Optimizing production performances with simulation: a case study in the fashion Industry

Virginia Fani, Bianca Bindi, Romeo Bandinelli, Rinaldo Rinaldi

Department of Industrial Engineering, University of Florence, Viale Morgagni, 40, 50134, Firenze – Italy (virginia.fani@unifi.it; bianca.bindi@unifi.it; romeo.bandinelli@unifi.it; rinaldo.rinaldi@unifi.it)

Abstract: This paper presents the follow up results of a project related to the development of a decision support tool for improving production performances in the fashion supply chain (SC). In detail, the work presents the application of a discrete-event simulation model on an optimized production plan in order to include stochastic events and manage their effects on the production scheduling KPIs (Key Performance Indicators) in the leather industry. The relevance of this work is related to the fact that one of the main critical issues considering scheduling in the fashion industry is the evidence that suppliers usually have to face with stochastic events, mainly referable to rush orders and delays in the expected delivery of critical components that require to be managed. For this reason, one of the main challenges they have is not trying to avoid the occurrency of these events, which strictly depends on the industry nature, but managing them, in order to understand their impacts on performances and reorganized the production plan. According to this, a dashboard of KPIs represents one of the main results of the developed simulation tool. The model has been applied to a real company, where rush orders and delays in the delivery of critical components are introduced to simulate the impact of stochastics events on the production plan.

Keywords: Discrete Event Simulation, Optimization, Planning, Fashion, Leather, Stochasticity

1.Introduction

As widely recognized in the literature, critical success factors (CSFs) in the innovative industry can be summed up considering the need of delivering the right product in the right quantity in the right place (Caniato et al., 2013). In other words, the "right" concept refers to the evidence that in this industry is not profitable being in the market with the wrong product, in the wrong time and in the wrong place.

Looking at the fashion industry, while choices about what are the "right product" and the "right place" are tasks of the marketing office and depend on market and trends analysis, the ones related to the "right time" depends on the marketing again in terms of target to be gained, but their feasibility are strictly related to the production plan performances. According to this, if challenges in the fashion industry mainly deals with compressing time to market guaranteeing, at the same time, outstanding quality levels of products, even more in a context where product lifecycle has become shorter than the past, the relevance of optimizing production planning and scheduling performances is increasing in the last years.

Moreover, the complexity related to the fashion SC structure and the stochastic events that characterized this industry increases the required efforts.

On the one hand, production of fashion products is usually done by several external suppliers that can be totally or partially dedicated to the brand owner.

On the other hand, stochastic events that characterized this industry have to be managed, due to their high impact on being or not compliant with the requested delivery date. In detail, phenomena such as rush orders reflects the evidence that brand owners usually ask to their suppliers to include in their pre-defined production plans extra-orders with priority. Moreover, also the availability of critical components and the delays in their expected delivery date have to be taken into account, because their criticality reflects the impossibility to process the referred article, interrupting its production and requiring changes on the validated production plan.

The goal of the paper is to validate the usability of a general production planning simulation-optimization model for the fashion supply chain for a labour supplier operating in the leather accessories SC.

This is due to the relevance of this market segment in the Italian scenario and the high criticalities related to the availability of leather for managing production plans. Considering the first point, revenues of the Italian leather industry increased about the 6.4% comparing the results of the first 10 months of the 2017 with the ones of the previous year (http://www.aimpes.it). This is mainly related to the boom of the export abroad of leather goods, with 6.1 billion euros (+14.1% compared to the 2016) and bags, more than others luxury bags, as best-selling category. This result is quite confidentially related to the increased attention that consumers give to the high quality guaranteed by the Made in Italy products, pushing fashion companies to focus their attention on compensating higher processing time, related to the outstanding quality levels to be guaranteed, with the compression of the time to market needed to be competitive on the market. The availability of raw materials, first of all leather, is an important variable in managing production plans. It represents one of the main constraints that has to take into account in the production of leather goods.

2.Model description

2.1 Problem description

According to the high complexity that has to be managed by companies operating in the fashion SC, Production Planning and Control (PP&C) represents a relevant issue that these companies have to face with. Looking at the SC, uncertainty of demand increases moving from upstream to downstream (d'Avolio et al., 2015), making higher the efforts that suppliers have to put for realigning the pre-defined production plan considering the unpredictable events that occur. For example. considering the leather accessories labour suppliers' point of view, the monthly demand plan (i.e. list of requested quantity and delivery date per stock keeping unit – SKU) they receive include the amount of shoes that they have to produce by the month and the date they have to be delivered. Starting from this list, suppliers have to develop their production plan according to their strategical objectives (i.e. mainly related to resource saturation maximization), guaranteeing the compliance to the requested delivery date, that is the main KPIs that brand owners use for evaluating their supply base performances. Due to the fact that suppliers are located downstream along the SC, stochastic events often occur and they should not be managed at that moment because is too late for changing production scheduling guaranteeing, at the same time, the performance levels the brand owners require.

According to this, the proposed model will allow suppliers to conduct a scenario analysis that compares the KPIs (in terms of average advance, delay and resource saturation) related to different scenario that include or not one or more type of stochastic events (i.e. rush orders and/or delays in the expected critical components delivery date). Moreover, the implementation of the proposed model can be replicated considering different occurrency of stochastic events, allowing the comparison among the related impacts and the identification of the critical value for the stochastic events (i.e. the value over which a small increase of occurrency of each combination of them produces a huge decrease of KPIs value).

This model is a part of a general framework for the optimization of the entire supply chain of a single or multiple brand. In that framework, described in Figure 1, the model can be applied to every actor of the supply chain with different object function and parameters. In particular, in this paper the model was applied to a supplier that is part of the first tier level of the supply chain.

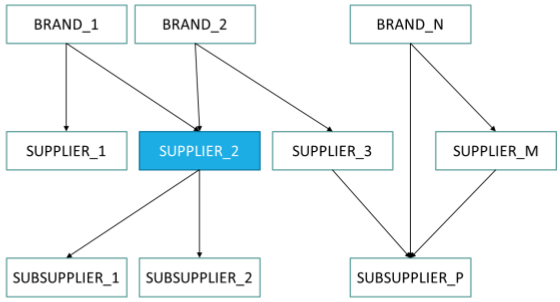

Figure 1: Framework of the optimization simulation model

2.2 Scientific background

The proposed model can be classified as PP&C optimization of a multi-level SC, composed by several small companies (mostly Small Medium Enterprises - SMEs) coordinated by a big company (which usually is the brand owner in the fashion industry), has been widely discussed in the literature from different points of view. A state of the art of models applied in the fashion industry can be found in Fani et al. (2017a). The more relevant work in this industry can be summarized in (Al-Zubaidi et al., 2004; Jung et al., 2004; Betrand and Van Onijen, 2008; Hu et al. 2013; Wong et al. 2014, Ait-Alla et al. 2014; Guo et al. 2015).

Ait-Alla et al. (2014) presented a mathematical model for production planning. The presented model can help the fashion suppliers in making decision considering the order allocations on different production plants and in the correct time scheduling and sequencing of these production orders. The model was applied to a case study represented by a fashion apparel supplier.

Guo et al. (2015) and Wong et al. (2014) studied some of the most important needs of the manufacturing companies. One of the most important needs is how to improve production visibility and decision making performance by implementing effective production monitoring and scheduling through the introduction of the RFId (Radio Frequency Identification) technology. Guo et al. (2015) presented a study of a medium-sized clothing manufacturer producing casual wear and sportswear. Wong et al. (2014) collected experimental data from a Chinese labour-intensive manufacturing company producing knitwear.

Rose and Shier (2007) investigated a particular cut scheduling problem that arises in the apparel industry. These authors presented two different integer-programming models, the *two-stage approach*, using a mixed integer linear program in order to optimize the processes of cutting and packaging.

Regarding the Objective Functions (OF) cost minimization was the main objective of the reviewed paper, despite several authors consider multi-objective production planning problem in the manufacturing industry, not only in the fashion segment (Ait-Alla et al., 2014; Hu et al., 2013) but also in all other sectors (Betrand and Van Onijen, 2008; Wong et al., 2014; Wu et al., 2011). In the reviewed works it was possible to find several OFs moving from minimize the production costs (Ait-Alla et al., 2014), the total setup, inventory and backorder costs (Rahmani et al., 2013), the hiring and layoff costs associated with the change of workforce level (Rahmani et al., 2013), the throughput and the idle time (Guo et al., 2015; Wong et al., 2014), and the tardiness (Ait-Alla et al., 2014; Betrand and Van Onijen, 2008; Guo et al., 2015; Wong et al., 2014).

By evaluating the industrial problems, the co-existence of multiple optimization objectives (Wong et al., 2014) is quite common. If we considered models with a multiple OFs (i.e. multi-objectives scheduling problems), these were often solved by translating all the OFs into a common terms (monetary terms), thus defining a total cost that need to be minimized. For example, in Ait-Alla et al. (2014) time measures (advances and delays) were translated in penalty costs that companies have to sustain. Instead Guo et al. (2008) used weighted sum method to turn multi-objective problems to single-objective ones.

In authors' opinion, the main limitation of all of these models is represented by the fact that all of them consider the optimization of a single level of the SC, using as input the production plan received from the upper lever and producing the scheduling and the delivery plan for the lower level of the SC. The proposed model tries to overcome this limitation proposing a framework and an architecture that can be applied to an entire SC (Fani et al., 2018).

2.3 Model Description

The proposed simulation model has been developed starting from the works of Fani et al. (2016), Fani et al. (2017) and Fani et al. (2018).

In detail, the production plan used as input for running the simulation model results from the application of the optimization model developed and tested for a metal accessories supplier by Fani et al. (2016), for a single supplier in the footwear industry by Fani et al. (2017) and for a part of footwear SC in Fani et al. (2018).

More information about the model and how the objectives have been evaluated can be found in the work of Fani et al. (2016), while the peculiarities taken into account for readapting the model parameters to a leather footwear suppliers in the one of Fani et al. (2017).

One of the follow up of this work is that it includes also the analysis of the impact that delays in the expected critical components delivery date have on KPIs value and the combined impact considering rush orders too. Moreover, the hypothetical scenario analysis allowed by the application of the proposed simulation model includes also the comparison between the KPIs value calculated considering the optimized solution as input of the model instead of the application of an earliest due date (EDD) approach when delays in the expected critical components delivery date occur.

Finally, for allowing the conduction of a scenario analysis the following KPIs have been included as output of the simulation model implementation: (i) average advances in production; (ii) average delays in production; (iii) average resource saturation. While the first two mainly refer to the CSFs for the brand owners, representing two of the main parameters (the second more than the first one) that the brand owners uses during the suppliers' selection, the third one is a KPI measured only by the supplier.

2.4 Model Architecture

The model architecture reflects the one proposed in the work of Fani et al. (2017), composed of the Java discrete-event simulator AnyLogic® (www.anylogic.com) and OpenSolver (www.opensolver.org) as the open solver optimization tool. The version of AnyLogic that has been used is the 8.2.3, and the version of the Solver is the 2.8.6. The solver has been used integrated on Microsoft Excel®.

The procedure to be follow includes these steps: (i) the implementation of the optimization model on the production plan, using OpenSolver; (ii) its import in the simulation model developed on AnyLogic; (iii) the conduction of more than one run of the simulation model that include or not stochastic events (i.e. rush orders and/or delays in the expected critical components delivery date); (iv) the comparison between the KPIs collected as model output with the identification of the critical value for the stochastic events.

3.Case Study

3.1 Model Implementation

The developed model has been applied into a real case study considering the production plan of a month of a labour supplier operating in an Italian leather accessories SC. The production plan derives from multiple brands' production orders. The model has been applied considering the assembling phase as the critical one, followed by a finishing one. Within raw materials, the leather has been considered the critical component of the production process. This way, a stochastic representation of its delay has been introduced in the simulation model. The adopted statistical distribution is the normal one. Moreover, due to the characteristics of this industry, rush orders have been considered in the simulation model according to a uniform statistical distribution.

The optimized production plan is the one considered in the work of Fani et al. (2017b), where the SKUs delivery dates are all compliant with the expected critical components delivery dates (considering a deterministic scenario). The SKUs to be produced are bags with different dimension and complexity, clustered into three different product categories (i.e. easy, medium and difficult). The model includes three assembly lines on which a pool of operators per shift works 8 hours per day, for a total capacity of 24 hours per day per workstation (i.e. 3 shift per day).

A gap analysis has been conducted for comparing the 8 scenarios described in Table 1.

Table 1: Scenario Analysis

	Optimization algorithm		Stochastic events included		
	MOF*	EDD	None	RO**	DCC***
Scenario					

0	X		X		
1	X			X	
2	X				X
3	X			X	X
4		X	X		
5		X		X	
6		X			X
7		X		X	X

* Multi-Objectives Function; ** Rush Orders; *** Delays in Critical Components

The scenario '0' refers to the application of the optimization model used by Fani et al. (2018) as input for the simulation model under deterministic condition (i.e. no rush orders, no delays in the critical components delivery dates).

The first scenario as the same optimized production plan of the scenario '0' as input, but includes only rush orders as stochastic events, while the second scenario includes only delays in the critical components delivery dates and the third one both of them.

The last four scenarios (i.e. from 4 to 7) reflect the previous ones using the EDD optimization algorithm instead of the one used by Fani et al. (2018).

4.Results

The KPIs used for comparing the analysed scenarios are the following: (i) max advances in production; (i) average advances in production; (iii) max delays in production; (iv) average delays in production; (v) sum of average advances and delays in production; (vi) absolute sum of average advances and delays in production.

Table 2, Table 3 and Table 4 sum up the KPIs dashboard for a significant subset of the analysed scenarios.

The first set of results have been evaluated using a production plan taken from the historical data of the suppliers, where the three assembly lines were saturated respectively for the 100%, 100% and 97%.

The production plan is composed by 1914 items, grouped into 110 production orders. The production phase scheduled with a finite capacity is the assembly one. Every assembly line has been considered to have the same production time and the items were divided into three different groups, due to their complexity. The easy bag has a production time of 45 minutes, while the medium 90 minutes and the difficult 120 minutes. The finishing phase has been considered equal for all the items.

As stochastics values, rush orders has been assumed at the 10% of the items of the production plan, and an average value of 6, once order per week. Critical components delays have been assumed with a value of more than two days for the 50% of the total items, with an average of 1.5 days. These values have been assumed using and analyzing the historical data of several suppliers working in this industry with the support of production managers and planner of leather accessories suppliers. In details, rush orders are due to samples and rework of previous orders, while delays of the critical component leather are mainly due to non-compliance at the quality control before entering the supplier.

Table 2: KPIs Dashboard for scenario 1 and 5

KPI/Scenario	MOF/RO	EDD/RO
Max advance[1]	0	-26
Average advance[1]	0	-1.87
Max delay[2]	28	8
Average delay[2]	3.45	1.76
Avg sum of adv and delay[3]	3.45	-0.11
Abs avg sum adv - delay[3]	3.45	3.63

[1][# days per advanced items]; [2][# days per delayed items] ; [3][# days per items]

Table 3: KPIs Dashboard for scenario 2 and 6

KPI/Scenario	MOF/DCC	EDD/DCC
Max advance[1]	0	-26
Average advance[1]	0	-1.29
Max delay[2]	8	12
Average delay[2]	2.89	2.67
Avg sum of adv and delay[3]	2.89	2.51
Abs avg sum adv - delay[3]	2.89	5.09

[1][# days per advanced items]; [2][# days per delayed items] ; [3][# days per items]

Table 4: KPIs Dashboard for scenario 3 and 7

KPI/Scenario	MOF/RO/DCC	EDD/RO/DCC
Max advance[1]	0	-25
Average advance[1]	0	-4.47
Max delay[2]	30	13
Average delay[2]	8.51	4.41
Avg sum of adv and delay[3]	8.51	0.06
Abs avg sum adv - delay[3]	8.51	8.88

[1][# days per advanced items]; [2][# days per delayed items] ; [3][# days per items]

Analyzing the results, it is possible to observe that, with the data used in this scenario, rush orders and critical components delays have different effects on the selected KPIs. Even if the EDD rule, as confirmed by the theory, minimize the orders delays in every scenarios, this effect is more relevant with the introduction of the rush orders than with the delay of the critical component. Whilst in scenario 1 and 5 the absolute average sum of advances and delay are almost equivalent, in scenario 1 the maximum number of days of delay is three times higher than in scenario 5 and the average delay is more than twice. On the other hand, analyzing scenario 2 and 6, is it possible to observe that the average delays are almost equivalent, while the absolute average sum of advances and delays in scenario 2 are the 56% of the scenario 6.

The comparison between scenario 3 and 7 shows the effects of both rush orders and critical components delay. With the data used in the simulation campaign, the results shows that the maximum delay with the multi objective function is higher 2.5 times than with the EDD rules and the average delays are the 300% higher. On the other hand, the absolute average sum of the advances and delays of the scenario 3 are the almost equivalent to the scenario 7.

From an industrial point of view, these results demonstrate that, with the data used in the simulation scenario, the KPIs obtained with the production scheduling obtained using the multi objective function used in a real context are lower than the traditional EDD rule. This effect is mainly due to the presence of rush orders, while EDD would be less performing in a real environment with the presence of stochastics events only due to the delay of the critical component.

In order to generalize these results, the analysed scenario have been changed decreasing and increasing the percentage of rush orders (both the frequency than the number of items per order), collecting the results with both MOF than EDD scheduling rules. Table 5 and Table 6 shoes the results of these simulation runs.

Table 5: KPIs Dashboard with MOF, RO and DCC

MOF	%RO	RO FR[1]	RO AVG[2]	MAX DELAY	ABS AVG DELAY
#0	10%	1	6	30	8.51
#1	5%	1	3	29	8.63
#2	20%	2	6	30	8.41
#3	10%	2	3	30	8.07
#4	30%	3	6	31	8.20
#5	15%	3	3	30	8.23

[1][# rush order per week]; [2][# of items per rush order]

Table 6: KPIs Dashboard with EDD, RO and DCC

EDD	%RO	RO FR[1]	RO AVG[2]	MAX DELAY	ABS AVG DELAY
#0	10%	1	6	13	8.88
#1	5%	1	3	12	8.72
#2	20%	2	6	12	8.80
#3	10%	2	3	13	8.60
#4	30%	3	6	13	8.80
#5	15%	3	3	12	8.66

[1][# rush order per week]; [2][# of items per rush order]

The number of items per rush order have been decreased in (#1, #3#, #5), while the rush order frequency has been increased in (#2, #4). As it is possible to observe from the results, even if a statistical analysis has not been conducted, the relation between the KPIs and the scheduling rules (MOF and EDD) is not influenced by rush order frequency and quantity.

5.Conclusion

This paper presents the results of an ongoing project related to the development of a decision support tool for improving production performances in the fashion SC. In detail, the work presents the application of a discrete-event simulation model on an optimized production plan in order to include stochastic events and manage their effects on the production scheduling KPIs in the leather industry. Regardless the numeric results of the case study, the main contribution of the paper is to validate the usability of a general production planning simulation-optimization model in a specific context, composed by a supplier operating in the leather accessories SC, where the stochastic events are represented by the rush orders and the delays of the expected critical components delivery date. The expected critical component, in this specific supply chain, has been represented by the leather raw material. The delay, that is very frequent, can be due mainly to two different events, the quality control of the raw material by the brand and unexpected delay in the production process of the raw material supplier.

Going into the values of the case study, results show that the simulation-optimization model, compared with a traditional EDD rule, guarantee higher KPI performances when the production plan is altered only by critical components delay, while the EDD rule result more performing with the presence of rush order.

Further steps of this work will be the application of the simulation-optimization model with a more complex leather Supply Chain composed by both brands than suppliers, with historical data coming from fashion companies, in order to validate the strength of the model.

References

Ait-Alla, A., Teucke, M., Lütjen, M., Beheshti-Kashi, S. and Karimi, H. R. (2014). Robust production planning in fashion apparel industry under demand uncertainty via conditional value at risk. *Mathematical Problems in Engineering,* 2014(2014), 1–10.

Al-Zubaidi, H. and Tyler, D. (2004). A simulation model of quick response replenishment of seasonal clothing. *International Journal of Retail & Distribution Management*, 32(6), 320–327.

Bertrand, J.W.M., Van Ooijen, H.P.G. (2008). Optimal work order release for make-to-order job shops with customer order lead-time costs, tardiness costs and work-in-process costs. *International Journal of Production Economics*, 116(2), 233–241.

Caniato, F., Caridi, M. and Moretto, A. (2013). Dynamic capabilities for fashion-luxury supply chain innovation. *International Journal of Retail & Distribution Management*, 41(11/12), 940–960.

d'Avolio, E., Bandinelli, R., Pero, M. Rinaldi, R. (2015). Exploring replenishment in the luxury fashion Italian firms: evidence from case studies. *International Journal of Retail and Distribution Management* , 43(10-11), 967-987 .

Fani, V., Bandinelli, R., Rinaldi, R. (2016). Toward a scheduling model for the metal accessories' suppliers for the fashion industry. *Proceedings of the Summer School Francesco Turco*, 13-15-September-2016, pp. 166-170.

Fani, V., Bandinelli, R., Rinaldi, R. (2017). A simulation optimization tool for the metal accessory suppliers in the fashion industry: A case study. *Proceedings - 31st European Conference on Modelling and Simulation*, ECMS 2017, 23-26 May 2017; pp. 240-246.

Fani, V., Bandinelli, R., Rinaldi, R. (2018). Optimizing production allocation with simulation in the fashion industry: a multi-company case study. *Proceedings - Winter Simulation Conference*, Part F134102, pp. 3917-3927.

Guo, Z. X., Ngai, E.W.T., Can, Y., Xuedong, L. (2015). An RFID-based intelligent decision support system architecture for production monitoring and scheduling in a distributed manufacturing environment. *International Journal of Production Economics*, 159, 16–28.

Guo, Z.X., Wong, W.K., Leung, S.Y.S., Fan, J.T., Chan, S.F. (2008). A genetic-algorithm-based optimization model for solving the flexible assembly line balancing problem with work sharing and workstation revisiting. *IEEE Transactions on Systems, Man and Cybernetics Part C - Applications and Reviews*, 38(2), 218–228.

Jung J. Y., Blau G., Pekny J. F., Reklaitis G. V., Eversdyk D. (2004). A simulation based optimization approach to supply chain management under demand uncertainty. *Computers & Chemical Engineering*, 28(10), 2087–2106.

May, G., Stahl, B., Taisch, M., Prabhu, V. (2015). Multi-objective genetic algorithm for energy-efficient job shop scheduling. *International Journal of Production Research*, 2015, 1–19.

Méndez, C. A., Cerdá, J., Grossmann, I. E., Harjunkoski, I., & Fahl, M. (2006). State-of-the-art review of optimization methods for short-term scheduling of batch processes. *Computers & Chemical Engineering*, 30(2006), 913–946.

Phanden, R. K., Jain, A., Verma, R. (2011). Integration of process planning and scheduling: a state-of-the-art review. *International Journal of Computer Integrated Manufacturing*, 24(6), 517–534.

Rahmani, D., Ramezanian, R., Fattahi, P., Heydari, M. (2013). A robust optimization model for multi-product two-stage capacitated production planning under uncertainty. *Applied Mathematical Modelling*, 37(2013), 8957–8971.

Ribas, I., Leisten, R., Framinan, J. M. (2010). Review and classification of hybrid flow shop scheduling problems from a production system and a solutions procedure perspective. *Computers & Operations Research*, 37(8), 1439–1454.

Rose, M. D., Shier, R. D. (2007). Cut scheduling in the apparel industry. *Computers & Operations Research* 34(11), 3209–3228.

Wong, W. K., Guo, Z. X., Leung, S. Y. S. (2014). Intelligent multi-objective decision-making model with RFID technology for production planning. *International Journal of Production Economics*, 147(2014), 647–658.