Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 54-1 (2021) 140–145

A Digital Twin-based approach for multi-objective optimization of short-term production planning

Maria Chiara Magnanini*. Oleksandr Melnychuk* Anteneh Yemane** Hakan Strandberg*** Itziar Ricondo**** Giovanni Borzi** Marcello Colledani**

*Department of Mechanical Engineering, Politecnico di Milano, Milano, Italy (e-mail: mariachiara.magnanini@ polimi.it)
**Enginsoft, Italy
***Enginsoft Nordic, Sweden
****IDEKO, Spain

Abstract: Short-term multi-product production planning strongly depends on manifold considerations which can be related to backlog production, product-type prioritization, machine capacity, and set-ups. Different manufacturing systems conditions may lead to different objectives. In this context, it is rather difficult to define a-priori optimal production plans. This paper presents an effective approach for short-term production planning of multi-product systems based on the integration of a Digital Twin and a multi-objective optimization method. The proposed approach has been implemented in a real industrial case of the railway sector. Numerical results show that useful insights can be inferred from the proposed methodology.

Keywords: Production planning and control; Intelligent decision support systems in manufacturing; Modeling of manufacturing operations; Intelligent manufacturing systems; Multi-objective optimization.

1. INTRODUCTION

Short-term production planning is related to weekly – or daily – production plans with the aim of satisfying production objectives in the given period. Nowadays, companies are pushed to deliver their products on time with the required quality and to have at the same time a sustainable resource consumption (Colledani et al., 2014). Therefore, manufacturing companies seek in optimal production planning not only the satisfaction of customer requirements but also production efficiency.

Then, the problem of optimal production planning cannot identify only one objective, but it has become intrinsically multi-objective. In particular, short-term multi-product production planning strongly depends on manifold considerations which can be related to backlog production, product-type prioritization, machine capacity, set-ups and quality strategy. Moreover, disruptive events or priority changes may force the company to prioritize one objective on another one, and therefore it brings the already optimized production plan not to be optimal anymore.

In addition, the influence of these aspects on the optimization is directly related to the production system dynamics. Digital Twins (DT) represent a useful approach to this aim. In fact, grounding on data from the real shop-floor, a DT provides the digital representation of the physical system. In this way, the performance of the system in terms of relevant KPIs can be derived for given input.

Recent developments in digitalization and smart manufacturing brought to the integration of DT in optimization frameworks for production planning. The main advantage consists in more accurate performance evaluation depending on the system dynamics, which may result in the identification of optimization patterns useful for gathering insights about optimal production strategies.

In this paper, an effective approach for short-term production planning of multi-product systems based on the integration of a DT and a multi-objective optimization method is presented. The main contribution is given by the output of the optimization algorithm which returns not only one optimal production plan, but a set of optimal production plans with respect to the specified objectives. Therefore, the user can independently implement one production plan being aware of its effect on all interested KPIs, and being sure about its optimality.

The paper is organized as follows. In the following Section, an overview of the related literature is provided; Section 2 presents the proposed methodology; in Section 3 the proposed methodology is applied to a real industrial case in a high value-added production system of the railway sector; finally, Section 4 provides the conclusion and future research.

1.2 Related literature

Product replacement, customization of manufacturing, leading to the just-in-time concept and intelligent production modes are the challenges that recently increase competition among modern manufacturing companies and besides accelerate digitalization and optimization of their production systems (Stoldt et al., 2018; Guo et al., 2020). Sustainable

10.1016/j.ifacol.2021.08.077

and smart innovative solutions are required to keep manufacturing companies competitive on the market and resilient to its trends (Romero-Silva and Hernández-López, 2019; Marinagi et al., 2014). To establish proficient management with cost-effective decisions that formulate production policies of manufacturing system, data about the system behaviour that circulates in the system has to be thoroughly analyzed (Vafeiadis et al., 2019). Modern demand to the existing enterprises include aggregating of all control and management in one system in order to be able to analyze and regulate production control policies (Vafeiadis et al., 2019). Widespread approach for analyzing the behavior of a production system over time is simulation (Höppe et al., 2016; Schönemann et al., 2016; Müller-Boyaci and Wenzel, 2016; Feng and Fan, 2013).

A simulation model represents the elements of the system and the relations between them: in simulation runs, the model is used to replicate system's behavior and to generate results which can be transferred into the real system (Schönemann et al., 2016). Although, manufacturing market is changing instantly and to react to this rapid changes simple simulation model of production system becomes not enough, manufacturing requires resilient simulation model that reacts to the changes of input dynamically (Tao et al., 2019). With a help of data from the shop-floor sensors flowing into the advanced production management system it becomes possible and simulation model evolves into Digital Twin (DT) – ultra-realistic, high scaling simulation, which uses the best available physical models, sensor data and historical data for mirroring one or more real systems (Kunath and Winkler, 2018; Tao et al., 2019). This innovative technology has been used in the Industry 4.0 related works as a tool to realize the interaction and interconnection between physical and virtual spaces (Bao et al. 2018). From the perspective of the manufacturing system, DT-based modelling of product, process, resource and operation are crucial for intelligent and predictive manufacturing (He and Bai, 2020). DT technology opens up new possibilities in terms of monitoring, simulating, optimizing and predicting real-time states of cyber-physical systems (CPSs): adopting digital twins allows operators to monitor productions, test deviations in an isolated virtual environment, and further strengthen the security of process industries (Eckhart and Ekelhart, 2018).

DT in combination with other innovative technologies has a great potential to change nowadays manufacturing paradigm (Min et al., 2019). Multistage optimisation based on this technology takes a place in various areas of businesses and considers different aspects for optimisation, such as manufacturing technology (Söderberg et al., 2017; Xu et al., 2020), data analysis (Chakraborti et al., 2020), process monitoring and diagnosis (He et al., 2019), etc. Commonly, the DT modeling based optimisation is a repeating cycle practice loop which is formed to continuously control and optimize Key Performance Indicators (KPIs) with optimisation tools (Min et al., 2019). For the establishment of the innovative DT based optimisation strategy some methods and tools from the simulation based optimisation may be inherited, such as optimization of the inventory represented by Pareto frontier (Amodeo et al. 2007). Pareto frontier can be a very useful and comprehensible tool when the multi-objective optimization (Lotov and Miettinen, 2008). Significant papers about DT optimisation in production systems have been published during last few years (Guo et al. 2020; Liu et al. 2020a; Liu et al. 2020b; Schuh et al. 2020). Guo et al. (2020) puts forward digital twin with real-time data gathering for the optimisation purposes to find the balance between the takt time, cost of operators and load fluctuation between workstations in air conditioner production line. Takt time is very important indicator in majority of businesses: when takt time is too small stock gets full, on the other hand when it's bigger than it should be production plan may be not completed and this follows to the penalties for manufacturing company.

Due to the customization and personalization trends in manufacturing, production batches become smaller and the topic of value creation optimization becomes utterly important, so Schuh et al. (2020) exposes DT-based optimization of value creation in single and small batch production. Crucial aspect of the production process organization is part flow management that includes sequencing of ordered parts to produce, accordingly Liu et al. (2020a) studies order-batch grouping and operation planning with a help of DT based optimisation.

2. METHODOLOGY

2.1 Outline of the proposed approach

The optimization approach proposed in this work is based on four modules. The goal of the proposed approach is to go beyond classical optimization approaches, which iteratively modify the configuration of solutions until the target performance level is achieved. In fact, in this approach a parametric model mirroring the real production system (DT) represents the kernel for performance evaluation. A set of design objectives and constraints defines the optimization space. The multi-objective optimization module investigates the solution space according to the specified objective function which includes different weighted objectives. Finally, a set of trade-off solutions is returned by the algorithm. The framework architecture has been presented in (Magnanini et al. 2020).

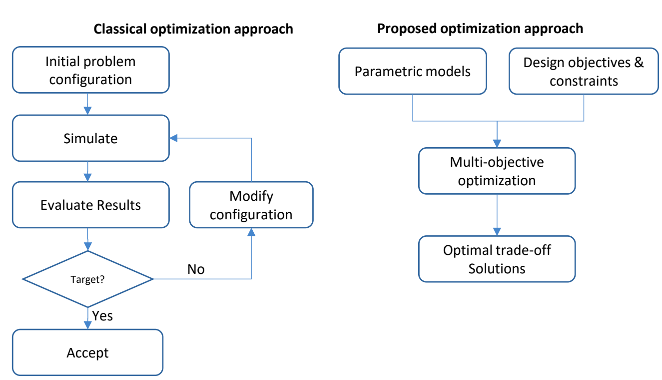

Fig. 1. Comparison between classical optimization approaches and the proposed optimization approach.

2.2 Digital Twin

The kernel of the optimization approach is based on a parametric Digital Twin (DT). DTs are widely used in production systems analysis as a valuable tool for the process chain evaluation, they play a major role in the production, maintenance, and after-sales services (Melesse et al., 2020). In combination with other advanced technologies digital twin become even more useful and powerful tool (Tao et al., 2019).

DT model which was developed in frame of the current research aims to incorporate virtual and physical data throughout a product lifecycle, which leads to generation of vast data amount that can be processed by advanced analytics and used for purposes of sensitivity analysis and optimisation. DT was developed in discrete event simulation software Siemens Plant Simulation[1]. The software provides customized user-friendly tool that allows to estimate inventory level, planning of resources and forecast production rates, as well as perform what-if analysis to enable the user to evaluate the impact of the specific system process in the output Key Performance Indicators (KPIs).

The developed DT includes a formal modeling of the resource dynamics which enables the DT to be integrated with data gathering solutions at shop-floor level. Moreover, when part tracking is active in the real manufacturing system, the DT uses the system state in terms of location of the parts to be initialized when interrogated by the user. In this way, the DT is constantly updated with the actual system condition. Moreover, the probability of generating defects for each machine has been added, according to historical data, in order to add randomness to the system and simulate rework processes which occur in real manufacturing systems. Thanks to the resource formalization, the routing of the parts can be managed outside of the commercial simulation model, providing additional degree of flexibility for the exploration of alternative production scenarios.

The DT returns the main system KPIs as system throughput distribution, yield, estimation of the total work-in-progress and estimation of the system state after given time intervals.

2.3 Design objectives & constraints

The objectives of the optimization workflow are defined based on the requirements of the manufacturing system. According to most of the production department planners, the two main objectives are prioritized as:

1) Increasing the output production rate (efficiency) of the entire system, where the throughput is given by:

TH (system) = Output of finished parts in a week / No of days

This is evaluated from the simulation model and is a non-linear quantity.

Objective 1 -> Maximize (TH(system))

2) Ensure a steady production output on daily basis, without having extreme peak and drop in production. In addition to the increase of the production rate, sequencing of products should allow to avoid erratic production output rate, by allowing smoother work distribution at the painting line.

Production variability = STDEV (TH(daily))

Objective 2 -> Minimize STDEV (TH(daily))

Constraints:

1 - Minimum production rate must be finished in the given week (weak constraint)

2 – Respect user specified constraints as prioritized lots, line assignments etc.

Decision variables:

The decision variables are represented by the following:

Var1: prioritization of the parts planned for production.

2.4 Multi-objective optimization

In multi-product production planning, the decision maker frequently needs to deal with different objectives which are typically in conflict, thus the trade-off must be quantitatively evaluated. In order to address such conflicting objectives a multi-objective optimization method capturing the key parameters of the production planning by considering multiple objectives is developed. The impact of alternative policies which are oriented towards production logistics, (lot sizing, production sequencing, part routing etc…,) and policies oriented towards product quality, (rework, feed-forward control, selective inspection and others) are considered into an integrated system's performance evaluation framework. These policies are modelled with their parameters in the digital twin and are evaluated through the multi-objective optimization platform in order to derive the optimal combination of the alternative policies. Finally, it provides the optimal combinations of production routing, inspection policy and defect reduction strategies at each stage of the system to find the best trade-off between quality improvement effort (time) and effective production rate.

The general structure of input information and the output of the multi-objective optimization are presented in Figure 2. The input data is processed from production order management systems about product types, quantities, deadlines. Moreover, it takes input data about the current state of the manufacturing system and parts flowing in the system by interacting with manufacturing execution system and other user defined objectives and technical constraints through input data interfaces. The optimization workflow elaborates this data and explores feasible solution spaces. This process is guided by algorithms and conditions that model the different technical constraints about machines, processes KPIs, other user defined criteria and objectives.

[1] www.plm.automation.siemens.com

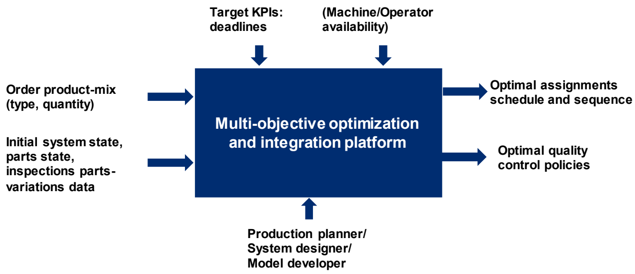

Figure 2. Function modelling (IDEF0) of the multi-objective optimization and integration platform.

The platform is developed by using the capabilities of the commercially available process automation and optimization platform modeFRONTIER[2] which supports multi-objective optimization and integration between multi-domain software modules. It performs the design space exploration, process integration, optimization and orchestrates the execution of the digital simulation and analysis tasks; and optimizes one or more aspects of the production plans by iterating across a range of parameter values toward specified target conditions while observing the defined problem constraints. Furthermore, it can export optimal solution details to other tools, in order to perform post optimization verification before implementation at shop floor level.

2.5 Optimal trade-off solutions

The main advantages of applying multi-objective optimization lies in its power to determine the best trade-off solutions, namely the Pareto set, while considering competing objective parameters. Without such a method, one objective cannot be improved without sacrificing the performance of the other criterion. In this study, a production plan is judged to be Pareto-optimal, if it is not entirely dominated by any other plan. Once the Pareto set has been identified, the action of comparing the various Pareto-optimal solutions to choose the preferred solution for the specific case under consideration is based on exogenous factors (outside the computer model), and is carried out by the human decision-makers.

According to the specific industrial case, the KPIs that indicate the system's objectives can be adapted; e.g., to improve product quality by reducing the delay of the quality information feedback between critical process stages and by tightly controlling the material flow routing to reduce process lead time and inventory in the system. An example, in the generic Pareto Frontier shown on in Figure 3. The goal is to minimize the two objective parameters, and the curve plots represents the best design candidates offering the optimal trade-offs between these two objectives.

[2] www.esteco.com/modefrontier

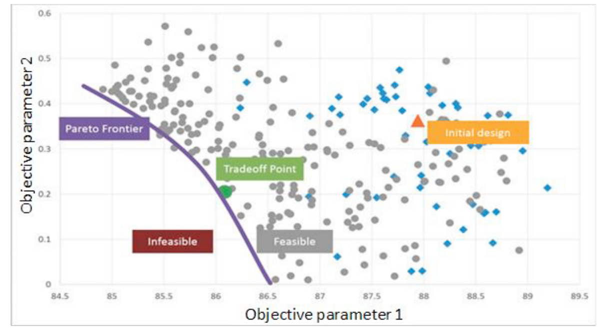

Figure 3. Example configuration of a Pareto Frontier with two objectives.

3. INDUSTRIAL CASE-STUDY

3.1 System description

This optimization approach for planning is demonstrated within a manufacturing company producing axles for the railway sector. First, a description of the production system is presented. The three main divisions of the axle manufacturing system consist of: 1) forging, 2) machining and 3) painting processes. The forging division performs forging and thermal treatments, and some pre-machining operations. This use-case focuses on machining and painting departments.

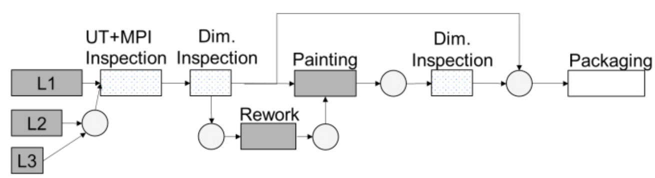

Figure 4. Graphical representation of the multi-stage production system.

The machining operations performed in the machining division are rough turning, finish turning and stone grinding. There are two parallel lines to carry out the machining, which will be called line 1 (L1) and line 2 (L2). L1 is an automatic production line, handled by a gantry system, where the gantry performs handling operations from one station to the next one in the flow in an automatic way, with limited buffer between stations (minimum buffer and waste lean approach). L2 is older, but functionally it performs almost the same operations, while the loading and unloading are carried out by hoist cranes with manual intervention. Larger buffers are allowed from station to station in L2, which are stored on the floor. Apart from this internal machining capacity, the company can also subcontract the machining of some axles. This third machined axle income has been called line 3 (L3). Inspection operations are also performed in the machining division, where ultrasonic testing (UT) and magnetic particle inspection (MPI) are carried out for all L1, L2 and L3 incoming axles. From the painting process perspective, axles can be discriminated into two classes, those that need painting and others which do not. It is important to keep a rather balanced load of the painting area . Painting requirements of the axles also may differ. This process can generate disturbances in the whole chain that can vary the expected daily throughput of axles. The planning activity is therefore a challenging task that up to now has been carried out using ERP data and expert knowledge, with high manual intervention. Furthermore, different resource allocation policies (e.g. painting resources or shifts) have been tested in a trial and error way, directly on the shop-floor. The short-term production planning approach described in this paper has been customised to the problem of the manufacturing of railway axles. It has been decided to apply optimization based planning to the machining and painting stages of the axles. It will be considered as data input the axles to be machined in a week, both L1 and L2 axles, as well as the ones expected to come from subcontracting, L3. A Digital Twin has been built as a digital testing model, supported by an optimisation environment to automate the planning of the machining and painting of the axles.

3.2 Optimization problem and objectives

In this case, several objectives have been selected and multi-objective optimization have been ran. In particular, the interest of the production manager was to pursue a steady production with respect to all axle type, especially with respect to the axles which do not require painting and to the axles requiring the painting phase. In fact this represents a major change in the process chain which therefore must be managed accordingly, so that any area is unsaturated and production capacity wasted. Other secondary objectives include also lot completion time. The total lot completion time can be reduced by the adjustment of two factors: (i) the reduction of the total setup time through a smart sequencing of products, (ii) the reduction of the interruption at the painting line. Since only some axle types need painting, the sequences of axles impact the workload profile at the painting line, which can occur to be extremely loaded (high work-in-progress and long queues at the painting areas, with the risk of rework due to time constraint), or it can occur to be empty, because no lots needing the painting phase are being produced. This would cause the area, which is considered a cost bottleneck, quite critical from the viewpoint of the workload balancing. This has been achieved by managing the lot sizing as well as the lot sequencing. The DT provided the performance evaluation by accounting for the actual initial state of the system, and therefore by accounting for backlog production, as well as quality characteristics and rework strategies which may have an impact at system level not predictable otherwise.

3.3 Numerical results

In this Section, results from the multi-objective optimization of the proposed use-case are provided and commented. The influence of lot sizing and lot sequencing on the two selected objectives – standard deviation of all axles to be produced and standard deviation of painted axles – is evaluated and accounted for in the Pareto frontier which results from the multi-objective optimization approach.

In Figure 5, the effect of only lot sequencing is shown. There are multiple factors that affect the smoothness of daily production output. These main factors are: 1) initial parts in the system 2) processing times of the lots 3) lot sizes.

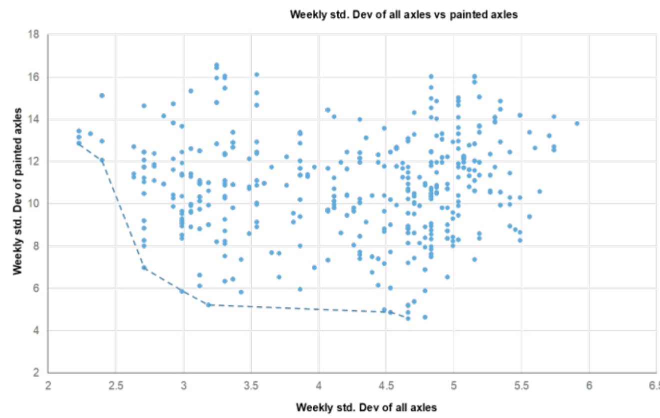

Figure 5. Pareto frontier of optimal production plans.

One important pattern that has been noticed is that the best sequence starts mostly with small lots on line 1, that need painting afterwards. Since there are sufficient amount of parts in the system at the start, dispatching a high lot of size and faster products will saturate the output on the first day. Therefore, the optimal solution selects lots with small size which takes longer processing time (painted axles).

The second aspect is the distribution of lot sizes selected in the sequence. It is followed by higher and lower number of lot sizes, which will balance the daily output of the system. This alternation of higher lot sizes followed by lower lot sizes reduces the impact of the setup times (approximately equal for all lots) on the variation and avoids days with irregular high production output followed by low production output. The important factor in smoothing the output of the painted axles is the intermittent dispatching of the painted axles followed by unpainted axles into the line. This is a relevant characteristic in order to avoid a high production of painted axles followed by lower output, causing erratic output at the end of the line.

Figure 6 shows the effect of lot splitting in comparison with the effect of lot sequencing. In the optimization mode where both the sequence and the lot sizes are changed shows higher number of solutions, due to the combination of both the sequencing and lot splitting. Most of the additional new feasible solutions are generated closer to the pareto frontier. The lot splitting has improved the solutions in terms 1) increasing the daily output of axles, 2) reduced the variation of output and 3) reduction of lead-time. Although the computation time for the optimizer using both the sequence and lot splitting takes longer time compared to the optimizer by considering only the sequence, there are significant improvements on the solutions obtained from the platform. Specifically, 8 hours on a laptop with i7 processor is needed to obtain the complete Pareto frontier. Indeed, this time is suitable with the application.

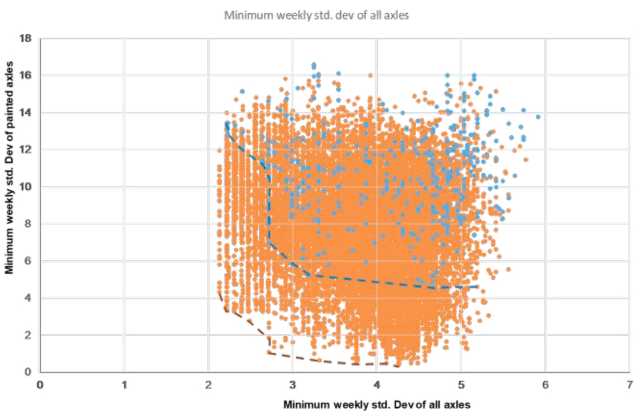

Figure 6. Estimated daily production variation for all axles and painted axles with lot splitting (in orange) and only sequencing (in blue).

4. CONCLUSIONS

This paper presents a multi-objective optimization approach which integrates a Digital Twin for dynamic performance evaluation. The novel approach is successfully applied to a real industrial case dealing with high value-added production in the railway sector. Numerical results show that trade-off between identified objectives significantly change the optimal production plans. Therefore a flexible methodology for short-term production planning as the one presented in this work can support manufacturing companies for efficient and sustainable production.

ACKNOWLEDGEMENTS

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 723698. This paper reflects only the author's views and the Commission is not responsible for any use that may be made of the information contained therein.

REFERENCES

Amodeo, L., Chen, H., & Hadji, A. (n.d.). Multi-objective Supply Chain Optimization: An Industrial Case Study. Applications of Evolutinary Computing, 732–741.

Bao, J., Guo, D., Li, J., & Zhang, J. (2018). The modelling and operations for the digital twin in the context of manufacturing. Enterprise Information Systems, 1–23.

Chakraborti, A., Heininen, A., Koskinen, K. T., & Lämsä, V. (2020). Digital Twin: Multi-dimensional Model Reduction Method for Performance Optimization of the Virtual Entity. Procedia CIRP, 93, 240–245.

Colledani, M., Tolio, T., Fischer, A., Iung, B., Lanza, G., Schmitt, R., & Váncza, J. (2014). Design and management of manufacturing systems for production quality. CIRP Annals-Manufacturing Technology, 63(2), 773-796.

De Bruecker, P., Van den Bergh, J., Beliën, J., & Demeulemeester, E. (2015). A model enhancement heuristic for building robust aircraft maintenance personnel rosters with stochastic constraints. European Journal of Operational Research, 246(2), 661–673.

Eckhart, M., & Ekelhart, A. (2018). Towards Security-Aware Virtual Environments for Digital Twins. Proceedings of the 4th ACM Workshop on Cyber-Physical System Security - CPSS '18.

Feng, Y., & Fan, W. (2013). A system dynamics-based simulation model of production line with cross-trained workers. Journal of Statistical Computation and Simulation, 84(6), 1190–1212.

Guo, H., Chen, M., Mohamed, K., Qu, T., Wang, S., & Li, J. (2020). A digital twin-based flexible cellular manufacturing for optimization of air conditioner line. Journal of Manufacturing Systems.

He, B., & Bai, K.-J. (2020). Digital twin-based sustainable intelligent manufacturing: a review. Advances in Manufacturing.

He, R., Chen, G., Dong, C., Sun, S., & Shen, X. (2019). Data-driven digital twin technology for optimized control in process systems. ISA Transactions.

Höppe, N., Seeanner, F., & Spieckermann, S. (2016). Simulation-based dispatching in a production system. Journal of Simulation, 10(2), 89–94.

Ingels, J., & Maenhout, B. (2015). The impact of reserve duties on the robustness of a personnel shift roster: An empirical investigation. Computers & Operations Research, 61, 153–169. doi:10.1016/j.cor.2015.03.010

Kunath, M., & Winkler, H. (2018). Integrating the Digital Twin of the manufacturing system into a decision support system for improving the order management process. Procedia CIRP, 72, 225–231.

Liu, Q., Leng, J., Yan, D., Zhang, D., Wei, L., Yu, A., … Chen, X. (2020a). Digital twin-based designing of the configuration, motion, control, and optimization model of a flow-type smart manufacturing system. Journal of Manufacturing Systems.

Liu, Z., Chen, W., Zhang, C., Yang, C., & Cheng, Q. (2020b). Intelligent scheduling of a feature-process-machine tool supernetwork based on digital twin workshop. Journal of Manufacturing Systems.

Lotov A.V., Miettinen K. (2008). Visualizing the Pareto Frontier. In: Branke J., Deb K., Miettinen K., Słowiński R. (eds) Multiobjective Optimization. Lecture Notes in Computer Science, vol 5252. Springer, Berlin, Heidelberg.

Magnanini, M.C., Colledani, M., & Caputo, D. (2020). Reference architecture for the industrial implementation of Zero-Defect Manufacturing strategies." Procedia CIRP 93: 646-651.

Marinagi, C., Trivellas, P., & Sakas, D. P. (2014). The Impact of Information Technology on the Development of Supply Chain Competitive Advantage. Procedia - Social and Behavioral Sciences, 147, 586–591.

Melesse, T. Y., Pasquale, V. D., & Riemma, S. (2020). Digital Twin Models in Industrial Operations: A Systematic Literature Review. Procedia Manufacturing, 42, 267–272.

Min, Q., Lu, Y., Liu, Z., Su, C., & Wang, B. (2019). Machine Learning based Digital Twin Framework for Production Optimization in Petrochemical Industry. International Journal of Information Management.

Müller-Boyaci, P., & Wenzel, S. (2016). Simulation Toolkit for autonomous control in serial production networks of automotive suppliers. Journal of Simulation, 10(2), 123–136.

Reggelin, T., Lang, S., & Schauf, C. (2020). Mesoscopic discrete-rate-based simulation models for production and logistics planning. Journal of Simulation.

Romero-Silva, R., & Hernández-López, G. (2019). Shop-floor scheduling as a competitive advantage: A study on the relevance of cyber-physical systems in different manufacturing contexts. International Journal of Production Economics, 107555.

Schönemann, M., Schmidt, C., Herrmann, C., & Thiede, S. (2016). Multi-level Modeling and Simulation of Manufacturing Systems for Lightweight Automotive Components. Procedia CIRP, 41, 1049–1054.

Schuh, G., Kelzenberg, C., Wiese, J., & Kessler, N. (2020). Creation of digital production twins for the optimization of value creation in single and small batch production. Procedia CIRP, 93, 222–227.

Söderberg, R., Wärmefjord, K., Carlson, J. S., & Lindkvist, L. (2017). Toward a Digital Twin for real-time geometry assurance in individualized production. CIRP Annals, 66(1), 137–140. doi:10.1016/j.cirp.2017.04.038

Stoldt, J., Trapp, T. U., Toussaint, S., Süße, M., Schlegel, A., & Putz, M. (2018). Planning for Digitalisation in SMEs using Tools of the Digital Factory. Procedia CIRP, 72, 179–184.

Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019). Digital Twin in Industry: State-of-the-Art. IEEE Transactions on Industrial Informatics, 15(4), 2405–2415.

Tobias Reggelin , Sebastian Lang & Christian Schauf (2020). Mesoscopic discrete-rate-based simulation models for production and logistics planning, Journal of Simulation.

Vafeiadis, T., Kalatzis, D., Nizamis, A., Ioannidis, D., Apostolou, K., Metaxa, I. N., … Tzovaras, D. (2019). Data analysis and visualization framework in the manufacturing decision support system of COMPOSITION project. Procedia Manufacturing, 28, 57–62.