13th IFAC Workshop on Intelligent Manufacturing Systems
August 12-14, 2019. Oshawa, Canada

A Digital Twin-based scheduling framework including Equipment Health Index and Genetic Algorithms

E. Negri*, H. Davari Ardakani, L. Cattaneo*, J. Singh**, M. Macchi*, J. Lee****

**Department of Management, Economics and Industrial Engineering, Politecnico di Milano, 20133 Milano Italy (e-mail: elisa.negri@polimi.it (corresponding author), laura1.cattaneo@polimi.it, marco.macchi@polimi.it).*
***NSF Industry/University Cooperative Research Center on Intelligent Maintenance Systems (IMS), University of Cincinnati, United States (davarihn@ucmail.uc.edu; singh2jn@ucmail.uc.edu; jay.lee@uc.edu)*

Abstract: The advent of Industry 4.0 technologies and in particular the Cyber-Physical Systems, Digital Twins and pervasive connected sensors is transforming many industries, among which smart scheduling is one of the most relevant. This paper contributes to the research on scheduling by proposing a framework to include equipment health predictions into the scheduling activity and embedding a field-synchronized Equipment Health Indicator module into the DT simulation. The metaheuristic approach to scheduling optimization is performed by a genetic algorithm, that is connected with the DT simulator and provides various generations of scheduling alternatives that are assessed through the simulator itself. The paper also proposes a practical Proof-of-Concept of the innovative framework, by developing an architecture to identify how the various framework modules are implemented and by applying the framework to a real application case, set in a laboratory assembly line environment.

Keywords: Scheduling, Digital Twin, Simulation, Equipment Health Index, EHI, CPS, Genetic Algorithm

1. INTRODUCTION AND OBJECTIVES

Scheduling is one of the most important activities that manufacturing companies deal with in order to have an efficient and effective production. It covers the short-term production planning, the process through which the production orders are allocated and sequenced to the production resources (Pinedo 2009). A series of algorithms, frameworks and methods to optimize globally or locally for the scheduling problems with different objectives and in various contexts have been proposed in literature (Pinedo 2009). The scheduling process presents an inner complexity due to the fact that (i) it deals with large quantities of data of different nature and is subject to continuous readjustments over time; some data are of stochastic nature; (ii) it is based on a simplified model of the production system which does not take into account the complexities of real-world systems. Previous research aimed to address these two challenges by using simulation models of the production system which incorporate various interrelationships between different data and the equipment behaviour and as a result, better reflecting the real system behaviour (Luca Fumagalli et al. 2017, 2018). In fact, the simulation can compute various production system characteristics including dynamicity, stochasticity, complex interrelations, among others (Law and Kelton 1991). Recent advancements in Industry 4.0 (Zheng et al. 2018; Anna De Carolis et al. 2017; A. De Carolis et al. 2018; Davis et al. 2012), has paved the way for building more advanced and robust scheduling capabilities, by utilizing the pervasive connected sensors, Cyber Physical Systems (CPS) (J. Lee, Bagheri, and Kao 2015; Jazdi 2014), and the advanced simulations, i.e. Digital Twins (DT) (Macchi et al. 2018). Such advanced scheduling systems can be updated in real-time based on current and predicted future state of the manufacturing assets and the production system. (Ji and Wang 2017).

This paper aims to contribute to previous research by devising a new meta-heuristic scheduling framework which leverages on the field-synchronized simulation, according to the DT paradigm, to include equipment health status. The framework shapes the roles and interrelations of the various modules needed for the scheduling optimization. The paper also proposes the development of an architecture to build a scheduling tool that applies this framework into real-world production systems. In order to validated the proposed methodology and as a Proof-of-Concept of the scheduling tool, a laboratory experiment is designed and in this study. This demonstration integrates the triad of equipment health, scheduling optimization and DT simulation. This combination can further be developed in order to obtain a robust production scheduling and achieve self-aware production systems.

The present paper is structured as follows: section 2 introduces the background concepts from literature, section 3 describes the proposed methodology, section 4 discusses the practical application, by illustrating the developed architecture and the laboratory environment and section 5 provides a summary and conclusions.

2. BACKGROUND

Scheduling problems have been extensively treated in research works in the past: optimization approaches may be exact, heuristic or meta-heuristic (Jourdan, Basseur, and

Talbi 2009; Ruiz and Maroto 2005). Since the production systems scheduling problems in production systems are generally considered NP-hard, exact algorithms often do not offer a viable solution whereas the metaheuristic solutions allow us to find a good solution in a reasonable amount of time following an iterative approach (Mati and Xiaolan Xie 2004). Genetic algorithms (GA) have been widely used in different forms for complex scheduling problems, especially in the context of job shops (Salido et al. 2016), flexible job shops (Driss, Mouss, and Laggoun 2015), cellular manufacturing (Paydar and Saidi-mehrabad 2017), flow shops (Fu et al. 2018), hybrid flow shops (Li et al. 2015).
With the advent of Industry 4.0, advanced technologies may strengthen the power of scheduling approaches, in particular:

1- CPS are smart embedded systems that combine computing and communication capabilities with actuation on the field (E. A. Lee 2008); as such, they open the possibility to self-aware and context-aware manufacturing (Garetti, Fumagalli, and Negri 2015).
2- CPS systems require seamless integration between computational models and physical components. To attach importance to the virtual space and implement this seamless convergence, a concept based on DT of the equipment and its data was initially defined to depict the behaviour of the real entity. It was firstly proposed in the aerospace field (Shafto et al. 2012), but afterwards it became the subject of a rich research stream also in the industrial engineering sectors (Rosen et al. 2015). The DT is a simulation that runs in parallel to the real system it simulates, with a continuous synchronization with the field through physical parameters update (Negri, Fumagalli, and Macchi 2017).

When combining CPS with DT, it is possible to think of predictive manufacturing (J. Lee et al. 2013). In fact, one of the main uses of DT in the aerospace field was to replicate the crack paths and to predict the failures due to cracks and fatigue (Tuegel 2012). When it moved to the industrial engineering, it took a role of overall lifecycle monitoring of products (Abramovici, Göbel, and Neges 2015) or production systems (Rosen et al. 2015), of which the prediction of failures and in general the equipment health monitoring are a part of (Liu et al. 2015).
Inspired by this background, the computation of equipment health can be incorporated in the scheduling process. Indeed, it is possible to predict possible failures when allocating the jobs to the machines in the production system, and to choose scheduling alternatives that slows down the machine degradation process and as a result prolongs the lifespan of the production machines. Previous attempts at incorporating machine health into scheduling consist of linear programming models (Obeid, Dauzère-Pérès, and Yugma 2012; Kao et al. 2018). The new challenge is now to exploit the CPS and DT capabilities to create a real-world synchronized simulation model aimed to represent the machine health and to support scheduling. Here lies the novelty of this paper: to embed the DT paradigm (field-synchronized simulation, in particular for the health monitoring) into a GA-based scheduling, in order to surpass the linear programming approaches proposed in the past.

3. PROPOSED FRAMEWORK

The innovative framework is in alignment with previous works which proposed to simulate GA-generated scheduling alternatives in order to compute relevant performances that require to model the dynamicity, stochasticity and complex interrelations within a production system (Luca Fumagalli et al. 2018). The novelty of this framework resides in the fact that the simulation is synchronized with the field through the Equipment Health Index (EHI), according to the structure shown in Fig. 1. The process includes the following steps:

1- The GA module generates alternative schedules through genetic operators that consider the *fitness functions,* i.e. the performances of the alternatives in the previous generation, in this way reaching a meta-heuristic optimization (Çaliş and Bulkan 2015).
2- The simulation model of the production system to be scheduled takes all the scheduling alternatives generated by the GA and runs the individual simulations. Relevant parameters needed to compute the fitness function are calculated according to the simulation run and are made available for the following generation of alternatives.
3- The EHI module is an additional module embedded in the simulation model. It takes specific signals from sensors on the equipment to be monitored and predicts the behaviour of the equipment health using continuously updated data. In this sense, it is the module that synchronizes the simulation model to the physical system, creating a DT. It is therefore clear that unexpected events on the physical system are immediately considered in the next data update.

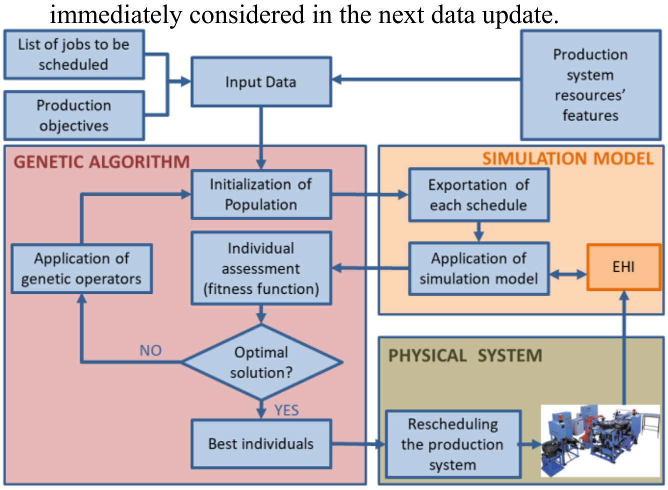

Fig. 1 - Framework for EHI inclusion in scheduling

The logic flow of the proposed scheduling framework is therefore the following:

1. The following input data is fed into the model: list of jobs to be scheduled (for the creation of alternatives populations), production objectives (for the fitness function), and production resources (for building the simulation model and the GA).
2. The GA generates a new population made of several individuals, that are scheduling alternatives. Each alternative consists of a sequence of jobs to be processed, and the resources on which they are allocated in case

there are different alternative resources or paths in the production system.

3. Each individual of the population is simulated in the EHI-enforced simulation model. For each schedule it is possible to compute the production performances, input into the fitness function designed to contain the production objectives. The simulation also predicts any failure or alert due to equipment health problems. The EHI module analyzes the sensor information coming from the field and provides as output to the main simulation model. Fig. 2 provides an illustration of how the EHI synchronizes the simulation with the field sensor: the EHI keeps the simulation model synchronized, by updating its failure rate function in time at any time instant. When the simulator is used for computing the production performances, the simulator is detached from the field synchronization and starts with several iterations of the GA by taking into account the latest failure rate function in time following a Monte-Carlo approach. This is represented in Fig. 2, as the failure rate is lastly updated when the GA is launched and used for the various simulation runs.
4. The GA has a finishing criterion which is activated when the fitness function does not improve anymore (after a defined number of subsequent generations). In this case, it means that the local optimum has been reached and the best individuals can be identified (i.e. the scheduling alternatives that provided the best scores of the production performances), and the production schedule can be considered concluded.
5. In case the previous point did not find a local optimum, the GA applies genetic operators to the best alternatives of the previous generation and goes back to point 2.

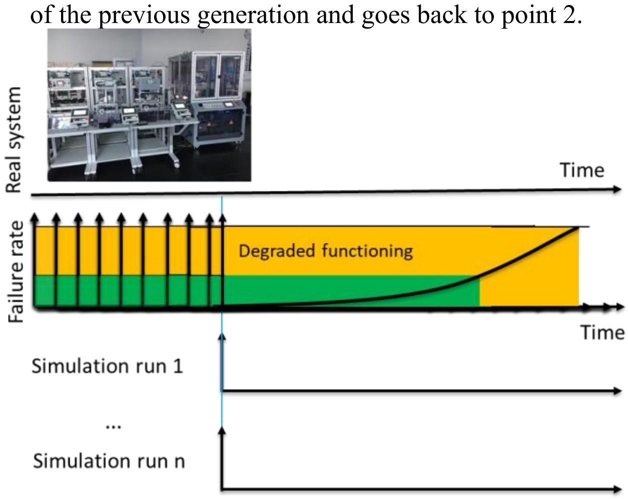

Fig. 2 – EHI module role description

4. PRACTICAL APPLICATION

4.1 Architectural development

The framework is supported by an architecture that lies at the basis of a scheduling tool. Fig. 3 represents its architecture that is composed of the following parts:

1) REAL MACHINE (or machine sub-system) feeds the database with signals about the interesting variables of the real behaviour of the analyzed system. is being acquired from field devices from multiple sources such as add-on sensors, actuators, PLC (Programmable Logic Controllers), CNC (Computer Numerical Control machines) etc. Signals could be data on different levels, as described in the ISO 13374 (ISO 13374-1 2005; Guillén et al. 2016): 1- Acquired data; 2- Manipulated data; 3- Detected state; 4- Assessed health; 5- Assessed prognosis.

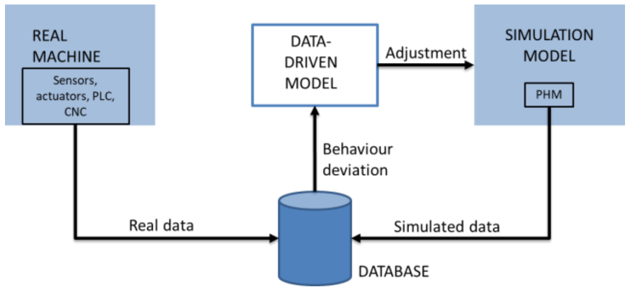

Fig. 3 - Architecture of the scheduling tool

2) SIMULATION MODEL of the analyzed system feeds the database with the simulated signals replicating those generated by the real machine. As mentioned in Section 4, the simulation model is a DT, as an EHI module is embedded and connected to the field devices that continuously update it according to the equipment health, through Prognostics Health Monitoring models, in order to carry out the reliability of the system, considering time and conditions variables.
3) The DATABASE collects data from both the real machine and the simulated model, decoupling the two levels of the DT (physical and cyber). By storing historical series of data from both the sources, it is possible to compare them and detect the deviations between the behavior of the real system and its simulation model.
4) The DATA-DRIVEN MODEL takes the behavior deviations between the real and simulated system as input, which is detected in the historical series of data. The output of the data-driven model is an adjustment of the simulation model parameters. This adjustment provides incremental updates to the simulation model to synchronize it with the real system.

This adjustment loop ensures synchronous linage and high fidelity within the simulation model, the database, and the data-driven model to have increasingly precise estimations of the system reliability.

This system is developed in MATLAB and Simulink, selected according to the methodology proposed by (Luca Fumagalli et al. 2019). It provided an straight-forward way to integrate various parts of the system into the simulation model of Simulink.

4.2 Application case

As a Proof-of-Concept, the framework and architecture were applied to a real assembly system belonging to the Industry 4.0 Lab (I4.0Lab) of the School of Management of the Politecnico di Milano (L Fumagalli et al. 2016). The I4.0Lab line consists of several stations which is designed to assembles a simplified phone. Fig. 4 illustrates the schema of the seven stations of the I4.0Lab including one manual loading/unloading station, one station to place the front cover on an empty carrier, a drilling station that drills holes in the front cover, a robot to assemble the printed circuit boards and the fuses, one quality check with a visual inspection camera, one station to assemble the back cover and finally one station to press the simplified phone components together. Each station is equipped with Programmable Logic Controllers (PLC), Sensors, and Human Machine Interface (HMI). There are no buffers and the automated conveyor is the only handling system within the system. The entire assembly line is connected to two computers: one is equipped with the MES (Manufacturing Execution System), from which the production orders are launched and the production is controlled; the other monitors the energy consumption. Both computers store values on MS Access databases and it is possible to configure the databases to store more sensor values. All the stations and the computers are connected to the laboratory network and have their own IP address. The information exchanged between the plant devices and the servers are transmitted via OPC-UA protocol. All the line signals to model the DT are mapped and the FMECA analysis (IEC 60812 2018) of the line is available and used to model the EHI module.

The DT is based on a DES (Discrete Event Simulation) model which describes all the stations in the line and their behaviour. As an example, Fig. 5 shows the blocks that are used to represent the drilling station and to replicate the behaviour of the pallet carrying the product on the line.

After creating the simulation model, it is necessary to build the GA, setting various parameters, such as the number of individuals in a generation (here it was 10), the number of jobs in a list (here it was 50), the mutation rate (here it was 2%) and the finishing criteria (here they were: established minimum and maximum numbers of generations and established number of generations in which the variation of the fitness function value with respect to the previous one is less than a fixed threshold, i.e. reached convergence and local optimum found).

The fitness function was set as the minimization of the makespan. The simulator also provides the standard deviations of the obtained makespans, since it must be evaluated also in its variability due to the stochastic nature of the followed Monte-Carlo approach (30 repetitions for each individual).

As an initial Proof-of-Concept, field-synchronized EHI predictions were included in the scheduling activity. The spindle in the drilling spindle, which is the most critical equipment within the production line, was considered for the initial development of the EHI module. Two accelerometers installed on the spindle collect vibration data. The data-driven EHI model, which is trained based on the historical data collected from the drilling station, performs health assessment and determines the current health index of the drilling spindle and its probability of failure within a certain time span (Fig. 2).

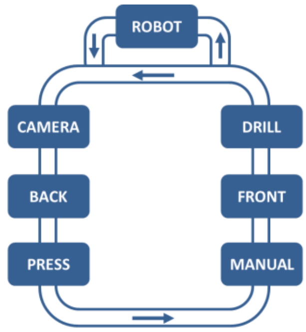

Fig. 4 - Schema of the I4.0Lab stations

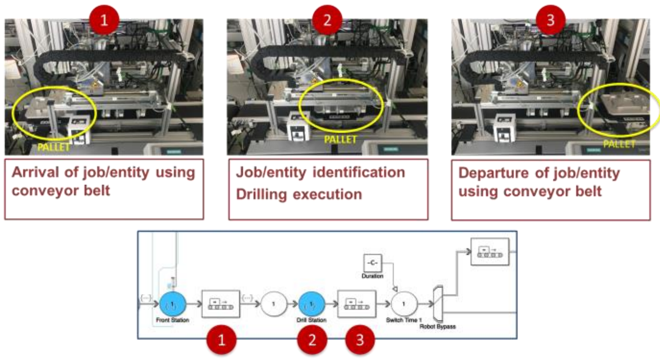

Fig. 5 - Simulation model for the drilling station

Fig. 6 shows an example of a list of jobs given as input into the scheduling tool. Each job has a unique ID and for each station, the numbers indicate the operations the station needs to perform, according to an established numbering convention. In this way, each product ID has its own specific production tasks defined.

ID	jobcode	front	drill	robot	camera	back	press
1	1010	1	1	0	0	1	1
2	1020	1	0	1	1	1	1
3	1030	1	3	4	1	0	0
4	1040	1	2	3	1	1	1
5	1050	1	2	2	1	1	1
6	1060	1	2	2	1	1	1
7	1070	1	1	0	0	1	1
8	1080	1	0	1	1	0	0
9	1090	1	1	3	1	0	0
10	1100	1	1	2	1	1	1

Fig. 6 - List of jobs as input into the scheduling tool

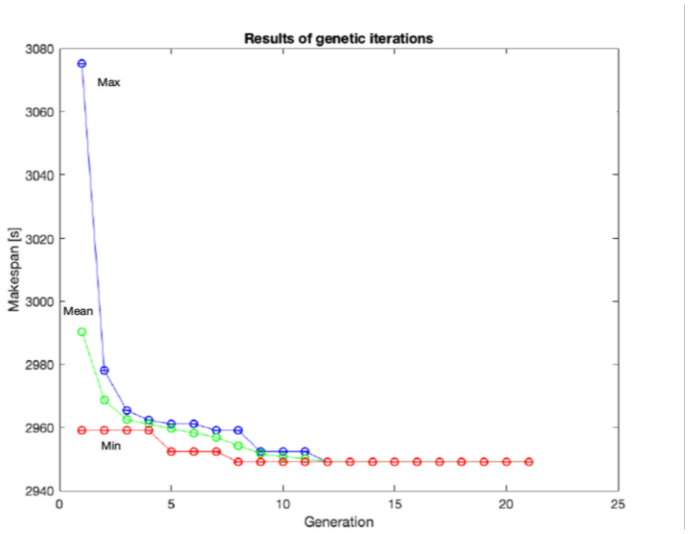

Fig. 7 - Application case results (without EHI module)

Fig. 7 and 8 show the results of the Proof-of-Concept of the proposed framework and architecture on the same list of 50 jobs to be scheduled. In particular, the graphs report the generations on the x-axis and the makespan on the y-axis. For each generation the makespan of the best performing schedule ("Min"), the makespan of the worst performing ("Max") and the average of the makespans ("Mean") are identified. Fig. 7 shows the results of the framework without EHI module, while Fig. 8 reports the results with the addition of the EHI module (for each generation, mean, max and min schedules are shown as average ± standard deviation). As it is possible to notice, the algorithm goes to convergence in both cases. As expected, the introduction of the EHI module brings to slightly worse makespan values (since here there is the addition of expected failures that negatively impacts schedules but reflects a more realistic behaviour of the system). This allows the system to have an estimate of the variability due to the calculated failure rate.

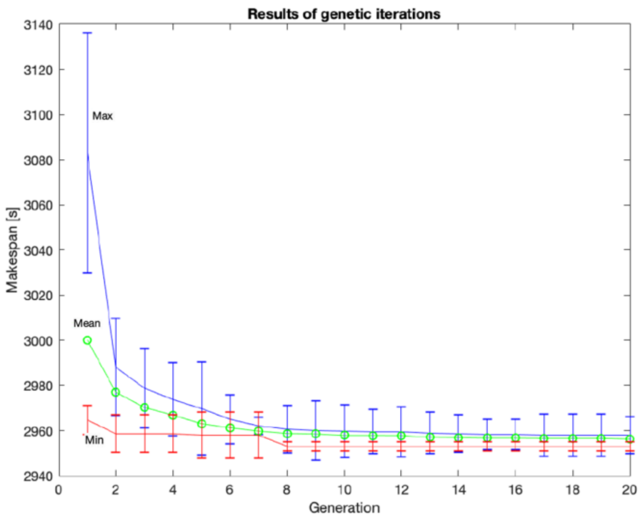

Fig. 8 - Application case results (with EHI module)

5. CONCLUSIONS

With the advent of Industry 4.0 technologies, there exists new possibilities for improving scheduling performances, by exploiting CPS and DT capabilities to offer predictive analyses for reactive and adaptive control. This paper contributes to the research in this topic by providing an innovative production system scheduling framework based on GA and field-synchronized simulation and its Proof-of-Concept. The framework leverages on previous works joining GA and simulation models, but it is innovative as it incorporates synchronization with the field, according to the DT paradigm. In this way, the cyber part (simulation, EHI and GA) and the physical part (field devices) of the CPS are building a DT that is able to provide the health prediction of the equipment and couple it with the scheduling tool, in the form of failure rate predictions in time. Therefore, scheduling results are more effective as they take into account the degradation path of the production equipment and they can be updated according to the change in the field equipment health.

This paper reported an initial Proof-of-Concept to demonstrate the proposed framework. Future works include EHI modules for all the equipment pieces within the system to have a wider prediction base. Moreover, the DT simulation will be improved by synchronizing other data from the field including machine state, energy consumption etc. This will enlarge the potential development of scheduling systems based on DT simulation and its embedded EHI predictions. In the future, will also also incorporate other sources of stochastic data, such as risk factors and operator behaviours. The framework will also be tested in a fully industrial environment after the completion and validation of the laboratory Proof-of-Concept.

ACKNOWLEDGEMENTS

This research work has been possible thanks to the use of the Industry 4.0 Laboratory of the School of Management of the Politecnico di Milano (lab site: www.industry40lab.org) and of the NSF Industry/University Cooperative Research Center on Intelligent Maintenance Systems (IMS) of the University of Cincinnati.

REFERENCES

Abramovici, Michael, Jens Christian Göbel, and Matthias Neges. 2015. "Smart Engineering as Enabler for the 4th Industrial Revolution." In Madjid Fathi (ed): *Integrated Systems: Innovations and Applications*, 163–70.

Çaliş, Banu, and Serol Bulkan. 2015. "A Research Survey: Review of AI Solution Strategies of Job Shop Scheduling Problem." *Journal of Intelligent Manufacturing* 26 (5): 961–73.

Carolis, A. De, M. Macchi, E. Negri, and S. Terzi. 2018. "Guiding Manufacturing Companies towards Digitalization." In *2017 International Conference on Engineering, Technology and Innovation: Management Beyond 2020: New Challenges, New Approaches, ICE/ITMC 2017 - Proceedings*.

Carolis, Anna De, Marco Macchi, Elisa Negri, and Sergio Terzi. 2017. "A Maturity Model for Assessing the Digital Readiness of Manufacturing Companies." In *APMS 2017, Part I, IFIP AICT 513*, 13–20.

Davis, Jim, Thomas Edgar, James Porter, John Bernaden, and Michael Sarli. 2012. "Smart Manufacturing , Manufacturing Intelligence and Demand-Dynamic Performance." *Computers and Chemical Engineering* 47: 145–56.

Driss, Imen, Kinza Nadia Mouss, and Assia Laggoun. 2015. "A New Genetic Algorithm for Flexible Job-Shop Scheduling Problems" *Journal of Mechanical Science and Technology* 29 (3): 1273–81.

Fu, Yaping, Hongfeng Wang, Min Huang, Jinliang Ding, and Guangdong Tian. 2018. "Multiobjective Flow Shop Deteriorating Scheduling Problem via an Adaptive Multipopulation Genetic Algorithm." *Proc. of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* 232 (14): 2641–50.

Fumagalli, L, M Macchi, A Pozzetti, M Taisch, G Tavola, and S Terzi. 2016. "New Methodology for Smart

Manufacturing Research and Education: The Lab Approach." *Proceedings of the Summer School Francesco Turco* 13–15–Sept: 42–47.

Fumagalli, Luca, Marco Macchi, Elisa Negri, Adalberto Polenghi, and Edoardo Sottoriva. 2017. "Simulation-Supported Framework for Job Shop Scheduling with Genetic Algorithm." In *Proceedings of the XXII Summerschool "Francesco Turco", Palermo (Italy), 13th-15th September 2017*, 1–8.

Fumagalli, Luca, Elisa Negri, Edoardo Sottoriva, Adalberto Polenghi, and Marco Macchi. 2018. "A Novel Scheduling Framework : Integrating Genetic Algorithms and Discrete Event Simulation." *Int. J. Management and Decision Making* 17 (4): 371–95.

Fumagalli, Luca, Adalberto Polenghi, Elisa Negri, and Irene Roda. 2019. "Framework for Simulation Software Selection." *Journal of Simulation (Available online)*, 1–18. doi: 10.1080/17477778.2019.1598782

Garetti, M., L. Fumagalli, and E. Negri. 2015. "Role of Ontologies for Cps Implementation in Manufacturing." *Managem. and Production Engineering Review* 6 (4).

Guillén, A J, A Crespo, M Macchi, and J Gómez. 2016. "On the Role of Prognostics and Health Management in Advanced Maintenance Systems." *Production Planning & Control* 27 (12): 991–1004.

IEC 60812. 2018. "Failure Modes and Effects Analysis (FMEA and FMECA)." *BSI Standards Publication*.

ISO 13374-1. 2005. "Condition Monitoring and Diagnostics of Machines — Data Processing, Communication and Presentation— Part 1: General Guidelines." *British Standards Institution* 3: 31.

Jazdi, N. 2014. "Cyber Physical Systems in the Context of Industry 4.0." In *Automation, Quality and Testing, Robotics, 2014 IEEE Int. Conference On*, 1–4.

Ji, Wei, and Lihui Wang. 2017. "Big Data Analytics Based Fault Prediction for Shop Floor Scheduling." *Journal of Manufacturing Systems* 43: 187–94. https://doi.org/10.1016/j.jmsy.2017.03.008.

Jourdan, Laetitia, Matthieu Basseur, and E-G Talbi. 2009. "Hybridizing Exact Methods and Metaheuristics: A Taxonomy." *European Journal of Operational Research* 199 (3): 620–29.

Kao, Yu-ting, Stéphane Dauzère-pérès, Jakey Blue, and Shi-chung Chang. 2018. "Computers & Industrial Engineering Impact of Integrating Equipment Health in Production Scheduling for Semiconductor Fabrication." *Computers & Industrial Engineering* 120: 450–59.

Law, Averill M., and David W. Kelton. 1991. *Simulation Modelling and Analysis*. Second Edi. McGraw-Hill international Editions.

Lee, Edward A. 2008. "Cyber Physical Systems: Design Challenges." *2008 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC)*, May, 363–69.

Lee, J., B. Bagheri, and H. 2015. "A Cyber-Physical Systems Architecture for Industry 4 . 0-Based Manufacturing Systems." *Manufacturing Letters* 3: 18–23.

Lee, Jay, Edzel Lapira, Behrad Bagheri, and Hung an Kao. 2013. "Recent Advances and Trends in Predictive Manufacturing Systems in Big Data Environment." *Manufacturing Letters* 1 (1): 38–41.

Li, Dongni, Xianwen Meng, Qiqiang Liang, and Junqing Zhao. 2015. "A Heuristic-Search Genetic Algorithm for Multi-Stage Hybrid Flow Shop Scheduling with Single Processing Machines and Batch Processing Machines." *Journal of Intelligent Manufacturing* 26 (5): 873–90.

Liu, Qinming, Ming Dong, Wenyuan Lv, Xiuli Geng, and Yupeng Li. 2015. "A Novel Method Using Adaptive Hidden Semi-Markov Model for Multi-Sensor Monitoring Equipment Health Prognosis." *Mechanical Systems and Signal Processing* 64–65: 217–32..

Macchi, M., I. Roda, E. Negri, and L. Fumagalli. 2018. "Exploring the Role of Digital Twin for Asset Lifecycle Management." *IFAC-PapersOnLine* 51 (11): 790–95.

Mati, Y., and Xiaolan Xie. 2004. "A Polynomial Algorithm for a Two-Job Shop Scheduling Problem with Routing Flexibility," 157–62.

Negri, Elisa, Luca Fumagalli, and Marco Macchi. 2017. "A Review of the Roles of Digital Twin in CPS-Based Production Systems." In *Flexible Automation and Intelligent Manufacturing, FAIM*.

Obeid, Ali, Stéphane Dauzère-Pérès, and Claude Yugma. 2012. "Scheduling on Parallel Machines with Time Constraints and Equipment Health Factors." In *8th IEEE International Conference on Automation Science and Engineering*, 401–6.

Paydar, Mohammad Mahdi, and Mohammad Saidi-mehrabad. 2017. "A Hybrid Genetic Algorithm for Dynamic Virtual Cellular Manufacturing with Supplier Selection," 3001–17.

Pinedo, Michael L. 2009. *Planning and Scheduling in Manufacturing and Services*. Springer.

Rosen, Roland, Georg Von Wichert, George Lo, and Kurt D Bettenhausen. 2015. "About The Importance of Autonomy and Digital Twins for the Future of Manufacturing." In *IFAC-PapersOnLine*, 48:567–72. Elsevier Ltd.

Ruiz, Rubén, and Concepción Maroto. 2005. "A Comprehensive Review and Evaluation of Permutation Flowshop Heuristics." *European Journal of Operational Research* 165 (2): 479–94.

Salido, Miguel A., Joan Escamilla, Adriana Giret, and Federico Barber. 2016. "A Genetic Algorithm for Energy-Efficiency in Job-Shop Scheduling." *International Journal of Advanced Manufacturing Technology* 85 (5–8): 1303–14.

Shafto, Mike, Mike Conroy, Rich Doyle, Ed Glaessgen, Chris Kemp, Jacqueline LeMoigne, and Lui Wang. 2012. "Modeling, Simulation, Information Technology & Processing Roadmap. Technology Area 11."

Tuegel, Eric J. 2012. "The Airframe Digital Twin : Some Challenges to Realization." In *53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, 1812.

Zheng, P., H. Wang, Z. Sang, R. Y Zhong, Y. Liu, C. Liu, K. Mubarok, S. Yu, and X. Xu. 2018. "Smart Manufacturing Systems for Industry 4 . 0 : Conceptual Framework , Scenarios , and Future Perspectives." *Frontiers of Mechanical Engineering* 13 (2): 137–50.