DESIGNING AND OPTIMIZING PRODUCTION IN A HIGH VARIETY / LOW VOLUME ENVIRONMENT THROUGH DATA-DRIVEN SIMULATION

Virginia Fani, Bianca Bindi, Romeo Bandinelli
Department of Industrial Engineering
University of Florence
Florence, Viale Morgagni 40/44, 50134, ITALY
E-mail: virginia.fani@unifi.it

KEYWORDS
Data-driven simulation, Case study, Production, High Variety / Low Volume (HVLV).

ABSTRACT

HVLV environments are characterized by high product variety and small lot production, pushing companies to recursively design and optimize their production systems in a very short time to reach high-level performance. To increase their competitiveness, companies belonging to these industries, often SMEs working as third parties, ask for decision-making tools to support them in a quick and reactive reconfiguration of their production lines. Traditional discrete event simulation models, widely studied in the literature to solve production-related issues, do not allow real-time support to business decisions in dynamic contexts, due to the time-consuming activities needed to re-align parameters to changing environments. Data-driven approach overcomes these limitations, giving the possibility to easily update input and quickly rebuild the model itself without any changes in the modeling code. The proposed data-driven simulation model has also been interfaced with a commonly-used BI tool to support companies in the iterative comparison of different scenarios to define the optimal resource allocation for the requested production plan. The simulation model has been implemented into a SME operating in the footwear industry, showing how this approach can be used by companies to increase their performance even without a specific knowledge in building and validating simulation models.

INTRODUCTION

As suggested by the name, High Variety/Low Volume (HVLV) environments are manufacturing scenarios characterized by high product variety, frequent production order changes and small lot dimensions. As reported by White and Prybutok (2001), another possible definition of HVLV could be "non-repetitive companies", where all the production stages operate on a non-repetitive base (Portioli-Staudacher and Tantardini, 2012). In this context, frequent changes of production mix have to be managed, often requiring the re-optimization or even re-design of production flows. HVLV represents a strategic choice for all the companies that aims to provide quick and reactive production, such as the ones working in dynamic and uncertain contexts like the fashion industry. For instance, a HVLV approach is frequently chosen by SMEs that, due to their size, have low volumes to produce and several clients to work with as third-party suppliers, facing with the trade-off between flexibility and high efficiency (Katic and Agarwal, 2018). Most of the manufacturing SMEs operates as job-shop, declared to be a HVLV manufacturing environment requiring skilled and flexible workforce to produce a wide range of products (Haider and Mirza, 2015; Huang and Irani, 2003). Each production unit produces a large variety of part types in small batches, characterized by their own routing and sequenced tasks (Slomp et al., 2009). The existing literature on HVLV is focused on the improvement of operational efficiency (Adrodegari et al., 2015; Cransberg et al., 2016; Hendry et al., 2013), even using approaches often adopted in high volume and low variety mass markets (Thomassen and Alfnes, 2017). For instance, even it is a common misunderstanding that lean is suitable for mass production only, it has been proposed to guarantee flexible productions in high variety environment (Haider and Mirza, 2015; Slomp et al., 2009). In lean paradigm, the elimination of non-value-added activities and wastes, such as overproduction and buffer, aims to reduce lead time, guaranteeing more responsiveness to customer demand (Haider and Mirza 2015). Other causes of waste are represented by long waiting and queue times that may occur due to the over-saturation of resources (Haider and Mirza 2015) or unbalanced scheduling plan (Fernandes et al, 2014; Fernandes et al, 2020), resulting in large work in process (WIP). The identification and monitoring of an appropriate set of indicators represents a key aspect especially within dynamic contexts, where changes in key performance indicators (KPIs) have to be immediately followed by the most appropriate reaction. As shown in literature (Haider and Mirza 2015; Slomp et al., 2009), main KPIs for production performance are WIP, lead time (LT), productivity, takt time (TT) and resource utilization. Despite the clear gainable benefits, KPIs monitoring and resource balancing are time-consuming activities, especially in HVLV contexts where they have to be often conducted due to the frequent change of production mix. In fact, each item has its own production cycle in terms of tasks list, sequence and processing time, requiring production layout reconfiguration and re-assignment of tasks to resources (Haider and Mirza, 2015). Even if discrete-event simulation (DES) is widely used to optimize and predict the performance of job shops, frequent changes in production orders and unexpected events, typical of HVLV environments, ask for real-time models able to evaluate different scenarios in a very short time. Data-driven is an approach to simulation to overcome the long time needed to build and validate models in real environment, automatically re-building the model from data stored into structured dataset without any need to run programming code (Wang et al., 2011). According to this, they can be applied to both traditional and intelligence manufacturing systems (Zhang et al., 2019), interacting with real environments to update simulation models with on-field feedback (Goodall et al., 2019). In this paper, the data-driven approach has been used to give quick tips to final users to easily re-build the simulation model to optimize and balance resources' workload recursively. The proposed parametric data-driven model for HVLV scenarios has been applied in a footwear SME, representing the fashion industry one of the main dynamic sectors due to the high variants to be managed (d'Avolio et al., 2016), where simulation has already been successfully applied for optimizing production (Fani et al., 2017; Fani et al., 2018; Hassan et al., 2019). The work is structured as follows: in the first section, a clear overview of the purpose of the work is given; in the second section, the proposed data-driven model is described and the iterative procedure for its application summed up; the third section shows its implementation on a real scenario in the footwear industry; finally, main conclusions and further developments are shown.

PROBLEM STATEMENT

In HVLV environment, several KPIs have to be constantly monitored in operational dashboards. First, daily productivity (i.e. the number of units produced per day) represents a target value to be reached or, generally, to be maximised according to the resource availability. Frequently used within lean production systems, TT (i.e. the average time between the start of production of one unit and the next one) is a key indicator of the production rate, to be respected for matching the demand. If a process is unable to produce at takt time, in fact, additional resources or process re-engineering is needed to reach the productivity target. Besides TT, LT (i.e. the amount of time from the start of a process until its conclusion, including processing and waiting times) is another parameter to be measured and monitored to reach the productivity target. A shorter LT, in fact, results in a higher productivity. Because within most plants the largest contributor to LT was queue time (i.e. the amount of time a unit spends waiting before being processed), reducing queue time further reduces LT. The waiting time strictly depends on the queue length, a part of the work in process (WIP): queue size is the number of units waiting for being processed, while WIP is the overall number of items in a production system, including both waiting and processing items. From a lean perspective, the optimal WIP size should be equivalent to the number of workstations, having queue size equals to zero through the implementation of the one-piece-flow approach. Finally, resource utilization strongly influences WIP, because over-saturated resources represent bottlenecks in unbalanced production systems. According to this, the main key performance indicators monitored in the proposed data-driven simulation model are productivity, TT, LT, queue size and saturation. The related target values defined by companies can be reached changing variables that occur in production. For instance, additional capacity impacts on LT, reducing queue time and increasing productivity. Even the described KPIs reflect the critical success factors for companies working in several production contexts, main challenges for HVLV strategy are related to the frequent need of re-optimize or even re-design the production flows. According to this, the main challenge in HVLV strategies are not related to specific KPIs to be monitored but to identify the most suitable decision-support tool to make quick and reactive changes in production based on their value. Given certain production plan (i.e. Stock Keeping Units – SKUs - mix, delivery quantities and due dates) and production cycle per SKU (i.e. processing time per each task) as fixed input, capacity can be increased in many ways, such as enlarging the amount of working hours per day or adding more resources. Considering containers as handling units, related parameters have to be included in the analysis due to their impact on production performance. First, each containers can include a variable number of items, impacting on the processing time required per handling units and, consequently, on the queue over the system: higher container capacity is, less one-piece-flow approach is followed, increasing the WIP and slowing the overall production flow. Similarly, buffer capacity between workstations represents a variable that moves from 1, reflecting the one-piece-flow approach, to unlimited capacity, reducing the occurrence of waiting workers on the production line. Finally, restrictions on the number of containers to be daily moved over the production system can be included, especially when production is outsourced and target values are defined in supplier agreements.

MODEL DESCRIPTION

Starting from the problem statement, the proposed data-driven simulation model has been defined. The commercial simulator used is AnyLogic®, chosen for its interface with commercial databases, as well as for the easy importing procedure and its built-in database, adopted to store the input data needed to realize the data-driven model. In addition, the possibility to implement Java functions has been used to parametrize the processing times per SKU and the assignment of workers to workstations. The database structure has been defined to make easier the import of a production plan, as well as a separate table to manage the production cycle of each SKU. For instance, in order to guarantee an easy management of changes in production mix, the database table related to production cycles has been structured including SKU, sequence, task, and task time as columns: a new SKU will only require to add rows related to its own tasks list and sequence. Moving to the parameters of each element, none of them has been included in the model as fixed value, but as a variable to be updated according to the dedicated field on the database uploaded at the model running. For instance, the assignment of each task per SKU to a workstation and a worker who processes it has been done directly on the database. Once the database structure for a parametric modeling of input and variables has been developed, the database views for collecting data to calculate the performance indicators have been realized. For instance, a datalog to track the queue size per workstation during the model running has been coded. The tracking frequency for queue size has been parametrically defined as model parameter to be easily changed before the model execution, in order to make the final user able to evaluate the trade-off between collecting more frequent information and increasing the execution speed. The model can be applied in real scenarios according to the iterative procedure shown in Figure 1.

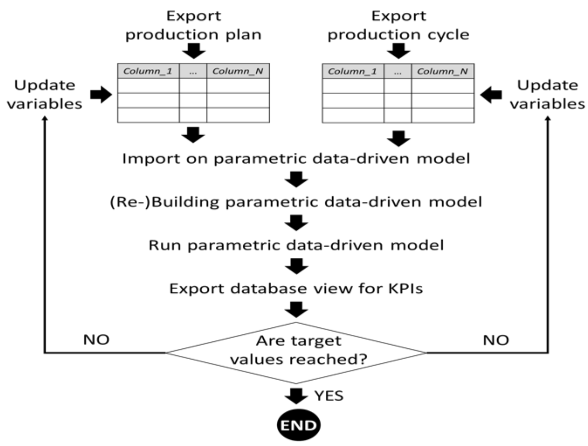

Figure 1: Proposed data-driven simulation model

Looking at Figure 1, the proposed procedure for the implementation of a parametric data-driven simulation model can be described as follows. First, the input data have to be exported from the company ERP and enriched filling values related to the variables included in the model. For instance, even the production cycle for the SKUs included in the production plan is given, the assignment of each task to a specific resource working on a certain workstation has to be done at this point. Once all the variables have been filled, the database structure for the model is ready and can be imported on the simulator database. Moreover, parameters such as containers and buffer capacities are set to be acquired by the model itself. The parametric data-driven model is then built according to the database values using the Java language available in AnyLogic®. In more detail, the generic layout of the realized discrete simulation model is composed of a parametric source and a generic "workstation" agent, as shown in the following paragraph. Moreover, the "worker" agent has been used together with dataset and schedule objects to dynamically define assignments and shifts respectively. At the model start, the assignment of workers to workstations is done using the Java language and processing time per item processed on each workstation is defined according to the value stored in the database table related to production cycles. Once the model has been run, the database views previously defined on the simulator to monitor the KPIs are exported and the values analysed. The comparison between the KPIs value coming from the simulator and the target values will determine if new iteration of the procedure is needed or not. New iterations mean changing the variables and parameters setting according to the results, in order to update the database and run again the re-built model. For instance, the productivity target could not be reached and resources will have to be re-assigned to better balance the production system, reducing queue and levelling workers' saturation.

CASE STUDY

The As-Is Scenario

The proposed simulation model has been applied into a footwear company to demonstrate its applicability in real scenarios. The footwear production cycle begins with the cutting process, followed by stiching, lasting and assembly and, finally, quality control and packing. The cutting department cuts all the parts needed for each shoe, then gathers the parts into kits (i.e. one kit includes all the parts for each pair of shoes). Cut kits then move to the stitching department for assembly. In the stitching department the operations are divided into simple steps and each worker is given few tasks, even only one. Generally, two stitching lines can support one assembly line. Once the stitching has been completed, the upper must be lasted before the outsole can be attached. Lasting is the operation that gives shoe its final shape. After the upper is heated and fitted around a plastic metal, or wood foot form called "last", the insole, midsole, and outsole are cemented to the upper. The last steps are quality control and, if shoes are compliant to the final check, their packing. Moving towards the case study, the simulation model has been applied to the stitching department of the company., composed by 4 production units organized as job shops: the first one is the preparation unit, where cut materials delivered in kit are re-organized in the stitching handling units, usually boxes, together with the other components needed (e.g. laces); the second and third units provide uppers and tongues respectively, assembled together in the last production unit. A simplified schema of the production units included in the case study is shown in Figure 2. Workstations (i.e.

"WSX" in the diagram) can be sewing machines or workbenches for manual activities, while workers (i.e. "wX" in the diagram) are resources that can be assigned to different type of tasks and machines.

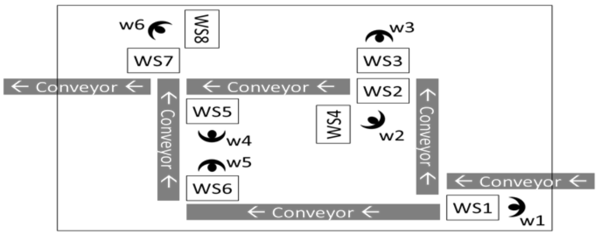

Figure 2: Resources in production units

Conveyors are used to speed the movement of handling units, but boxes can also be manually moved from one workstation to the next one according to the task sequence in the SKU production cycle. Moreover, a SKU can be worked by the same station more than once, as well as a single worker can be assigned to more than one workstation. Last, moving from one SKU type to another, different workstations can be used and different sequences can be followed, according to the SKU production cycle. For instance, considering a box filled with the generic item SKU1 entering the system shown in Figure 2, it will be processed according to the SKU production cycle, starting with tasks assigned to the worker w1 on the workstation WS1. Once w1 has completed the assigned tasks for all the SKUs included in the handled box, he will put the box back on the conveyor to move it from its workstation to the next one. Looking at the diagram, if the next task for the SKU has to be processed by w2 or w5, they can take the box directly from the conveyor; on the other hand, in case of task assigned to w4, no conveyor links the involved workstations and it is the worker himself who moves the box from the previous to his workstation. As shown in the diagram, w2 processes tasks on both WS2 and WS4, depending on the SKUs production cycle: for example, considering WS2 as sewing machine and WS4 as workbench for manual activities, SKU1 could require only sewing tasks while SKU2 also manual activities like the application of decorations or patches. Finally, non-sequential sewing activities on the same workstation could be included in the production cycle, requiring for example to process SKU2 on WS2, then on WS4 and then again on WS2. Boxes are usually mono-SKU, meaning that each box contains a certain number of the same SKU that requires the same tasks. In the case study, the capacity is equals to 2 pairs of shoes per box and 2 types of SKUs are included in the production mix.

The Application of Data-driven Simulation

Starting from the organization of the stitching department, the data-driven model for the case-study is composed by three building blocks, modelled as diagrams: one for the box and shoes generation, the second for the task processing and the third for the shoes sink and box recycling, as shown in Figure 3, Figure 4 and Figure 5 respectively. According to the resource assignments on the database, a specific number of workers, as agents, and workstations, as flowcharts, are generated at the model start.

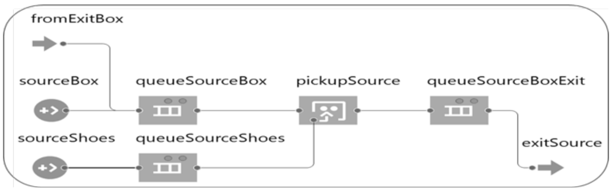

Figure 3: Source station workflow

The source diagram in Figure 3 generates both the boxes and shoes entering into the production system. According to the data stored in the database, the *sourceBox* element creates a fixed number of boxes (i.e. 300 in the case study), representing the maximum number of boxes allowed in the production system. The company has chosen to fix the number of allowed boxes to limit the WIP in the production system, but the simulation model can be run even setting an unlimited number of boxes. The *fromExitBox* element receives the empty boxes arriving from the *exitBox* station in Figure 5. The *sourceShoes* element generates shoes according to the production plan exported from the ERP and stored into the database, both in terms of pairs of shoes and scheduled date. The *pickupSource* element assigns shoes to boxes according to the box capacity: as shown in Figure 3, boxes and shoes are independent agents before the pickup element while filled boxes became the handling units after that. Filled boxes then move to the *queueSourceBoxExit* buffer, representing the company warehouse before the production area. The *exitSource* element dispatches each filled box to the right resource according to the workstation with sequence equals to "1" for the SKU contained in the box. That data is read on the database table related to the production cycle per SKU. More in details, the *exitSource* element in Figure 4 moves the filled boxes to the right *enterServiceXX* element in Figure 4.

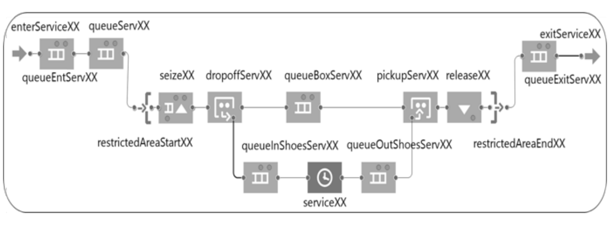

Figure 4: Generic workstation workflow

Figure 4 represents tasks processing on workstations, from the assignment of a filled box to its dispatching to the next workstation. Along the production system, boxes move from *ServiceXX* to *ServiceNN* until the final workstation listed on the SKU production cycle. Similarly to *exitSource* in Figure 3, the *exitServiceXX* element in Figure 4 defines the criteria to move filled boxes to the next workstation, reading the sequence equals to “n+1” for the SKU contained in the box on the dedicated database table. The *restrictedAreaStartXX* and *restrictedAreaEndXX* elements are used in order to define the total number of boxes into a workstation. The size of *queueEntServXX* and *queueExitServXX* elements defines the capacity of the intermediate warehouses before and after the workstation respectively. The queuing discipline for bringing the right box to be processed from the conveyor (i.e. *queueEntServXX*) is priority-based. If a single box can be processed on the same workstation more than once, in fact, priority has to be given to boxes that have already been processed on the workstation. The *dropoffServXX* and *pickServXX* elements replicate the activities of unloading and loading of shoes done by the workers in each workstation. The *queueInShoesServXX* element defines the maximum number of shoes that can be unloaded from the boxes and release on the worker table. The *seizeXX* and *releaseXX* elements assign a specific worker to the workstation, choosing between the ones enabled from database to that workstation and according to their availability. Once the worker has been assigned, he will not be released until shoes in the *queueInShoesServXX* are completely worked, to manage workers assigned to more than one workstation. The *queueEntServXX* differs from the *queueInShoesServXX* because, while several boxes can be processed into the first buffer by different workers, once shoes have been removed from boxes and released on the worker table they will be processed by himself. To reflect the company’s aim to implement a one-piece-flow strategy, the *queueEntServXX* buffer has been set to 1, while the *queueInShoesServXX* equals to the parameter related the number of shoes placed within a generic box.

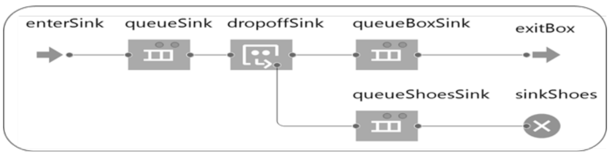

Figure 5: Sink and recycle workflow

Once the production cycle has ended, boxes enter the last building block (i.e. Figure 5), where shoes are unloaded from boxes and destroyed by the *sinkShoes* element. Boxes are moved to the *queueSourceBox* element through the *exitBox*, waiting to be filled with new shoes (i.e. Figure 3).

The Results

Starting from the described scenario, the database has been filled and imported on the simulator, according to the production plan given as input, as well as the assignment of resources to tasks hypothesised by the company that includes 36 workers and 55 workstations. A single run of 12 months with 12 replications has been carried out and the first 15 days represent the warm-up period. Microsoft PowerBI® has then been used to graphically report and navigate that results. For the analysed company, the main KPI to be monitored is productivity, with a target value to be reached of 165 pairs of shoes, mixed as 110 pairs of SKU type “1” and 55 pairs of SKU type “2”. Reaching that target value has been the first objective for the company for implementing simulation, to both analyse if that productivity will be got and if possible bottlenecks could be identified in advance. The model running reached the daily target of 165 pairs of shoes, but 5 workstations showed an average queue size of more than 10 boxes, identified by the company as limit value. 2 workers operates on the critical workstations (i.e. the first worker on two workstations and the second on other three), showing each of them a saturation slightly less than 100%. According to this, the second scenario asked by the company aims to identify how many resources should be added to decrease the average queue size under the limit value. For example, new workers could be assigned to different tasks previously associated to other workers and even to different workstations. In the case study, the tasks associated to the almost saturated workers w1 and w2 have been partially re-assigned to a new resource (i.e. w37). Even if w37 did not reached a high saturation, the new configuration does not represent a suboptimal solution, because it better fits with the company need of resources able to absorb the frequent request of extra-capacity to match the high variable demand. Once the best balancing has been identified for the analysed production mix, the company asks for a quick re-building of the simulation model after changing the SKUs to be produced. In fact, the change of production mix for the analysed footwear company occurs every 4-5 weeks with a very short notice from the brand owners, requiring a re-balancing of the production line that should cover 3 days at most. The main issue the company has faced with is that, even re-balancing in advance, the first week of production for the new SKUs mix is usually spent to understand the reasons of disruptions physically detected on the production line. According to this, the expected results from using simulation have been the reduction of wrong re-balancing for changes in production mix and, consequently, a reactive re-assignment of resources to guarantee the productivity target. In the case study, instead of the two SKUs included in the first model runs, the change mix had replaced one of them with another SKU. The first run of simulation has been done re-building the data-driven model with the same number of workers and workstations, updating only database values related to SKU types and production cycles. The database views show a productivity of 157 pairs of shoes, 8 less than the target. Due to queue trends and saturation of two workers close to 100%, some of the processed tasks have been re-assigned to the under-saturated worker added in the last scenario. Once the data have been updated and the simulation model run, the productivity indicator reaches the target value. Finally, the last scenario analysed by the company refers to how to readapt the production line to double the productivity. The approach followed has been, first, doubling the number of workers assigned to each task, processing each one the 50% of the production. According to the iterative procedure showed in Figure 1, once the data-driven model had been run with the updated production plan and resource assignment as input, the final user has analysed the results in terms of production performance. As expected, the productivity target has been reached doubling the involved resources. Many improvements could be introduced to optimize the resources balancing, due to the high undersaturation of many workers. The iterative tasks re-assignment and KPIs evaluation procedure has been conducted allocating tasks splitted to several resources to few ones, until the optimal configuration of resources to guarantee the productivity target has been identified. The application of that procedure reduces the number of workers. from 74 to 53.

CONCLUSION

The present work demonstrate the successful application of the proposed data-driven simulation model to a HVLV real context. The case study has demonstrated how an iterative approach to data-driven simulation can support companies in decision-making process towards production performance improvement. More in details, this work demonstrates how the limitations of traditional simulation modelling into a dynamic environment can be overcome, reducing the time needed to find the optimal solution in terms of association workstation-tasks, number of workstations and number of workers. Beside this, further developments can be identified starting from the main results listed above. On the one hand, a data-driven approach to the 2D and 3D modelling can be included in the proposed model to assess other KPIs, such as layout optimization to minimize workers' movement along the production line. On the other hand, manual updates on database parameters after each iteration represent a key value for reaching simulation benefits by low-tech users but could not fit more structured companies. According to this, the proposed data-driven model can be extended towards new trends, such as running optimization algorithms within the simulation model or introducing Industry 4.0 technologies like Artificial Intelligence to improve performance and reduce computational time.

REFERENCES

Adrodegari, F., Bacchetti A., Pinto R., Pirola F., Zanardini M. 2015. "Engineer-to-order (ETO) production planning and control: An empirical framework for machinery-building companies". *Production Planning and Control* 26(11), 910–932.

Cransberg, V., Land M., Hicks C., Stevenson M. 2016. "Handling the complexities of real-life job shops when implementing workload control: A decision framework and case study". *International Journal of Production Research* 54(4), 1094–1109.

d'Avolio, E., Bandinelli, R., Rinaldi, R. 2016. "How product development can be improved in fast fashion industry: An Italian case". *IFIP Advances in Information and Communication Technology* 467, 718–728.

Fani, V., Bandinelli, R., Rinaldi, R.. 2017. "Optimizing production allocation with simulation in the fashion industry: A multi-company case study". In *Proceedings of the 2017 Winter Simulation Conference (Las Vegas, Nevada)* 3917–3927.

Fani, V., Bindi, B., Bandinelli, R., Rinaldi, R.. 2018. "Optimizing production performances with simulation: A case study in the fashion industry". In *Proceedings of the XXIII Summer School Francesco Turco (Palermo, Italy)*. 200–205.

Fernandes, N.O., Land, M.J., Carmo-Silva, S. 2014. "Workload control in unbalanced job shops". *International Journal of Production Research* 52(3), 679–690.

Fernandes, N.O., Thürer, M., Pinho, T.M., Torres, P., Carmo-Silva, S. 2020. "Workload control and optimised order release: an assessment by simulation". *International Journal of Production Research* 58(10), 3180-3193.

Goodall, P., Sharpe, R., West, A. 2019. "A data-driven simulation to support remanufacturing operations". *Computers in Industry* 105, 48–60.

Haider, A. and Mirza, J. 2015. "An implementation of lean scheduling in a job shop environment". *Advances in Production Engineering & Management* 10(1), 5–17.

Hassan, M.M., Kalamraju, S.P., Dangeti, S., Pudipeddi, S., and Williams, E.J. 2019. "Simulation Improves Efficiency and Quality in Shoe Manufacturing". In *Proceedings of the 31st European Modelling and Simulation Symposium* 231–236.

Hendry, L., Huang, Y. and Stevenson, M. 2013. "Workload control: Successful implementation taking a contingency-based view of production planning and control". *International Journal of Operations and Production Management* 33(1), 69–103.

Huang, H. and Irani, S. 2003. "An enhanced systematic layout planning process for high-variety low-volume (HVLV) manufacturing facilities". In *Proceeding of the 17th International Conference on Production Research*.

Katic, M. and Agarwal, R. 2018. "The Flexibility Paradox: Achieving Ambidexterity in High-Variety, Low-Volume Manufacturing". *Global Journal of Flexible Systems Management* 19(s1), 69–86.

Portioli-Staudacher, A. and Tantardini, M. 2012. "Lean implementation in non-repetitive companies: a survey and analysis". *International Journal of Services and Operations Management* 11(4), 385–406.

Slomp, J., Bokhorst, J.A.C., and Germs, R. 2009. "A lean production control system for high-variety/low-volume environments: a case study implementation". *Production Planning and Control* 20(7), 586–595.

Thomassen, M. K. and Alfnes, E. 2017. "Managing Complexity". In *Proceedings of the 8th World Conference on Mass Customization, Personalization, and Co-Creation (Montreal, Canada)*.

Wang, J., Chang, Q., Xiao G., Wang N., Li S. 2011. "Data driven production modeling and simulation of complex automobile general assembly plant". *Computers in Industry* 62(7), 765–775.

White, R. E. and Prybutok, V. 2001. "The relationship between JIT practices and type of production system". *Omega* 29(2), 113–124.

Zhang, L., Zhou, L., Ren, L., Laili, Y. 2019. "Modeling and simulation in intelligent manufacturing". *Computers in Industry* 112, 103123.