CPS) as dual elements composed of a physical production item and its digital counterpart: the digital twin (DT) [1].

Many examples exist where digital copies of machines, devices, products or entire production systems are used to improve performances, make predictions and take decisions. However, humans, which still have a relevant impact on process quality, performances and continuous improvement [2], have been excluded, up to now, from the digital representation of the factory. The human factor is usually considered only within industrial and workplace design to improve ergonomics, prevent hazards, and to train and educate, rather than for continuous decision-making and production system control. Yet, in order to create production systems that seamlessly complement human capabilities, the digital factory has to include a precise and realistic digital representation of humans, the Human Digital Twin (HDT). In such a model, workers' behaviour is predicted by analysing historical data and psychophysiological status, aiming to optimise processes and to make better decisions. In so doing, a multi-objective optimisation is pursued targeting not only production system performance but also improvement of workers' wellbeing in all its facets from physical health to the acquisition of new skills.

This research explores the concept of HDT from a modelling perspective proposing a meta-model that supports the definition of workers' digital representation in manufacturing. The model has been applied and validated in an injection moulding application.

The rest of the paper is structured as follows. Section 2 is dedicated to reviewing the literature related to HDTs while section 3 discusses the need for flexible and modular representation of the worker within the shop floor. Section 4 presents the core of the meta-model and section 5 presents a real case study. Finally, section 6 concludes this paper.

2. Human digital twin: state of the art

NASA introduced the concept of DT in 2012 as "an integrated multi-physics, multi-scale, probabilistic simulation of a flying vehicle or systems" [3]. From that moment, this concept has evolved and has been adopted in several domains. Thanks to the technologies introduced by the Industry 4.0 paradigm, DTs became incredibly relevant in the manufacturing industry. DTs have been successfully used to mirror and simulate industrial settings, for predictive maintenance, for virtual commissioning, for anomaly detection, and for optimisation of the product life cycle.

Despite several examples being available in the context of products, devices, and machines, only a handful of works addressing the HDT (or more in general human modelling in industrial contexts) can be found. Workers have been considered, in the overall factory digital representation, mainly from a high-level perspective by creating mere static digital models [4]. However, such models are not enough to dynamically mirror the worker as the DT is more than a representation having to estimate the status and to simulate the behaviour of the things it represents.

Most recent research provides only models aimed to represent workers, without addressing the connection between the digital and physical world, the data management, and, more specifically, how to create a HDT. Romero et al. described the human operator through its capabilities, categorising them into physical, sensorial, and cognitive [5]. Another research, focusing on creating a reference framework for user monitoring in the context of Industry 4.0, considers only physiological parameters [6], which have also been included by Wang in its human programming interface [7]. D'Addona et. Al proposed a man-in-the-loop automation system focusing not only on the optimization of production performances but including also the human operator as a full-fledged part of the whole process [8]. Finally, May et Al. [9] developed a Human-centric Factory Model that characterises workers based on three dimensions (anthropometry, functional capabilities, and knowledge/skills/expertise), but without detailing how to measure, collect and use these data. Bilberg and Malik [10] adopted a Kinect sensor to monitor the human presence inside the workspace and track the interference-volumes and frequencies between humans and robots, creating a geo-spatial representation of the worker. The collected data have been used to optimise robot trajectories online to reduce collisions. The most exciting results and application of HDTs, however, do not come from the manufacturing sector. Shen et al. [11] created a digital representation of workers operating in the construction sector by automatically collecting physiological parameters, including human heart rate, breathing rate, upper body posture angle, travelling speed, and acceleration to identify workload severity. From the same sector, Cheng et al. [12] merge workers' spatio-temporal and thoracic posture data to identify the activity type and assess productivity in real-time. In different contexts, physiological data have been used to model physical fatigue and workload [13]. In the medical field, the HDT has been introduced to allow a detailed and continuous inspection of the health status and personal history, thus allowing predicting the occurrence of illnesses in order to prevent or treat them [14]. Such a digital representation promises to evolve from the legacy way treatments are delivered, "one-size-fits-all", to the so-called "personalized medicine". Again, in this field, few examples realize the automatic exchange of data between humans and their digital counterparts. Among them, a conceptual framework has been introduced by Liu et al. [15], describing how to exploit human health-related data produced by IoT-connected wearable devices to feed DTs. Finally, in the fitness field, HDTs have been used to predict athletes' performance and optimize training, by collecting and tracking fitness-related data such as food income, activity, and sleep [16].

3. A holistic representation of the worker

Realising the full potential of HDT in the context of smart manufacturing demands a variety of aspects to be considered. Indeed, decisions have to be made regarding the support platform architecture (software/hardware) and technology scouting to identify possible existing solutions. Still, these can only be undertaken downstream of a smart factory modelling process that considers all the key players involved in the manufacturing process, be they inanimate devices or human beings.

An integral part of the modelling process entails identifying data sources and collecting, analysing, and exchanging information between the physical and digital factory. Again, workers and machines/robots are both sources and recipients of information flows.

Over the years, various methodologies and tools have been developed to support the modelling of the physical components of a factory to build digital twins. As we have seen, although essential, human actors are rarely represented, thus generating shortcomings and sub-optimalities in the management of the production process. Workers are one of the most relevant stakeholders of a company. Considering their preferences and expectations is fundamental to create a motivated workforce. These elements can contribute to plan the right career plan, define training activities, and future job profiles. Moreover, personal needs are strongly related to motivation, which affects performance indicators [17]. For these reasons, it is of utmost importance to maintain an organic, comprehensive, and continuously up-to-date representation of the workers' status.

As is already the case with devices and products, for which various models suit the type of analysis to be performed, distinct but complementary representations of the workforce must be considered to meet the interests of the factory and the individual's needs holistically. A human being is a multifaceted entity and can be characterised by many different dimensions, each of them allegedly requiring a dedicated model. Experience, knowledge, skills, capabilities, wellbeing, and performance indicators are all elements that characterise a worker and that could be encompassed in his/her digital representation.

The most common attributes presented in the literature are physical and anthropometric traits and functional capabilities. Body size and other anthropometric data are the basis for ergonomics and workstation design [18]. The use of simulation and 3D environments are today widely adopted. A precise physical representation of the worker can contribute to the successful design of workstations by simulating ergonomics [19] [20]. The worker's presence in space (position, orientation, and volume) and its evolution over time is also a relevant characterisation.

As for functional capabilities, they are usually adopted in medical and social sciences in studies on disability and ageing. However, many research works have been carried out recently in the context of manufacturing, where the relation between worker capabilities, workplace, job, and performance is increasingly considered [21].

Skills, together with capabilities, are fundamental to assign the right job and tasks to the right worker, and they strongly correlate with company performance. Many taxonomies exist today for skill characterisation. Particularly relevant are ESCO [22] and O-NET [23].

Finally, the psychophysical status is also a relevant facet that contributes to a complete representation of the worker. Pain, illnesses, and injuries are all elements considered in ergonomics. However, with the widespread adoption of wearable technologies, also physiological parameters are becoming relevant in the context of manufacturing. Physiological data can be used to infer the insurgence of phenomena such as fatigue [24] and mental stress [25], which, in turn, have a relevant impact on process performance.

4. The meta-model for human digital twin

As mentioned, HDTs are useful tools to describe, monitor, and simulate workers' behaviour in a production environment. Therefore, it is essential to model the human being in terms of physical, psychophysical and behavioural traits. In particular, workers influence each other and relate to the shop floor and to the product. Moreover, for the HDT to be adherent to reality (workers' state, behaviours and dynamics), it must be updated continuously by analysing information flows obtainable through fixed and wearable devices.

Therefore, in order to realise digital twins that are flexible, customisable and dynamic we have identified the following priorities in the development of a meta-model:

1) The HDT must be definable through a modular and flexible syntax that is understandable to humans and machines alike.
2) It must be possible to describe the relationships between humans and between humans and the environment so that the control and decision systems can have a complete view of the state of affairs.
3) It must be possible to describe data sources in detail and characterise them adequately (data type, frequency, units of measure, maximum and minimum values, functions applicable to the signal, etc.).

According to these priorities, this section presents the main elements of the meta-model developed to represent the human digital twin and its relationships with the environment and devices.

This meta-model is grounded on two principles, which are proper to Domain Driven Development (DDD) and Object-Oriented Programming (OOP), namely, inheritance/generalisation, and aggregation/composition. The former enables us to create hierarchies of entities (the base class) permitting the definition of progressively more specialised concepts; the latter provides the ability to define complex concepts as a set of simpler parts. In this way, we can provide the modeller with ready-made libraries of entities to instantiate, and the means to define his/her own concepts as needed. A set of primitive data and binary formats and serialisation processes (in JSON or XML) finally guarantee that the model can be transferred without loss of information and transformed into digital twins by dedicated software.

Figure 1 illustrates the topmost elements of the proposed meta-model using the UML class diagram notation. The main component is the root class entity, characterised by attributes (primitive data types or other entities). An entity can aggregate other entities to define complex objects and containers (such as lists, sets, trees, etc.). The entity class can be extended at the modeller's will. However, the proposed meta-model includes some semantically meaningful extensions for supporting interoperability. In this section are presented only those extended entities that are considered pivotal to the definition of HDTs, namely, workerModel, connection, functionalModel, context, dataSource, and event.

The entity called **workerModel** represents the human actor within the factory. In order to offer a flexible modelling tool but with a precise semantic meaning, the meta-model identifies three primary descriptive elements that characterise the worker from different points of view.

The **workerCharacteristic** represents any enduring human characteristic like skills, experience, functional (sensory, intellectual, communication, physical capabilities), anthropometric characteristics, needs or preferences. An enduring feature is not necessarily a permanent one as it can potentially change over long periods (e.g., experience gain) or as a consequence of a particular episode (e.g., skill acquisition through training). Differently, **workerCondition** describes a

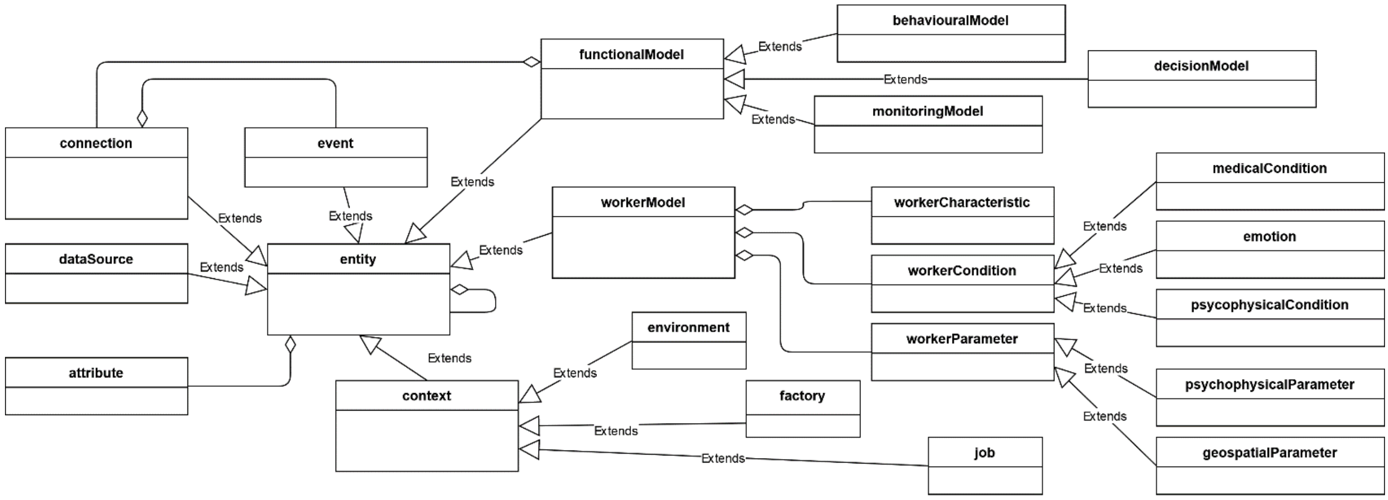

Figure 1 HDT meta-model

worker's temporary condition. This class is extended into different sub-classes making room for the concept expansibility. As an initial subset, three sub-classes are identified: **medicalCondition**, **emotionalCondition** and **psycophysicalCondition**. The **medicalCondition** can include instances like illnesses or injuries described using specific medical standards. The **emotionalCondition** supports the representation of workers' feelings. The **psycophysicalCondition** admits the modelling of conditions like physical fatigue, mental stress, loss of attention, anxiety and pain, relevant to assessing workers' wellbeing and optimising process performance. Finally, the class **workerParameter** envelops all the dynamic parameters that can be collected from the worker. These can be categorised in **psycophysicalParameter**, including heart rate, heart rate variability, galvanic skin conductance, or **geospatialParameter** like localisation or posture.

The **contextModel** is used to describe what surrounds the worker. Different classes are defined, including environment, factory and job. The class **environment** is used to describe ambient characteristics like humidity, noise, pollution, or lighting. **Factory** describes more complex elements that not only influence the worker but also interact with him/her, like machines, equipment, and robots. The class **job** represents the complete set of duties assigned to a worker during a specific working period (e.g., a shift).

The **dataSource** entity describes items that produce data streams within the shop floor. These can be, among others, shop or machine sensors, wearable devices, automation controls, and software applications. Every data source is connected to a physical entity operating in the shop floor and to the workerParameter or environmentalParameter that it feeds.

A state machine can describe the evolution of a digital twin (human or not) over time. In this sense, events perturb the status of this entity, driving its development over time. The **event** class describes the events that change the HDT status, evolving any of its entities or attributes. Connections define the endpoints of the affected entities or attributes.

The **functionalModel** describes all those computational processes that can elaborate entities and attributes, making the HDT capable of simulating, predicting, reasoning, and deciding. The class functionalModel aggregates one or more events that can be used to update the state of the HDT depending on the result of the computation performed. Inputs are defined as connections to the entities needed by the model (e.g., physiological parameters and worker conditions for detecting fatigue level). Internally, functional models can employ any mean of data processing and calculation such as mathematical functions, machine learning, or empirical models. These, if necessary, can be stored as binary blobs and annotated to be managed correctly. The functionalModel class can be further extended into sub-classes. The **monitoringModel**, for instance, targets specific entities and attributes monitoring their evolution, elaborating specific attributes and detecting possible deviations (e.g., fatigue detection, mental stress detection, loss of attention, worker tracking). The **decisionModel** applies decision policies to the HDT. Decisions may entail modifying existing connections (e.g., assigning a task to a worker) or specific attributes (e.g., cobot speed). Finally, the **behaviouralModel** elaborates on the current status of the HDT to make predictions, and simulates its evolution (e.g., to detect risky situations).

The entity **connection** describes links between two other entities, specifying the relationship nature, direction (optional), and the communication interface. The use of this entity permits the modeller to aggregate entities in graphs, to have an independent, distributed creation and evolution of the HDT. The connection entity can be extended for better qualification. assignedJob (linking workers to jobs) and wornDevice (relating a worker and a data Source) are examples of possible specifications.

5. A HDT in an industrial scenario

The suitability of the meta-model presented in the previous section is demonstrated here through the definition of an HDT, which has been realised for the experiment presented in detail in [26] and adopted in the industrial scenario depicted in Figure 2. This has been realised thanks to the collaboration of Ghepi s.r.l, a Small Medium Enterprise located in Reggio Emilia (Italy). In this experiment, the HDT has been applied to estimate the worker's condition in quasi real-time, including physical and mental stress and to drive the collaboration between human operators and a collaborative robot (cobot).

Figure 2 Ghepi's work cell

The main goal of the experiment was to accomplish mutualism between a human and a cobot in an injection moulding work cell, improving both the worker's wellbeing and process performance. In this work cell, three tasks are performed, namely, moulding, finishing and assembly. A task can be as either commutable, which means that can be performed by both worker and cobot, or non-commutable, which can be carried out by only one of the two. A smart decision-maker dynamically assigns tasks to the worker or cobot defining different work cell configurations based on the worker's conditions (physical and mental stress), worker needs (e.g., rest), buffers levels and optimisation goals. In particular, the elements reported in Figure 3, representing the HDT model for the experiment, have been designed and developed on the basis of the HDT meta-model.

There are three main entities in the model: the worker (**ghepiWorker)**, the work cell (**ghepiWorkcell)**, and the decision-maker (**interventionManager**). The ghepiWorker is used to organise human data, including characteristics (**age, sex** and 13 more characteristics), physiological data (**galvanicSkinResponse**, **heartRate** and 12 more parameters), worker conditions (mental stress and fatigue). ghepiWorkcell is used to organise factory data, (buffer levels, system configurations, and tasks). The interventionManager is used to represent decision policies to be enacted elaborating data related to the worker's conditions like fatigue, mental stress, and buffer levels to define the cobot support level. The interventionManager reads data exposed by the ghepiWorker and the ghepiWorkcell to set the work cell configurations.

Different data sources are used to initialise and update the HDT. Physiological parameters are brokered by a **huaweiWatch**, continuously collecting data from an Empatica E4 wristband and Polar H10 Bodyband. Worker characteristics (like age and sex) have been harvested through a custom adaptation of the OREBRO musculoskeletal pain questionnaire, giving a detailed and static representation of the worker. Buffers have been monitored through an image processing module based on a vision system, whereas data on operations advancements and **cobot** availability are collected from a **PLC**. It is worth noting that data sources encapsulate models to ingest, filter, harmonise, and integrate collected data.

Three different monitoring models have been adopted: two dedicated to the worker and one to the work cell. Models dedicated to the worker, including **fatigueMonitoringSystem** and **heartRateVariabilityModel** exploit data from the workerModel, including physiological parameters and characteristics to identify fatigue and mental stress levels. The **bufferMonitoringModel** processed images from the cameras to compute buffers levels and regulate the FIFO logic.

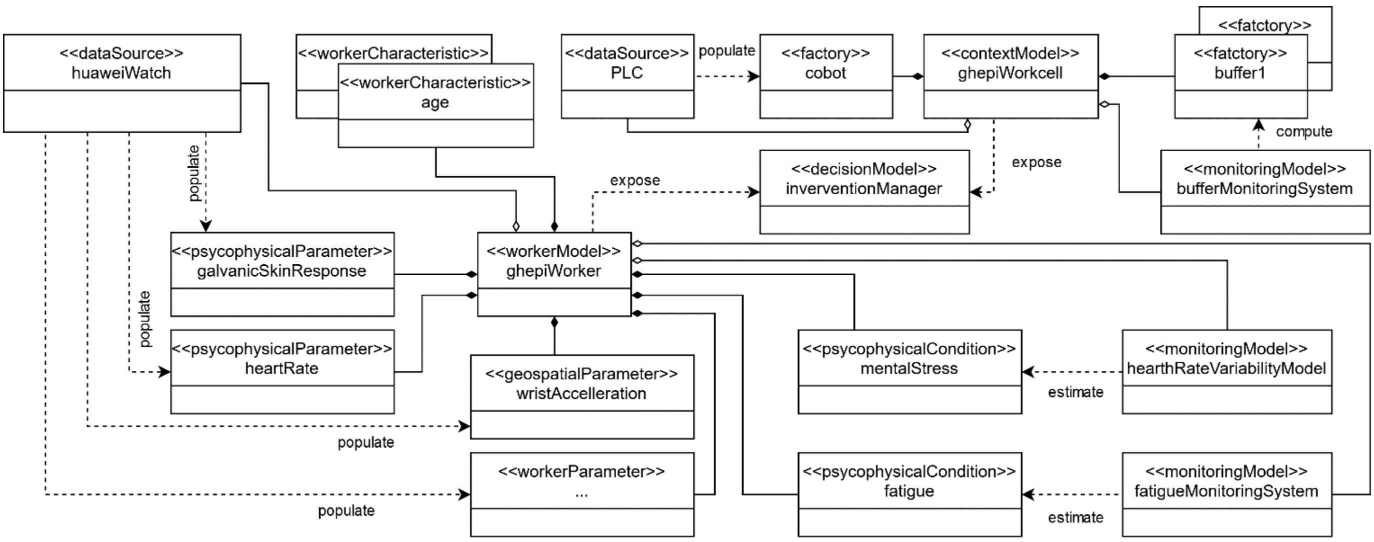

Figure 3 HDT model in an injection moulding work cell (part 1)

A specific model, represented in Figure 4, has been dedicated to the entities linked through connections that aggregate events. The monitoringModel(s) has connections with the interventionManager, characterised by different updating events, that specify that an entity of the HDT has been updated. The interventionManager has a connection with the ghepiWorkcell, characterised by a new configuration event, that specify the tasks allocated to the cobot and to the worker, update the HMI and deliver a notification through the worker's watch.

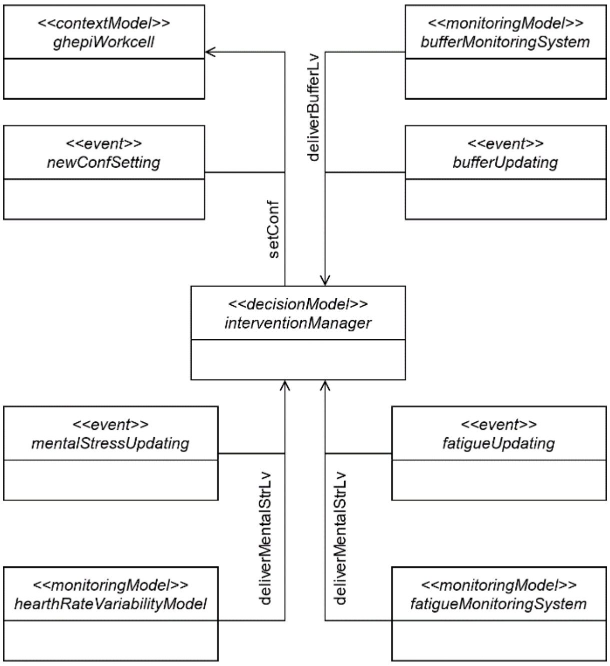

Figure 4 HDT model in an injection moulding work cell (part 2)

6. Conclusion

While there are various examples of DT meta-models and models dedicated to the factory, until now no one had dealt specifically with human. To cover this gap, the proposed work presents a meta-model that supports the modular composition of tailored HDTs, reducing development efforts and increasing the re-usability of its components. The meta-model has been instantiated and validated through an experiment in an injection moulding work cell to demonstrate its effectiveness and industrial relevance. The results showed the improvement of workers' wellbeing, while optimising the production and quality performance, as also described in the video available at [27].

Future activities will concentrate on the functional representation of the HDT to describe, in a hierarchical and modular approach, the functional composition of the HDT building blocks (e.g. data acquisition, data analysis, decision-making, etc.). Conformity to already existing approaches and standards will be also pursued. In particular, it is planned to use this meta-model as the basis for an extension of the RAMI Asset Administration Shell in the direction of a Worker Administration Shell.

Moreover, integration with existing factory DT models will be carried out. Therefore, the work carried out in [28] will be taken as a reference to increase extensibility, interoperability and multi-disciplinarity of our meta-model. Finally, libraries will be developed to support the creation of new HDT instances in order to allow the validation in other contexts.

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