*33rd European Modeling & Simulation Symposium*
18th International Multidisciplinary Modeling & Simulation Multiconference

2724-0029 © 2021 The Authors.
doi: xx.xxxx/xxxx

# Flexible Simulation for Manufacturing & Supply Chain Management

Agostino G. Bruzzone[1,*], Marcello Braglia[2], Marco Frosolini[2], Marina Massei[1], Kirill Sinelshchikov[3], Roberto Ferrari[3], Luca Padellini[2], Marina Cardelli[1]

[2] Simulation Team, SIM4Future, via Trento 43, 16145 Genova, Italy

[2] University of Pisa, Via Diotisalvi, 2, 56122 Pisa PI, Italy

[3] Simulation Team, Genova, Italy

[*]Corresponding author. Email address: agostino.bruzzone@simulationteam.com

## Abstract

Optimization of production processes is essential for competitiveness in industry and nowadays this activity can benefit from datasets combined with simulation based solutions. In this study the authors propose application of this approach to the field of shoe production chain, with particular attention to improvement of coordination among its participants.

**Keywords:** Supply Chain, Simulation, Logistics, Fashion Industry

## 1. Introduction

Introduction of innovative solutions and relative optimizations and improvements are key factors of success or even of survival in industry. Despite this fact, in various fields adoption of new technologies and methodologies is very limited. In some cases, it is caused by nature of operations, for example it could happen when an industry can't be fully automated, such as in the case of craftsmanship, but happens sometimes, also due to personal perception and preferences of decision makers. Indeed, some small and especially family-based activities try to continue operation in familiar way, until it is possible. In any case, at some point a production chain becomes poorly competitive, which puts relative decision maker in search for possible solutions, which could consist of adoption of innovative techniques for production or for governance of the process itself (Bruzzone et al., 2020a; Bruzzone & Longo, 2013a). Indeed, while in some cases it could be possible to automate, at least partially, production line, in others, main benefit would be provided by reshaping or modification of the production logic itself (Siemieniak, 2004; Masood, 2006); in such case the operation is not limited to a particular process but includes different aspects, which could be also interaction with suppliers and clients. In such case the improvement could be in cut of time required to supply materials, optimization of transportation costs, reduction of idle goods in the warehouse. However, results of such optimization could be difficult to assess due to complex nature of interactions. Indeed, an industrial process which involves multiple independent participants characterized by different policies, regulation and specific work-related characteristics, makes its behavior similar to that one of System of Systems (SoS) with consequent difficulties in prediction of result of specific interventions (Bruzzone et al., 2011; 2007).

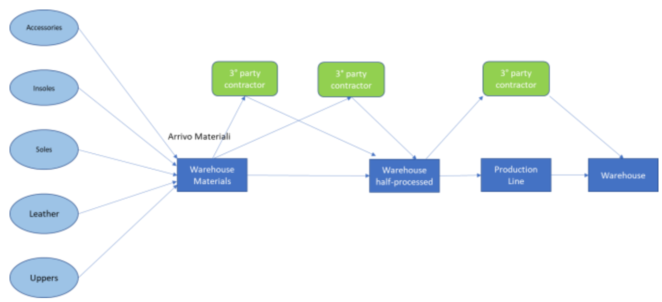


**Figure 1.** Shoe production chain

To address such issue, it is possible to build a simulation model capable to reproduce different aspects of entire production process,

© 2021 The Authors. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY-NC-ND) license (https://creativecommons.org/licenses/by-nc-nd/4.0/).

with the goal to be able to perform experimentation on the simulator, hence, to find optimal or near optimal solution, identify required resources and check for potential pitfalls (Jimeneze et al., 2012). Indeed, based on analysis of years of production-related data it could be possible to identify such parameters of participants as average and median lead time, typical deviation in delivery time etc.

Hence, utilization of this information could be used to create also a Monte Carlo simulation and to obtain not only most probable results for chosen configurations, but its statistical distribution, making possible even risk assessment of proposed changes (Raychaudhuri, 2008; Longo 2011). Indeed, this approach is nowadays used in variety industrial fields (Lamas-Rodríguez et al., 2020a). One of possible fields of application of this approach is related to the production chain of shoes, which is typically composed from different suppliers of materials, third-party manufacturers responsible for specific parts of the preparation as well as principal production site in which the final product is assembled and tested (Hassan et al., 2019). At the same time, available data could be used to feed machine learning algorithm in order to have even better estimation of outcome (Bruzzone et al., 2020b; 2019b).

## 2. Case Study

In order to illustrate possibility of optimization the authors analyzed case study related to the shoe production chain, presented in the figure 1. As it is possible to observe from the scheme, the scenario is characterized by the presence of several suppliers of material and parts (e.g. leather, insoles), sub-contractors responsible for elaboration of some of the materials and parts, principal production facility, in which the final product is assembled and stored as well as final clients which trigger entire manufacturing process. The process of interest starts from receiving of pre-orders from the clients, consequent placement of orders to material suppliers, receiving of materials with consequent control, redistribution of some of the materials among the sub-contractors for specific processing and finally assembly and quality control in the production site. From this point it is evident importance of proper interaction among all participants; indeed, delay in supply of a single component puts at risk delivery of entire lot to a client. Furthermore, number of interactions introduces uncertainty in time which passes between acceptance of order to the client and shipment of the ready product (Koh & Saad, 2006). In fact, in this particular case of interest one of the main objectives is related to reduction of production time while maintaining at required level other performance indicators. From this point, it is evident benefit of introduction of simulation-based decision support tool, capable to evaluate different strategies of acquisition of materials, distribution of orders and subcontracting. Indeed, similar solutions are very diffused nowadays and employed in different fields, starting from logistics and up to crisis management in critical infrastructures (Bruzzone et al., 2019a; 2017; Lamas-Rodríguez et al., 2020b).

## 3. Criticalities

The proposed case study involves some criticalities that require simulation to be properly addressed. One criticality is related to the transversal constraints related to the capabilities of leather producers (Braglia et al., 2020). Indeed, these suppliers are used to serve major corporation and are almost saturated by the existing demand, as result the orders arriving from medium size enterprises are added to the stack, but often are overpassed by other requests arriving from big players. Even the minimum quantity to order, considering the necessity to don't fall in very low priority group, are a constraint for small, medium size producers (Ball et al., 2002; Lorentz et al., 2013); these two factors combined together could delay the emission of the orders to the moment a sufficient cumulative request is ready, but in this way the orders are transmitted pretty late and there is an high probability that any new request by high priority customers could generate critical delays. The problem of leather supply is not easy to be addressed and should require to better understand the needs and opportunities using simulation to investigate alternatives over different scenarios. Another interesting way to mitigate this problem is to create combined orders among different SME (Small, Medium Size Enterprises) involved in shoes production. Indeed, by this approach it could be possible to obtain better positioning in terms of priority and service from leather producers (Ivanov, 2018). Another criticality existing in this context is due to the demand estimation, indeed in fashion industry there is usually not available history on previous demand of products, considering that they change in the new seasons. The lack of historical data on the demand of a new model of shoes, by the way almost all are new each season, don't allow to generate reliable forecasts by traditional approaches. In this case it is necessary to move up to the definition of new entities for the forecasts that could correspond to meta-items and that aggregate data of previous years of different models characterized by similar characteristics.

This issue is not trivial at all, because the aggregation characteristics have different nature dealing with different aspects that need to be considered and that involve the creation of multiple criteria for the aggregation to be recombined for the demand estimation. For instance, in the case of the shoes the aggregation criteria could at least include:

- Style (e.g. elegant high heels)
- Color (e.g. black, green, brown)
- Attributes (e.g. buckles, green highlights)
- Price Sector (e.g. low, medium, high)
- Distribution Channel (e.g. Speciality Stores, Internet)
- Target Type (e.g. teenagers, yoing adults, mature)
- Country Market (e.g. Italy, France, Europe, Japan)

This approach has been used in past to predict sales on specific channels for fashion leader by the authors and nowadays could be renewed by adopting Strategic Engineering Concepts (Bruzzone et al., 2009). In facts, by company digitalization it could be possible nowadays to have a continues update over the product lifecycle that could lead to redefine the process including within a Strategic Engineering Perspective (Madenas et al, 2014; Bruzzone et al., 2020a)

Indeed, the combined used of Artificial Intelligence and Data Analytics from these meta-categories could be used to identify the best clustering among the different criteria and to fuse back the estimates on each of them; one approach could be to adopt fuzzy logic to consider the meaning of the index and machine learning to support forecasting (Braglia et al., 2009; Bruzzon et al., 2013b). As soon as the analysis is finalized it turns possible to feed the simulator with proper estimates on demand to identify most promising solutions, while the use of machine learning guarantees the possibility to update continuously the models based on the evolution of the market.

## 4. The Model

Based on provided documentation and analysis of production process the authors developed a conceptual model, which takes into account various operations on different levels of details; the model aims to create a classical discrete event stochastic simulator, but open to be federated with a smart forecasting systems based on modern Strategic Engineering concepts (Law et al, 1987; Field et al., 2007). Indeed, while detailed simulation of internal production line of the principal facility is useful for proper optimization, internal processes of suppliers and sub-contractors are less relevant for the scope of the project, hence, they could be represented as black boxes - single virtual entities characterized by specific set of parameters. In the next figure it is illustrated a preliminary visualization of material exchange in the simulated supply chain.

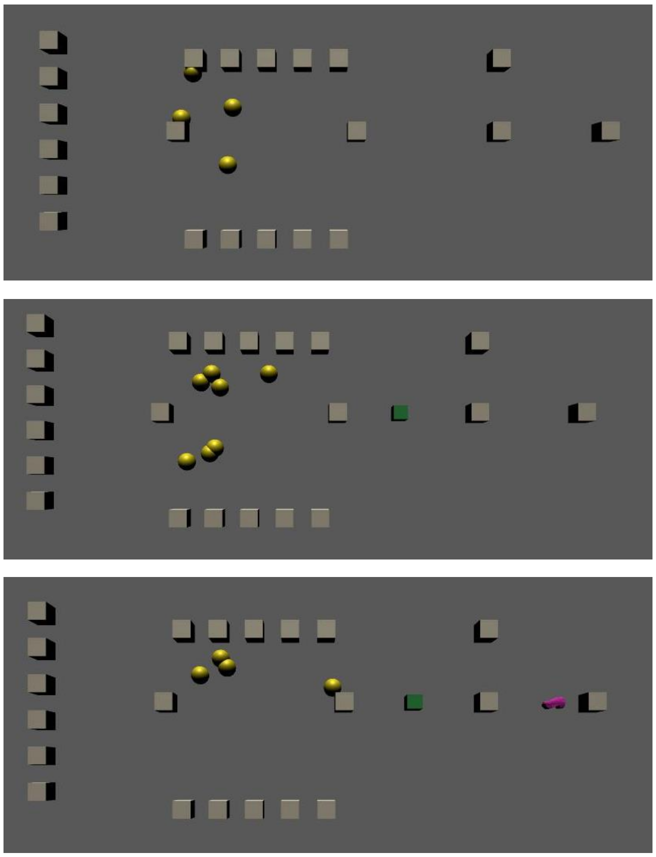

**Figure 2.** Production process in virtual environment

In the figure it is possible to see how the preprocessed materials (yellow) are distributed from corresponding warehouse to the 3rd party contractors (top image), kit for assembly of shoes (green) is sent in the production (middle image) and the finally assembled pair of shoes (violet) goes to the warehouse of ready products (bottom image).

The simulator could be adapted to be agent driven in case more sophisticate cooperative scenarios among multiple SME will be investigated (Caridi et al.,2005, Long 2016; Zhou et al., 2019)

During the execution, the program first analyzes data related to past production processes, taking care of identification of parameters of distribution of production time for single suppliers as well as for distinct categories of them. At this point the software is capable to predict behavior of the system under different boundary conditions, effectively allowing experimentation on the model. The simulator is implemented within Unity 3D environment by using C# and reuse Simulation Team Libraries for manufacturing. The major advantage to use this solution, is the possibility to support virtual simulation within an immersive environments also for other future purposes (Paul et al.,2019).

The Simulation is currently in development phase, while preliminary verification of the model is conducted with the subject matter experts.

At this step of development, the simulator is capable to analyze input files, create virtual representation of the supply chain with all its participants and simulate production process.

## 5. Conclusions

Optimization of production processes is one of keys to competitiveness and nowadays this activity could be significantly speed up and simplified thanks to utilization of simulation and data analysis solutions. Indeed, based on available datasets it is possible to construct specific models and to perform experimentation on them, reducing cost and time of this critical activity.

In this research the authors are focused their attention on development of the framework for supply chain optimization with particular interest to the case study of shoe production. The project is in active development phase; indeed, while the algorithm is mostly complete and passed preliminary testing, finalization of the user interface is ongoing.

## References


Ball, M. O., Ma, M., Raschid, L., & Zhao, Z. (2002). Supply chain infrastructures: system integration and information sharing. ACM Sigmod Record, 31(1), 61-66.

Braglia, M., Marrazzini, L., Padellini, L., & Rinaldi, R. (2020). Managerial and Industry 4.0 solutions for fashion supply chains. Journal of Fashion Marketing and Management: An International Journal.

Braglia, M., Frosolini, M., & Zammori, F. (2009). Overall equipment effectiveness of a manufacturing line (OEEML): an integrated approach to assess systems performance. Journal of Manufacturing Technology Management.

Bruzzone, A., Massei, M., & Sinelshnkov, K. (2020a). Enabling strategic decisions for the industry of tomorrow. Procedia Manufacturing, 42, 548-553.

Bruzzone, A., Sinelshchikov, K., Massei, M. & Schmidt, W. (2020b). Artificial intelligence to support retail sales optimization. In proceedings of 32 European Modeling & Simulation Symposium, pp. 430-434.

Bruzzone, A., Massei M., Sinelshchikov K., Fadda, P., Fancello, G., Fabbrini G. & Gotelli M. (2019a). Extended reality, intelligent agents and simulation to improve efficiency, safety and security in harbors and port plants. In proceedings of 21st International Conference on Harbor, Maritime and Multimodal Logistics Modeling and Simulation, HMS 2019, pp. 88-91.

Bruzzone, A., Massei., M., Sinelshchikov, K., Fabbrini, G., Gotelli, M. & Molinari, A. (2019b). Machine learning to support industrial digitalization and business transformation. In proceedings of 31st European Modeling and Simulation Symposium, EMSS 2019, pp. 390-393.

Bruzzone, A., Massei, M., Agresta, M., Sinelshchikov, K. & Di Matteo, R. (2017). Agile solutions & data analytics for logistics providers based on simulation. In proceedings of Conf. on Harbor Maritime and Multimodal Logistics M&S, 2017, pp. 164-171.

Bruzzone, A. & Longo, F. (2013a). An advanced modeling & simulation tool for investigating the behavior of a manufacturing system in the hazelnuts industry sector. International Journal of Food Engineering, 9(3), 241-257.

Bruzzone, A., Longo, F., Nicoletti, L., Chiurco, A., & Bartolucci, C. (2013b, September). Multiple forecasting algorithms for demand forecasting in the fashion industry. In 2013 8th EUROSIM congress on modelling and simulation (pp. 421-426). IEEE.

Bruzzone, A., Fadda, P., Fancello, G., Massei, M., Bocca, E., Tremori, A. & D'Errico, G. (2011). Logistics node simulator as an enabler for supply chain development: innovative portainer simulator as the assessment tool for human factors in port cranes. Simulation, 87(10), pp. 857-874.

Bruzzone, A. G., Bocca, E., Pierfederici, L., & Massei, M. (2009, July). Multilevel forecasting models in manufacturing systems. In Proceedings of the 2009 Summer Computer Simulation Conference (pp. 239-245).

Bruzzone, A. G., Bocca, E., Briano, E. & Poggi, S. (2007). Supply chain management and vulnerability. In Proceedings of the 2007 Summer Computer Simulation Conference, pp. 1080-1085.

Caridi, M., Cigolini*, R., & De Marco, D. (2005). Improving supply-chain collaboration by linking intelligent agents to CPFR. International journal of production research, 43(20), 4191-4218.

Field, F., Kirchain, R., & Roth, R. (2007). Process cost modeling: Strategic engineering and economic evaluation of materials technologies. Jom, 59(10), 21-32.

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

Ivanov, D. (2018). Revealing interfaces of supply chain resilience and sustainability: a simulation study. International Journal of Production Research, 56(10), 3507-3523.

Jiménez, E., Tejeda, A., Pérez, M., Blanco, J., & Martínez, E. (2012). Applicability of lean production with VSM to the Rioja wine sector. International Journal of Production Research, 50(7), 1890-1904.

Koh, S. L., & Saad, S. M. (2006). Managing uncertainty in ERP-controlled manufacturing environments in SMEs. International Journal of Production Economics, 101(1), 109-127.

Lamas-Rodríguez, A., Taracido-López, I. & Pernas-Álvarez, J. (2020a). Discrete Event Simulation for the Investment Analysis of an Offshore Wind Nodes Automatised Workshop.

Lamas-Rodríguez, A., Pernas-Álvarez, J. & Taracido-López, I. (2020b). Discrete event simulation in the design of a jackets nodes robotized welding workshop. In Proceedings of the 2020 Summer Simulation Conference (pp. 1-12).

Law, A. M., & McComas, M. G. (1987, December). Simulation of manufacturing systems. In Proceedings of the 19th conference on Winter simulation (pp. 631-643).

Long, Q. (2016). A multi-methodological collaborative simulation for inter-organizational supply chain networks. Knowledge-Based Systems, 96, 84-95.

Longo, F. (2011). Advances of modeling and simulation in supply chain and industry.

Lorentz, H., Töyli, J., Solakivi, T., & Ojala, L. (2013). Priorities and determinants for supply chain management skills development in manufacturing firms. Supply Chain Management: An International Journal.

Madenas, N., Tiwari, A., Turner, C. J., & Woodward, J. (2014). Information flow in supply chain management: A review across the product lifecycle. CIRP Journal of Manufacturing Science and Technology, 7(4), 335-346.

Masood, S. (2006). Line balancing and simulation of an automated production transfer line. Assembly Automation.

Paul, M., Leiber, D., Pleli, J., & Reinhart, G. (2019, September). Simulation of Reconfigurable Assembly Cells with Unity3D. In IFIP International Conference on Advances in Production Management Systems (pp. 223-230). Springer, Cham.

Raychaudhuri, S. (2008, December). Introduction to monte carlo simulation. In 2008 Winter simulation conference (pp. 91-100). IEEE.

Siemieniak, M. (2004, June). Working time losses in production lines with hybrid automation-case study. In Proceedings of the Fourth International Workshop on Robot Motion and Control (IEEE Cat. No. 04EX891) (pp. 293-297). IEEE.

Zhou, L., Zhang, L., Ren, L., & Wang, J. (2019). Real-time scheduling of cloud manufacturing services based on dynamic data-driven simulation. IEEE Transactions on Industrial Informatics, 15(9), 5042-5051.