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REAL-TIME SIMULATION IN MANUFACTURING SYSTEMS: CHALLENGES AND RESEARCH DIRECTIONS

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ABSTRACT

In the last years, the increase of data availability together with enhanced resource flexibility shed light on the possibility to develop planning and control methods with real-time inputs. Literature is rich of approaches to simulate, to quickly evaluate system performances, and to take decisions based on optimization criteria. Further, simulation has been identified as one of the pillars for the Industry 4.0 revolution. However, the lack of a generally recognized approach and methodology to deal with real-time decision-making through simulation is evident. Simulation approaches can and should play a central role in industry for the years to come. This position paper analyses the current research context with a brief state of the art on existing approaches, includes considerations about the issues for implementing Real-Time Simulation (RTS) concepts and their current state of development. Finally, it outlines research directions for the simulation community.

1 INTRODUCTION

In the current industrial scenario, the methodologies used to plan and control manufacturing systems are changing drastically and the related research is receiving the greatest attention. Indeed, manufacturing systems frequently change due to external drivers such as the irregularity of customer demand or the availability of new resources enabled by novel *Plug-and-Produce* concepts. For instance, robots can be moved from one system to another, manufacturing cells can be frequently reconfigured to adapt for product changes, or production lines may be re-shaped following new part-mixes scenarios. Further, the increasing demand for more customized products amplifies the need for adapting manufacturing processes and resources (Gunasekaran et al. 2011; ElMaraghy et al. 2012; Christensen 2013).

Industry 4.0 (I4.0) is an umbrella term used to represent all the innovative methodologies for the new generation of manufacturing technologies. I4.0 is based on CPSs, namely Cyber-Physical-Systems (Posada et al. 2015), which are virtual representations of physical resources that can store information, such as kinematic data, interfaces, data logs about performances, and others depending on the application. CPSs use computing hardware, software, and communication links to intelligently control the physical components (Drath and Horch 2014). Thanks to the I4.0 hype and changes in the industrial outlook, several application scenarios can be envisioned. It is possible to collect data and information about the system with a very high frequency, to understand emerging behaviors studying systems' data logs, or to evaluate alternative scenarios and their related risk with affordable time and cost.

Simulation is one of the main tools used to evaluate the performance of a system and support decision making. Posada et al. (2015) considered simulation as a key component for the success of I4.0, in particular in (1) the integration dimension as an end-to-end digital engineering integration tool, (2) the product and

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production dimension as a decision making tool, and (3) the human factor level, as it can improve the work organization and design.

Thanks to the aforementioned developments in industry and research, it is possible to imagine a situation in which the shop floor status in many manufacturing companies could be instantly available anytime (Chen et al. 2016). Further, increasing computational capabilities enhance decision-making and reaction time, besides enabling the usage of performance evaluation tools like simulation for taking very-short-term choices. Some contributions referred to simulators as replications of how humans think, imagining different situations before taking actions (Roßmann et al. 2014). This is called the *Sense-Think-Act* paradigm (Siegel 2003).

In this context, Real-Time Simulation (RTS) is the research direction that best fits the aforementioned requisites. Literature is rich of exemplaric approaches using simulation for real-time production control. One of the most comprehensive reviews on CPSs in industry (Monostori et al. 2016) described the operation modes for Discrete Event Simulation (DES) models in production systems, dividing them into: (1) off-line simulation, used for sensitivity analysis and robustness evaluation of production schedules prior their execution, (2) proactive simulation, used online with the aim of defining short-term actions after recognition of potential deviations from the optimal plan, and (3) reactive simulation, used online for the evaluation of alternatives after a disturbance has occurred. This paper will concentrate on the latter two points.

The aim of this paper is to outline the main issues which have emerged so far related to the application of RTS concepts, to identify which of them still constitute a challenge under the I4.0 framework, and to give propositions on which ones the simulation research community should put the greatest efforts on. The discussion is based also on the new features being introduced by I4.0 that will make extensive use of RTS and the role of simulation in the recent industrial shift. The rest of the paper is organized as follows. Section 2 identifies the main contributions in the literature and the main issues related to RTS implementation. Section 3 exposes the current components mentioned by the researchers in this field; Section 4 analyzes the challenges and issues to be solved in order to see the application of RTS and the related methodologies in industry in the foreseeable future; our final remarks are in Section 5.

2 BRIEF LITERATURE REVIEW ON RTS

In the manufacturing field, real-time Discrete Event Simulation (DES) has been defined as *"a computerized system capable of performing both deterministic and stochastic simulation in real-time or quasi real-time, to monitor, control, and schedule parts and resources in a discrete part manufacturing environment"* (Manivannan and Banks 1992).

Table 1 gathers the contributions on RTS we have analyzed from the literature, with no conceit of completeness. In this section, we wish to further interpret the main aspects which characterize RTS application with the aim to identify which problems have been addressed and which still remain an issue.

2.1 RTS Frameworks

Manivannan and Banks (1991) proposed a framework for real-time control of a manufacturing cell using simulation, which can be considered as one of the first comprehensive analyses on the way RTS has to be approached. The same authors identified the challenges for the successful implementation of real-time simulation models to be (1) data collection, (2) model generation and auto-validation, (3) model synchronization and initialization, and (4) efficient proactive scheduling models. The aforementioned issues have been clinched in one of the most recent reviews on this topic (Yoon and Shen 2006), where a classification of RTS approaches has been presented.

More recently, other schemes have been proposed. Tavakoli et al. (2008b) proposed a framework providing three main features: (1) flexibility: the framework has to be general in terms of input data and utility function model (for example, the sample frequency of data can be determined dynamically); (2) real-time readiness: the framework aims to make an effective use of data available at present time for simulation modeling; (3) fast-forwardness: it is always possible to feed the simulation with different types

Table 1: RTS-related topics addressed in the literature.

References	Framework proposal	Issues for RTS implementation											Applications				
		Data Collection	Automated Inputs	Auto-validation	Initialization	Synchronization	Model Generation	Reactiveness	Shared Information	Modeling Methods	Comm. Standards	Interfaces	Healthcare	Manufacturing	Electronics	Transport. Systems	Services
Andreev et al. (2010)								•							•		
Banks (1998)	•	•	•	•			•	•						•			
Bärring et al. (2017)		•												•			
Cardin and Castagna (2006)					•			•						•			
Cardin and Castagna (2009)	•	•	•		•									•			
Framinan, Perez-Gonzalez, and Escudero (2017)	•		•					•						•			
Hanisch, Tolujew, and Schulze (2005)		•			•	•	•									•	
Harmonosky, Farr, and Ni (1997)								•						•			
Himoff, Skobelev, and Wooldridge (2005)																•	
Kádár et al. (2010)	•	•	•			•	•	•							•		
Kim and Yano (1994)														•			
Luo, Fang, and Huang (2015)	•	•							•					•			
Manivannan and Banks (1991)	•																
Manivannan and Banks (1992)	•	•				•		•	•					•			
Marík et al. (2005)	•		•							•		•		•			
Mirdamadi, Fontanili, and Dupont (2007)	•	•	•	•	•	•		•									
Mohamed et al. (2017)	•	•	•														•
Monostori et al. (2016)	•							•			•	•		•			
Tavakoli, Mousavi, and Komashie (2008b)	•	•	•					•		•			•	•			
Nasiri, Yazdanparast, and Jolai (2017)		•															
Nelson (2016)								•									
Rao, He, Shao, and Zhang (2008)	•	•	•									•					
Robertson and Perera (2002)		•	•														
Scholl et al. (2010)		•			•												
Son and Wysk (2001)	•		•				•							•			
Spedding et al. (1997)		•	•					•						•			
Tavakoli, Mousavi, and Komashie (2008a)	•		•								•	•		•			
Gissrau and Gereke (2017)	•	•	•				•							•			

of inputs to perform "what-if" analyses. Historical data may be stored as well to gradually improve the response time of the system. Mirdamadi et al. (2007) detailed the functionalities of a simulator for the real-time production control and described a procedure for monitoring and execution of production by using simulation to determine the best control alternative. Rao et al. (2008) described a novel real-time simulation system for real-time shop floor control. The framework relies on the relationship between the simulator and the Manufacturing Execution System (MES). The system can collect data from the physical shop floor and communicate with a scheduling controller through the MES. It is also shown how the software infrastructure of a MES may incorporate RTS functionalities.

Further contributions about RTS architectures may be found in Mullarkey et al. 2000, Rabbath et al. 2000, Lee and Fishwick 2001, and Tavakoli et al. 2008a. All the frameworks are based on real-time input data acquired while the real system is evolving, and decisions must be made as soon as the problems are identified in the system. Therefore, the simulation-optimization loop is required to have fast-answer capabilities. For example, for the evaluation of the best control policies, every alternative policy that is generated for comparison has a corresponding simulation model for estimating its performances. Each of these models has to provide a sufficient statistical warrant that the performances are valid, therefore dedicating enough replications to its experiments. Most of the authors in the literature refer to computational time and, in general, fast answering capabilities, as one of the main issues to be solved for making RTS possible in the practice (see Table 1).

2.2 Data Collection

Data collection is one of the most time-consuming practices done at the beginning of a simulation project. Therefore, the optimization of this phase regards also non-real-time approaches. For example, Robertson and Perera (2002) proposed to automatically collect input data for a simulation model, thus saving a lot of valuable modeling time. The authors discussed on how to revisit the data input procedures for simulation and conjectured about hastening data-input phases through an intermediate database between ERP system and simulation input data. Tavakoli et al. (2008a) posed the foundation for a *flexible data input management system* as a vital part of a generic solution for quick-response decision making. The aim is to generalize the input procedure and make it applicable to a wide variety of manufacturing environments. More recently, Bärring et al. (2017) proposed *Value Stream Mapping* as a support to the initial data collection. The approach maps all the production phases as seen from the customer's perspective, then follows the value stream, drawing the processing steps and collecting data. Next, it evaluates the availability of data in the production system, and as the final step classifies the data into categories depending on availability. Still, this method cannot provide dynamic datasets for DES models.

2.3 Model Synchronization

Synchronization is the way to guarantee that the digital versions of real systems can reflect the current status of the system at any moment in time (Cardin and Castagna 2009). Moreover, in flexible and reconfigurable systems these updates shall be done in an automated way (for instance to adapt to a plugin of a machine, or the deterioration of a machine that leads to slower processing times). The exploitation of a digital model of a factory, coupled with a continuous synchronization of the information coming from the real system, has been previously addressed by Kádár et al. (2010). The authors identified the following problems to be tackled: (1) the acquisition and validation of the input data, (2) the responsiveness of the analysis, and (3) the capability of creating a snapshot of the real system to initialize the simulation model. In particular, the first and third point highlight a data synchronization and consistency problem between the real and the virtual environment. The synchronization between the system and its digital alter can be carried out in three ways (Banks et al. 2000): (1) by obtaining data continuously and connecting the data collection devices to an input data processor with the simulation software, (2) by developing a simulation model for each of the entities, resources, and queues, and restricting data collection activities to those altering temporal information, and (3) by making use of past, future and current event lists (e.g., in the case-study described by Manivannan and Banks 1991). The aforementioned notions are strictly related to the *cyber-physical equivalence* concept, a term used in the I4.0 literature that refers to the fact that the virtual and physical dimensions coexist and are synchronized in time (Roßmann et al. 2014).

2.4 Initialization

Initialization denotes the guarantee that simulation models refer to the same initial point in time, to assure that alternative production policies can be effectively compared. In order for the statistics of the alternative policies performance to be comparable to the ones of the real system, the real-time simulation must be initialized to the current real system state, or at least to the same state occurred in a certain time frame. Therefore, all real-time simulators do not start from an empty state, rather from a state in reality, in which all the variables of the model have to be set to the values of physical quantities at present time, thereby representing their initial values (Hanisch et al. 2005).

2.5 Validation

Planning and control activities using RTS typically rely on the assumption that a simulation model for the real manufacturing system exists and has withstood the validation process (Davis 1998). In a real-time scenario, the validation has to be performed with respect to the data representing the current state of the system. Auto-validation is the process through which the simulation models used in real-time are checked before being used to take decisions. Davis (1998) reasoned about the similarity of an auto-validation process to a system identification element in controllers for time-varying, continuous state systems (Ljung 1998). Identification means to estimate how the real process behavior is at the moment, in particular identifying mathematical formulations among the system variables and response performances. When no mathematical formulations of the system behavior are available, system identification usually works with gradient-based approaches (Davies 1970).

2.6 Applications

One of the most notable applications for RTS concepts in production systems is scheduling. The main idea behind the real-time scheduling using simulation is well described in Figure 1, taken from Rao et al. (2008). The system status is monitored by a supervisor module, which triggers the execution of scheduling algorithms. The scheduling solutions are passed to a simulation module, which evaluates the solutions and passes the definite ones to the execution controller, implementing them at system level.

Kim and Yano (1994) developed a job dispatching rule which varies dynamically based on information from DES models that evaluate a set of candidate rules. The authors implemented a threshold-based control rule. The control system periodically monitors the shop floor and checks the performance measures of the system. The selected dispatching rule is used until the difference between the actual performance and its estimation by simulation exceeds a given limit. Then, a new simulation is performed with the remaining operations in the system with the aim to select a new rule. Harmonosky et al. (1997) developed a heuristic approach to handle the jobs at the queue of a failed machine in a flow-shop system one by one, by considering newly arriving jobs at the failed machine until it is repaired. The method compares the expected waiting time at the failed machine with the expected waiting time at an alternative machine plus a penalty term due to rerouting time. It is worth to notice that the simulations are done off-line, long before any actual system breakdown occurs.

The authors of (Scholl et al. 2010) developed a high-fidelity simulation model built automatically through data queries. The simulation is used to increase the forecasting abilities of a semiconductor factory, with the aim of reducing the WIP waves occurring due to preventive maintenance schedules, which are formally done with limited if not missing information over the expected future system's status.

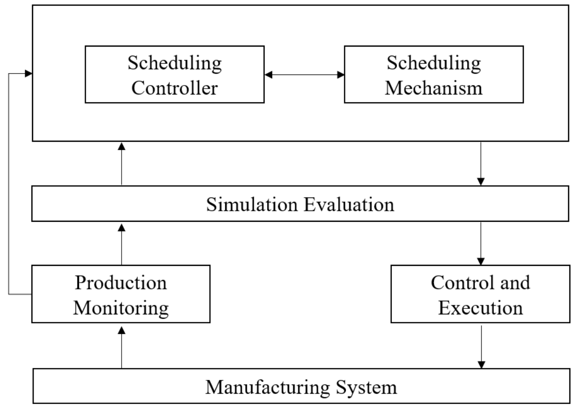

Figure 1: RTS architecture from Rao et al. (2008).

Luo et al. (2015) proposed a framework for real-time scheduling using the *ubiquitous manufacturing* concept. The authors used RFID technologies to facilitate shop floor conditions visibility and reduce uncertainties in scheduling. Framinan et al. (2017) proposed to use real-time production data in a flow-shop scheduling problem. The method uses data coming from the first machine in the system to estimate the rest of the system utilization state. Then, it uses this knowledge to create a batch of products to be sent to the first machine. It is assumed that the computational time is enough to elaborate and take decisions.

Other applications of RTS in other fields of industry can be found as well. Spedding et al. (1997) focused on the development of a simulation model which can be linked with a cell controller to achieve online adaptive control capabilities. The application case is a keyboard assembly cell. For each decision option, a simulation run is executed. The results of the simulation are evaluated and the best option candidate is selected. The authors drew attention to the time horizon of the simulations as a critical point that is also linked with the computational time. Cardin and Castagna (2006) explored the decisional component of a production facility built for educational purposes: the system is a job-shop with six workstations connected with transporters equipped with tags. The study made use of two simulation models, one for aligning with the real system (digital twin) and another for proactive decision making, such as deciding the routing of parts on transporters. These decisions depend on many factors, such as the number of transporters in the station batch or stations breakdowns. The multitude of decision possibilities is reflected in the number of alternative simulators that are initialized to the main simulation state and run for a fixed time horizon. The pilot model will then proceed based on the results of these evaluations. Tavakoli et al. (2008b) described a demonstration environment representing a mixed-model production line of six consecutive stations. A digital twin of the system is modeled in Arena and RFID tags work as triggers to update the entity types and attributes in the simulation model. In Mohamed et al. (2017), the authors proposed a data-driven simulation framework for planning snow removal projects considering weather and truck-related data collected by real-time sensors. The authors developed a simulation engine to simulate operations based on input information extracted from sensor data, and used the simulation results to study different plowing operations scenarios. Other applications can be found also in different research fields, for example in ship-design (Maríк et al. 2005), supply chain design (Himoff et al. 2005), and electronics (Andreev et al. 2010).

3 RTS-ARCHITECTURES

In this section, we show and describe in more detail two architectures for RTS (Figure 2), which are among the most influential works about RTS topics. We assume that a manufacturing system with a discrete process exists in a specific industrial context and has to be controlled according to a previously computed production plan.

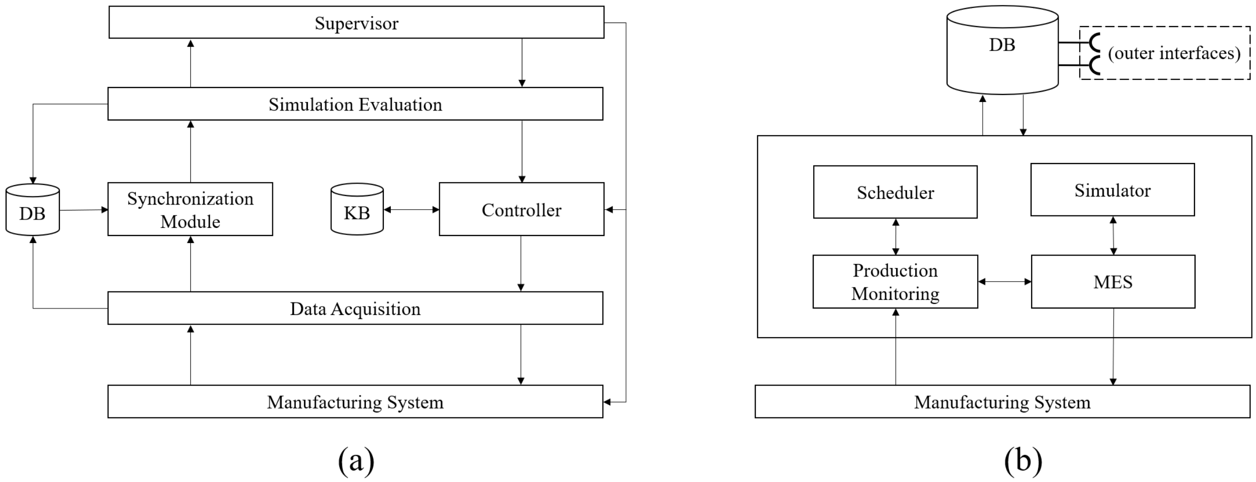

Figure 2: RTS architectures. (a) Manivannan and Banks (1991); (b) Monostori et al. (2007).

The first architecture (Figure 2a) is taken from Manivannan and Banks (1991). The main components of the platform are the following: (1) Data-collection hardware is made by sensors and devices to acquire data from the field. Notice that each manufacturing equipment that is represented in the simulation model must have its sensory hardware correspondent. (2) Static and dynamic databases (DB) contain machine and tool data, product data, maintenance data, performance measures, and they consist in the interface where information received from the sensors is connected to the virtual components representing the machine tool, either continuously or periodically. (3) The *Knowledge-base (KB)* is a database where the results obtained from previous simulation runs can be stored and retrieved to reduce the number of simulations. The authors suggest a structure of knowledge that allows for inheritance between similar components used in the system. Thus, when an item is added to the system, the level of knowledge about that resource is already available. Moreover, solutions already encompassed by the control system are stored and lay the foundations for the next decisions. Therefore, not all the events occurring in the system require a simulation campaign. For example, some critical events may have been already processed in the past and if the solutions applied in those cases are available and implementable, there is no need to launch new evaluations. (4) Simulation models (for the specific use-case, the authors refer to models characterizing the tool-wearing process of machining centers). The simulation runs are triggered by a model supervisor. (5) A cell controller. It interacts with the KB and retrieves the necessary input data to perform simulation using the model created. The cell controller updates the KB using the simulation outputs for future use.

The second structure is shown in Figure 2b and is taken from Monostori et al. (2007). Here, the data from the plant feed a general decision-making unit, composed by a production supervisor, a MES, a scheduler and a simulator, based on the database of the system status. The MES is interfaced with a factory simulator that evaluates the solutions before they shall be implemented.

By comparing the two architectures, we may state the following:

- Both architectures are compliant with the *Sense-Think-Act* paradigm.
- The first architecture considers explicitly the data collection and data input from databases.
- The second architecture centralizes the databases of the RTS loop and foresees the need of connection to other devices/ software components. With this perspective, we may state that the framework of Figure 2b is more I4.0-compliant.
- In the second framework, the MES (supervisor) is ”closer” to the manufacturing system, and directly controls a simulator with no intermediate connections.

- The simulator of the second architecture can be seen from two point of views: (1) as a visualization of the system current performance, in a way a digital twin of the system; (2) as a tool for evaluating several scenarios.

4 RESEARCH DIRECTIONS FOR THE SIMULATION COMMUNITY

Most contributions of RTS approaches in the literature assume the availability of simulation models, often static or generated through configuration files. However, these methods have clear limitations in keeping the pace of current changes of manufacturing systems since the problem of outdated models is simply shifted upstream into the design phase of the simulation tools. Moreover, simulation models are very time-demanding in their building phase especially for the data collection activity. The high cost and time required for data collection often result in useless simulation models, because they are not promptly aligned with the system changes, hence their fame as *throw-away* models (Son and Wysk 2001). Therefore, the existing frameworks encounter their limits when used with high input frequencies and changeable system configurations. Following, we list our considerations about specific issues in RTS on which more research is still needed.

Data management. Real-time data in production management have been discussed in different contributions, such as in Waschneck et al. 2016. In general, the existing approaches for data collection do not take into consideration the real-time issues arising from big streams of data coming towards a centralized unit. As stated in a recent General Electric report (GE-Automation 2016), taking as example the manufacturing industry of personal care products, a typical real-life scenario can produce 152,000 data samples per second, equivalent to 4 trillion samples per year. Beside the dataset size issues, one has to consider that depending on the decisions to be made at the moment, different subsets of data may be needed. Thus, there is the need for an intelligent data-handling unit. Data collection and the related data transfer communication standards (e.g., IEC 61499) are a central topic in I4.0-related research (Xu et al. 2018; Gissrau and Gereke 2017).

Adaptability. Self-adaptive simulation models should have the ability to change their logic by observing the data from the manufacturing systems, i.e., event type, event occurrence time, and change in the resource states. This problem corresponds to finding the simulation model that best fits the data collected from the system, and hence to have the system simulator always aligned with the real system. The main problem in a real-time scenario is that the simulator will be subject to very frequent changes, and it may never reach the steady state. As a consequence, all the performance measures may have to be computed with a simulation in the warm-up phase. Hence, validation techniques have to be adapted taking into considerations this volatility of the simulators.

Model Generation. In certain cases, a simulator might not even exist and has to be created. Formal models (e.g., Entity Relationship Graphs or Petri Nets) can be used for simulation of manufacturing systems as their use allows for versatility in the level of detail. Indeed, recent techniques such as process-mining (Van der Aalst et al. 2004) are a promising field of research to pursue the goal of simulation model creation from a stream of data.

Validation. Concerning validation, still little research has been done for system identification with discrete-event models. The general feeling is that traditional validation techniques (Sargent 2009) are stagnant in the industrial practice, yet these methods may be no longer suitable. Indeed, simulation model validation is usually done offline while an RTS loop requires it to be done online and, if possible, automatically. Moreover, while the emphasis of traditional simulation validation techniques is put on a set of limited performance indicators (e.g., number of pieces produced in a time window), the new techniques will have to consider the validation of functions (e.g., utilization profile of a machine) to synchronize flows at critical resources. Also recent works (Zheng et al. 2014; Zheng and Julien 2015) point out that research studies for CPS validation and verification techniques have not been done yet. They present an empirical study that was conducted through interviews to CPS developers. It is also proposed to use real-time simulations of physical processes themselves as the validation tool suite for CPSs. However, quantifying the accuracy of the models of physical components remains a challenge (Jensen et al. 2011).

Reactiveness. Fast-answering capabilities – which are an issue also in traditional simulation-optimization approaches – remain a challenge and their development can further unlock application scenarios for RTS. Parallelization techniques are promising for satisfying the computational requirements, and are also mentioned by other authors who foresee the imminent application of these techniques in the practice (Nelson 2016). The speed of decision making can also be pursued by exploiting the availability of models with different levels of detail, for example, by giving precedence to the ones requiring lower computational effort when the required decision must be taken in a limited time; alternatively, surrogate models for fast estimation can be used. Indeed, recent research (Lin et al. 2016) shows that it is possible to make use of multiple sub-models of the system – both simulation-based and analytical – to increase the accuracy of the model in predicting system performance measures. A proper control of granularity can allow for creating simulation models at different fidelities. However, the proper use of multi-fidelity modeling in simulation-optimization is still an open issue (Han and Görtz 2012).

In summary, RTS can be already applied to current industrial problems and its advantages can be readily tested. However, its correct implementation providing the potentials of a real-time scenario evaluation tool is yet to be seen, since many issues still remain unsolved. I4.0 represents an opportunity to further stress the potential of simulation as well as a testbed where to seek answers for the aforementioned challenges.

5 CONCLUSIONS

In manufacturing, a real-time operation involves a combination of different operations, such as sensing, processing, data-transmission, and actuation. Simulation can fit this framework, provided that the methodologies used so far can be changed after the rise of new requirements. In this paper, we have described the main issues that arise when aiming to apply real-time simulation as a short-term decision-making tool for manufacturing systems. We have outlined the main steps yet to be done in research for the implementation of real-time simulation strategies. Simulation models will have to be adaptable to changes in system configurations, automatically generated if needed, and validated online before taking decisions, all guaranteeing short computation times and fast answers. These features have been found only in niche fields. The limitations of this work are related to the non-completeness of the literature review. The future developments will be dedicated to a structured literature survey for each component of the RTS framework.

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