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OPTIMIZING PRODUCTION ALLOCATION WITH SIMULATION IN THE FASHION INDUSTRY: A MULTI-COMPANY CASE STUDY

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ABSTRACT

Production Planning and Control (PP&C) has been deeply analyzed in the literature, both in general terms and focusing on specific industries, such as the fashion one. The paper aims to add a contribution in this field presenting an optimization model for the Fashion Supply Chain (FSC), developed considering an interdependent environment composed by a group of focal companies that work with both exclusive and not-exclusive suppliers. The proposed framework will combine simulation and optimization models based on parameters, decision variables, constraints and Objective Functions (OFs) collected through a literature review. The framework has been developed in a parametrical way, in order to fit the peculiarities of the different actors operating along the FSC. The empirical implementation of the framework has been conducted using data coming from fashion companies belonged to the same network, considering rush orders as stochastics events for the scenario analysis and Key Performance Indicators (KPIs) assessment.

1 INTRODUCTION

The fashion industry is one of the sectors where many contributions can be found along the whole value chain, from the New Product Development (NPD) to the logistics and retail.

Nevertheless, most of them are focused on the definition of the Critical Success Factors (CSFs), such as high-quality products, compliance with delivery dates, cost reduction, and sustainability issues (May et al. 2015), the role of the IT, the alignment of the physical with the information flows (Caniato et al. 2015), the importance of quality control (Brun et al. 2014) and, even when they deal with workflow allocation, most of them are related to the brand owners' perspective. What is evident is that focal companies have faced with an increasing attention to KPIs. As a consequence, all of the SC actors have been required to increase their performances by the brand owners, in line with the increased market pressure. At the same time, it is noticeable that these results cannot be obtained operating at a single-company level, but considering the entire FSC, because the outstanding quality of a final product is strictly linked to that of its components and, in the same way, the delay of the final product depends on components delays.

Moreover, this evidence is more explicit in the fashion industry, where "time" represents the key word for being competitive on the market in a complex environment characterized by short product lifecycles, high product variety and fragmented supply bases.

According to this, the work aims to define a structured framework to optimize the production planning and scheduling of the production within a FSC, with the use of a solver and a simulator.

The paper is organized as follows. In Section 2, we have presented a brief literature review on production planning and scheduling models, with a focus on the fashion industry. The proposed model has been detailed in Section 3, and its application in a case study has been shown in Section 4. Finally, in the last section we discuss the main conclusions of this work.

2 SIMULATION OPTIMIZATION IN THE FASHION INDUSTRY

As previously anticipated, one of the main criticalities of the FSC is the high uncertainty of the demand, the reduction of the Time To Market (TTM) and a strict relation between the NPD and the SC (Ait-Alla et al. 2014; Hu et al. 2013, d'Avolio et al. 2015), whilst customers ask for a higher service level, mainly in terms of quality. For balancing these opposite aspects (i.e. short TTM and high quality product), several authors have developed scheduling models for production process in the FSC, even if most of the cases are focused on the retail companies' perspective (Ait-Alla et al. 2014; Hu et al. 2013).

2.1 Scheduling optimization models review

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. Several approaches in the definition of scheduling formulation can be found. Published reviewing papers on scheduling (Maravelias, 2012; Méndez et al. 2006; Mula et al. 2010; Phanden et al. 2011; Ribas et al. 2010) study different problems, moving from single to parallel machines, job or flow shop, and considering different level of data aggregation (i.e. strategical, tactical and operative), even if only few of them deals with the fashion industry. For example, scheduling models can include finite or infinite capacity, and finite capacity can be considered in terms of hours per resource (Rahmani et al. 2013) or units per resource (Ait-Alla et al. 2014), both referred to a single period. Looking at other parameters, differently from the majority of the other works, Rahmani et al. (2013) distinguish between regular-time and overtime production (with relative different capacity and costs), and including setup times and costs, even if the first ones are independent on jobs sequence. A mathematical model for production planning in the fashion industry considering the order allocations on different production plants, characterized by different lead times and production costs, is presented by Ait-Alla et al. (2014). Guo et al. (2015) and Wong et al. (2014) have studied how to increase manufacturers' performance supporting production monitoring and scheduling through RFId.

Rose and Shier (2007) present a two-stage-approach model that follows the logical structure of cutting and packaging problems and is solved using a mixed integer linear program.

Considering the OFs, costs minimization represents the main purpose of the reviewed works, even if several authors consider multi-objective production planning problem in the labor-intensive manufacturing industry, in general (Betrand and Van Onijen, 2008; Wong et al. 2014; Wu et al. 2011) or specifically in the fashion segment (Ait-Alla et al. 2014; Hu et al. 2013). The OFs included in the reviewed works are related to production costs (Ait-Alla et al. 2014), tardiness (Ait-Alla et al. 2014; Betrand and Van Onijen, 2008; Guo et al. 2015; Wong et al. 2014), throughput and idle time (Guo et al. 2015; Wong et al. 2014), hiring and layoff costs associated with the change of workforce level (Rahmani et al. 2013), and total setup, inventory and backorder costs (Rahmani et al. 2013). Considering multiple OFs per model (i.e. multi-objectives scheduling problems), these are often solved translating all the OFs in monetary terms, defining a total cost that has to be minimized. For example, time measures are converted in holding or penalty costs that companies have to sustain for advances and delays respectively (Ait-Alla et al. 2014). Guo et al. (2008) use weighted sum method to turn multi-objective problems to single-objective ones.

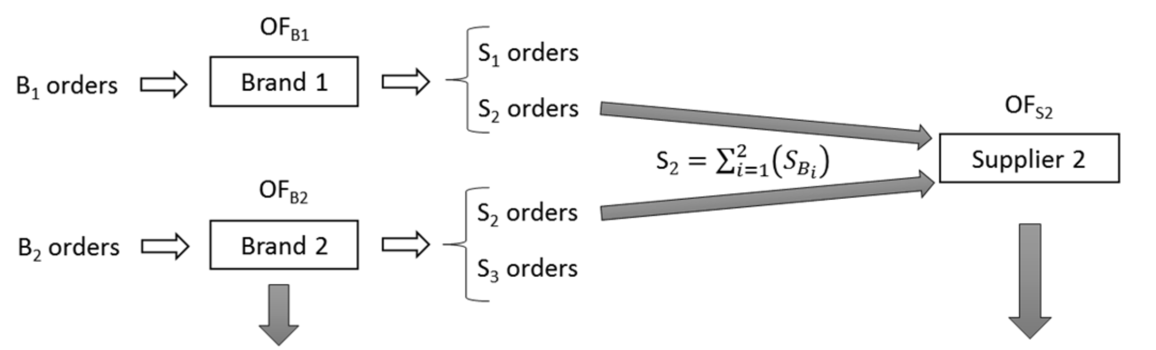
All of these model consider the optimization of a single level of the SC, using as input the production plan received from the upper lever and producing the scheduling and the delivery plan for the lower level of the SC.

3 MODEL DESCRIPTION

3.1 Problem Description

One of the characteristics of the fashion industry, due to the presence of the seasons, is that brand owners' demand is usually concentrated in short periods with a high pressure on the same supply base. Moreover, every focal company, according to its CSFs, has different objectives and requirements in the production plan. Every supplier receives a production plan from one or more brand owners, composed by orders with different and often opposite targets (i.e. due date respect, low labor cost, high quality etc..). From their side, as a matter of fact, despite the pressure of the brands, suppliers organize their production according to their CSFs, that can differ from the brand owners' ones. As result, the date requested by the brand owners does not often match with real data.

The proposed framework can be described and implemented with a two different steps procedure. In the first step, every brand owner independently defines a production plan and communicates it to its suppliers. The production capacity of every supplier, included into the brand owners' scheduling algorithm, is usually declared by the supplier itself and expressed as a total number of equivalent unit that can be produced per week or per day. This available capacity is often over-estimated because each supplier, that usually works for different companies, has to guarantee the saturation of its production lines considering the high variability of the fashion companies' demand. This results in a misalignment between the real available production capacity and the one communicated by each supplier to each brand owners. Moreover, suppliers are not interested in declaring the real production capacity, but aim to collect the largest number of orders to maximize their production lines saturation. In the second step, every supplier collects the received production plans and, according to its objectives and its real production capacity, defines a personal production plan. In order to align these information, brand owners periodically (usually weekly) ask suppliers the updated delivery dates of the orders which production has already started and a re-scheduling of some orders.



Week 20 – Optimized production plan			
Art. code	qt	due date	supplier
ITEM_01	50	15/05/2017	S_2
ITEM_02	40	22/05/2017	S_2
ITEM_03	70	29/05/2017	S_2

Week 20 – Actual production plan			
Art. code	qt	production date	supplier
ITEM_01	46	15/05/2017	S_2
ITEM_02	35	22/05/2017	S_2
ITEM_03	68	29/05/2017	S_2

Figure 1: Actual production plan schema description.

The actual production plan of the suppliers can differ from the optimized production plan, developed according to the brands CSFs, mainly due to two different reasons. The first one, as anticipated above, is the different suppliers' OFs; the second one is due to the stochastics events (e.g. failures, rush orders), that can occur during the week. Furthermore, brand owners know if their production plans will be respected or not only at the end of the period (i.e. the week), without having the possibility to change their production plan or re-scheduling a part of it before.

Considering two brands and three suppliers, both exclusive and not, a typical scenario is described in Figure 1, where the actual production plan results not able to guarantee the whole quantities included in the optimized product plan.

3.2 Model Description

Starting from the boundaries described above, the simulation-optimization model proposed in the paper has the objective to overcome these limits defining an algorithm able, as first result, to define an optimization model suitable by the different SC actors, and, as a second step, to provide a support to identify the sub-optimal brand owners' and suppliers' production plans.

According to the first objective, the optimization model has been developed in order to fit the different companies' peculiarities including an OF defined as a combination of weighted parameters chosen by the single company and reflecting its CSFs. In particular, the solver has been developed with the following function:

OF: $\mathrm{Min}\{\sum_{i \in I} (cw_i * C_i + dw_i * D_i + aw_i * A_i + ptw_i * PT_i)\}$,

where cw_i, dw_i, aw_i, ptw_i, are the weights of the various objectives, according to Guo et al. (2008), and C_i, D_i, A_i, and PT_i are respectively the costs, the delays, the advances and the processing time related to the production of the item i. More information about the model and how the objectives are evaluated can be found in Fani et al. (2016).

As second result, a "what-if" simulation analysis is included in the model, in order to show how the optimized results and the related KPIs can differ considering the uncertainty due to both internal (e.g. machine failures, reworks, employees unavailability) and external stochastics events (e.g. rush orders) at the supplier level. Moreover, simulation can be used to compare the impacts on KPIs resulted from different implementation of the optimization model in terms of changed inputs, such as OFs' weights or suppliers' production capacity.

Summing up, Figure 2 represents the information flow related to the model application on a SC network composed by two brands and a supply base with both exclusive and common suppliers.

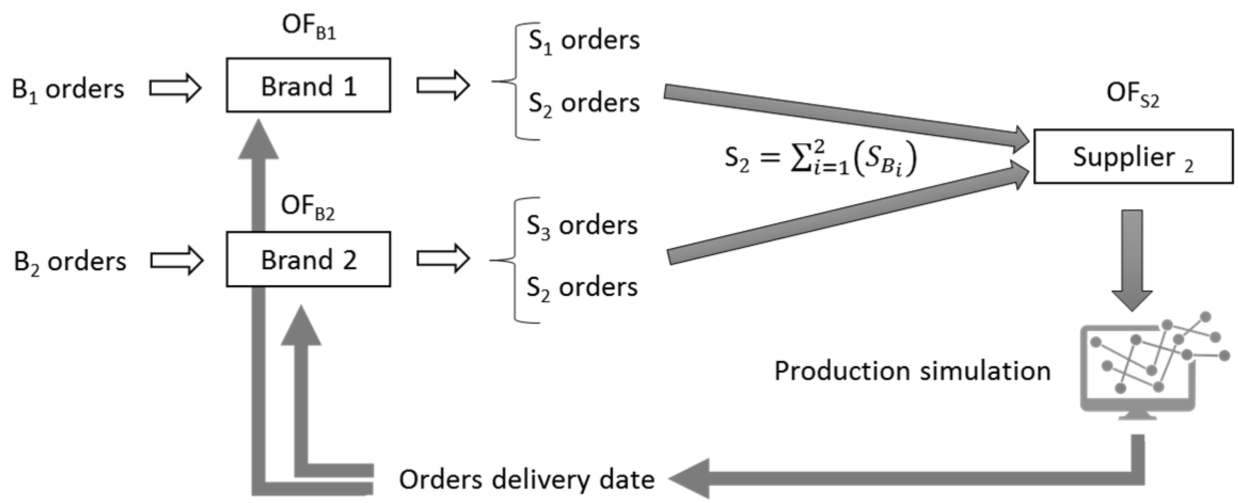


Figure 2: Model production plan schema description.

3.3 Model Architecture

The model is composed by a Java discrete-event simulator, AnyLogic® (www.anylogic.com, version 8.0), and an open solver optimization tool, OpenSolver (www.opensolver.org, version 2.8.6), used integrated on Microsoft Excel®.

The procedure for the model application is shown in Figure 3.

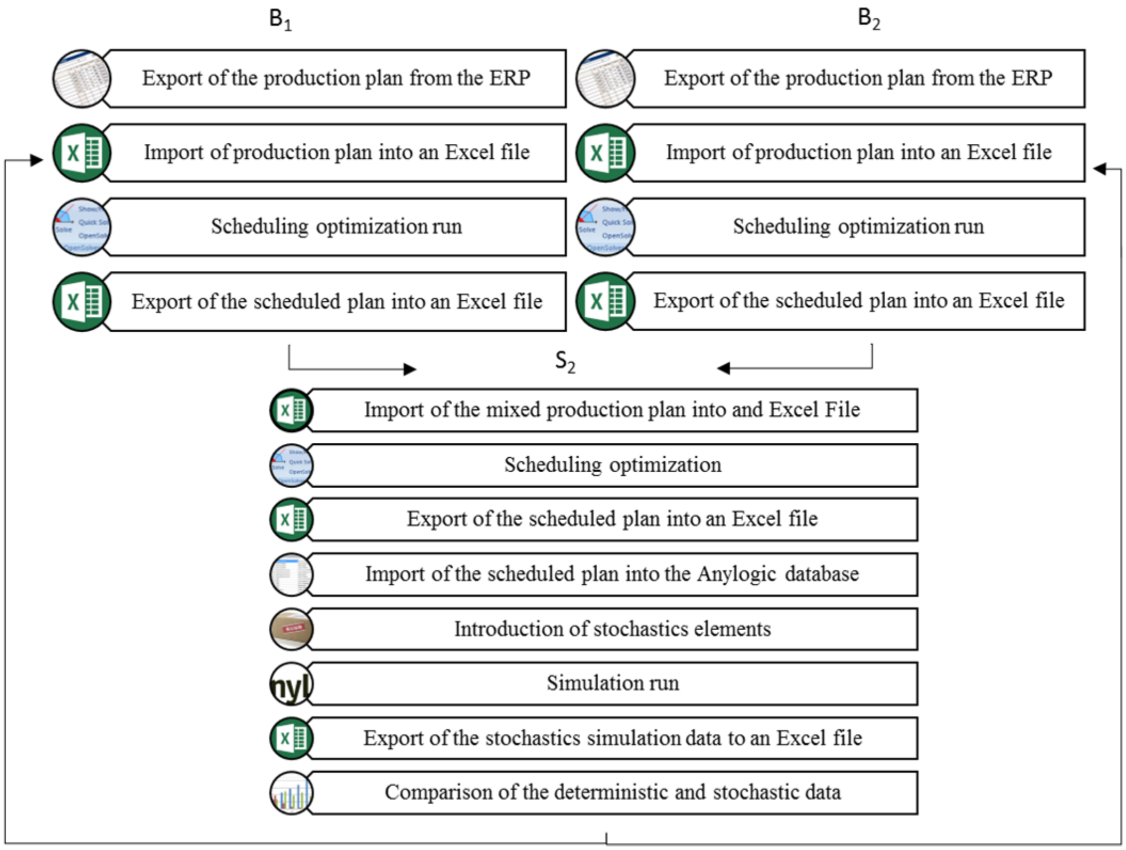


Figure 3: Scheduling Simulation Optimization procedure.

4 CASE STUDY

The case study is developed using a simplified set of data coming from two different brands, working with both exclusive and common suppliers. In detail, the set of data considered for each brand owner refers to one exclusive supplier and another that works for both the brands.

The brand owners operate in the leather accessories industry and produce bags with different dimension and complexity, clustered into three different product categories (i.e. easy, medium and difficult). All three of them are realized by a not-exclusive supplier (i.e. S_2 in Figure 2), that works for both the brand owners (i.e. B_1 and B_2). Once the optimization model has been applied to the three of them (i.e. B_1, B_2, S_2), the simulation model is used to conduct the scenario analysis for evaluating the effect of rush orders on the system performances. The importance of including rush orders is due to the uncertainty and high variability of the brand owners' production orders. Unexpected orders can represent a high proportion of the value of the production, up to the 20% of the total capacity.

4.1 Model Implementation

The model has been applied into a real case study considering two brand owners and a subset of their job orders that covers a period of one week and is related to a supply base composed by three suppliers.

The production plan created for each brand owner has been generated starting from the demand plan referred to the three analyzed product categories (i.e. easy, medium and difficult) that group the bags according to their complexity.

The used optimization model has been the one developed by Fani et al. (2016), re-adapted from the supplier perspective to the brand owner's one. More in detail, instead of focusing on the optimal assignment of each Stock Keeping Unit (SKU) to one of the Computer Numerical Control (CNC) machines, for the brand owners the goal is to find the optimal allocation for each SKU in terms of choosing the supplier that will work it. According to this, one of the main difference between the present case study and the one showed by Fani et al. (2016) is the resource type (machines in one case, suppliers in the present one). Another one is the way the production capacity has been calculated. On the one hand, brand owners consider the amount of SKUs each supplier declares he is able to guarantee per period, instead of minutes, as the available production capacity. On the other hand, considering the two brand owners included in the present case study, the capacity utilization is communicated in terms of number of equivalent bags per week and not referred to the specific SKU. In particular, the concept of "equivalent bag" depends to the definition of the three product categories: in fact, an "easy" bag is equals to 0.5 "equivalent bag", a "medium" bag to 1, and the "difficult" one to 1.3 "equivalent bag".

Moving from the brand owner to the supplier perspective, the optimization model is quite similar to the one used by Fani et al. (2016) in their case study, but the resources differ again: instead of the CNC machines that characterized the metal accessories suppliers, in the present case study are considered three workstations on which works one operator per each one of the three daily shifts.

The OF can be personalized varying the weights that composed it moving from one to another supply chain actor, in order to fit their different peculiarities (Fani et al. 2016), but in this first implementation the aim is to assess if some misalignments can be shown even in case of equal-weighted OFs. More in detail, the OF considered for the case study is the following: $\mathrm{Min}\{\sum_{i \in I} (cw_i * C_i + dw_i * D_i + aw_i * A_i + ptw_i * PT_i)\}$, where $cw_i = 1$, $dw_i = 1$, $aw_i = 1$, $ptw_i = 0$.

Once the optimization model outputs come out from each one of the two analyzed brand owners (i.e. B_1 and B_2), the job orders assigned to the not-exclusive supplier S_2 have been collected and represent the input for running the optimization model re-adapted for the suppliers.

The results of this second running are the object of the application of the simulation model to S_2, run twice with a twofold aim: on the one hand, the first running has been conducted replicating the same scenario modeled within the optimization tool to evaluate the effect of the over-saturation that usually affects not-exclusive suppliers that promise to each one of their customers (i.e. brand owners) an available capacity higher than the real one; on the other hand, rush orders are considered in the second running of the simulation model in order to evaluate how relevant is the impact of stochastics events compared to the one of suppliers' over-saturation.

With this purpose, the simulation model that replicates the supplier S_2 is composed by 3 workstations on which one operator per shift works 8 hours per day, for a total capacity of 24 hours per day per workstation (i.e. 3 shift per day). Downstream, all the activities that follow the described one, modeled considering the processing time (expressed by minutes per item), are grouped in a unique post-processing block that works at an infinite capacity (expressed by a post-processing lead time).

A gap analysis has been conducted in order to compare the three scenarios modeled through the simulation.

In particular, with the first scenario the impacts of the over-saturation of a common supplier (i.e. S_2) for two brands (i.e. B_1 and B_2) have been evaluated, while the others include also the analysis of the impact of rush orders, equal to 10% and 20% of the regular production orders respectively. These analyses compare the end processing date (i.e. the date when the item exits from the workstation) given back from the optimization model applied at the brand owner level (i.e. ProcessingDate_gap_A in Figure 4) and the simulation model applied at the supplier level (i.e. ProcessingDate_gap_B in Figure 4) respectively with the delivery date requested by the market planning.

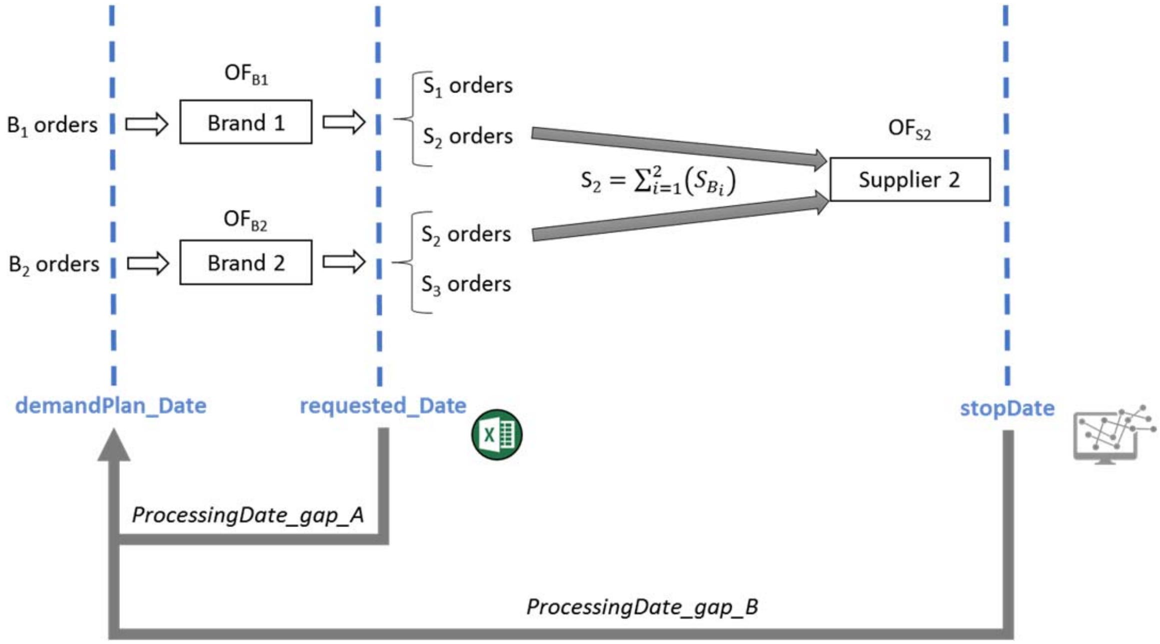


Figure 4: Gap analysis structure.

4.2 Results

The production plan is composed by 1,914 items, assigned to the common supplier S_2 over a period of one month. This value comes from the optimized production plans of B_1 and B_2, considering equal weights for the brand owners' OFs and the same supplier's declared capacity and production cost. Consequently, the overall available capacity of the common supplier (i.e. considering both the brand owners) doubles the real one.

The gap analysis conducted within the case study refers to the comparison of KPIs considering three different scenarios: the first one that aims to evaluate only the effects of the over-estimation of suppliers' capacity and the others that include also the impact of unexpected orders generated by the brand owners.

The result of the comparison between the ends of processing dates are shown in Table 1.

Comparing the gap_A and gap_B, the absolute value of deviation for the gap_B (i.e. demandPlan vs stopDate) almost doubles the one for the gap_A (i.e. demandPlan vs requestedDate). This result is aligned to the fact that the available capacity accorded by the not-exclusive supplier S_2 to each one of the brands B_1 and B_2 is almost equal to the real one available considering S_2. For example, considering a real capacity of 100 items per day for the supplier S_2, the one accorded to B_1 and B_2 has been around 100 items per day for each one of them. In particular, the first scenario results in an absolute value of deviation between the real end processing date and the one requested from the market analysis (i.e. processingDate_gap_A) equals to 7,510 items, while the gap between the date scheduled by the brand owners and the one requested from the final market (i.e. processingDate_gap_B) to 14,212 (+89%).

Table 1: Summary of the gap analysis results.

	gap_A	gap_B			Δ (gap_A vs gap_B)		
	End Processing Date	End Processing Date (no r.o.*)	End Processing Date (r.o.*=10%)	End Processing Date (r.o.*=20%)	Δ (no r.o.*)	Δ (r.o.*= 10%)	Δ (r.o.*= 20%)
Null absolute deviation [# of items with no delayed or advanced]	198 (10.34% of the items)	96 (5.02% of the items)	93 (4.86% of the items)	93 (4.86% of the items)	-52%	-53%	-53%
Absolute deviation [# days per delayed and advanced items]	7,510	14,212	15,168	15,599	+89%	+102%	+108%
Maximum delays [# days per delayed items]	14 (1.99% of the items)	22 (0.16% of the items)	27 (0.21% of the items)	32 (0.21% of the items)	+57%	+93%	+129%
Maximum advances [# days per advanced items]	6 (1.20% of the items)	3 (4.86% of the items)	3 (4.86% of the items)	3 (4.86% of the items)	-50%	-50%	-50%
Average delays [# days per delayed items]	3.35 (36.99% of the items above average)	7.13 (44.83% of the items above average)	7.63 (45.61% of the items above average)	7.85 (46.55% of the items above average)	+113 %	+128%	+134%
Average advances [# days per advanced items]	0.57 (28.37% of the items above average)	0.3 (14.89% of the items above average)	0. 3 (14.89% of the items above average)	0.3 (14.89% of the items above average)	-48%	-48%	-48%

* r.o. = rush orders

Looking more in details towards delays and advances resulted from the comparison between end processing date calculated at the brand owners and the supplier levels respectively and the requested one, the evidence is that the delays increase more than proportionally compared to the decreasing of advances moving from the gap_A to the gap_B analysis. In particular, while the average days of delays per item recorded at the brand owner level is equal to 3.35 days, the one resulted at the supplier level is more than doubled (i.e. +113%). On the other hand, the average days of advances per item less than half decrease, moving from 0.57 to 0.3 days.

These are the main evidences from the comparison that do not include rush orders (i.e. scenario 1), being focused on the impacts of over-estimation of supplier's production capacity running the optimization model at the brand owners level. In line with the expectation, the effect of the over-estimation is just more than proportional.

Considering the second and the third scenarios (i.e. with rush orders, equal to 10% and 20% of the production plan orders respectively), one of the main evidences resulted from the comparison between the first and these scenarios is the fact that rush orders impacts only on the delays, while advances are unchanged (i.e. the average advance is 0.3 days, with a maximum of 3 days for the 4.86% of the regular job orders).

More in detail, moving from the scenario with no rush orders to the one that includes them in a percentage of 10% on the regular production orders (i.e. scenario 2), the average days of delay per item increase of 7% (i.e. +128% if compared with the value calculated at the brand owners' level), with a maximum of 27 days.

Considering rush orders amount as the 20% of the regular ones (i.e. scenario 3), the average delay value increases of 10% and the maximum delay value per item moves from 22 to 32 days (+45%) if compared to the first scenario (i.e. no rush orders). The same values calculated compared this third scenario with the results of the optimization model run at the brand owners' level show a percentage of increasing equals to +134% and +129% for the average and the maximum days of delays respectively.

Moreover, the amount of items with a delay equals to or higher than 22 days (i.e. maximum delay value without rush orders) increases from the 0.16% up to the 3,66% of the items moving from the first to the second scenario (i.e. rush orders equal to the 10% of regular orders) and up to 4.91% moving to the third scenario (i.e. rush orders equal to the 20% of regular orders). Looking again at the third scenario, the items with a delay at least equals to the maximum value for the second scenario (i.e. 27 days) are 34, that represent the 1.78% of the scheduled items.

Finally, considering the absolute value of deviation between the real end processing date and the one requested from the market analysis when rush orders are included, their impact on this KPI is equal to +102% and +108% if it is considered the second and the third scenario respectively, instead of the +89% resulted from the comparison that takes into account only the over-estimation of suppliers' capacity (i.e. scenario 1 with no rush orders). On the other hand, if the amount of items with no deviation between the real delivery date and the one requested by the market has been evaluated, all the three scenarios do not differ each other, showing a gap with the market around -52% for all of them.

5 CONCLUSION

The present work describes a framework that combines simulation and optimization into a model for supporting production planning and scheduling along the FSC. According to this, the aim of this work, and the model itself, is twofold: on the one hand, the developed model has to be defined in order to be suitable to all the SC actors; on the other hand, simulation has to be used for allowing the scenario analysis and KPIs evaluation. The optimization model, that has to be used at the single-company level, has been developed considering a weighted multi-OF, in order to fit the peculiarities of the different actors operating along the FSC just changing the weights of the elements included in the OF, reflecting the specific company's CSFs. Moreover, variables and constrains have been parametrically defined. The discrete-event simulator is used to validate and compare various scheduled production plans produced by the optimization tool, introducing internal and external stochastics elements.

The optimization model has been developed using an open-source solver (OpenSolver) and a commercial simulator (AnyLogic®) has been chosen for the discrete-event simulation.

Finally, the developed framework has been validated using data coming from a set of fashion companies belonged to the same SC network, composed by two brand owners, belonged to the leather industry, that work both with one common and one exclusive labor supplier. The results of the scenario analysis have been collected in Table 2 and commented in the previous section.

First of all, the empirical application of the proposed model through a case study allows to validate its adaptability to different companies belonged to the FSC (i.e. brand owners and labor suppliers in this case). On the other hand, the implementation of the model on a real case make easier to understand how the KPIs assessment can be conducted using the simulation, introducing rush orders not included in the optimization model and analyzing their different impacts on KPIs changing their percentage. The results of the gap analysis have been collected and refer to three scenario: the first one without considering rush orders, while the second and the third ones take them into account generating into the system unexpected orders equal to the 10% and the 20% of the production plan respectively. These comparison have been conducted to show what are the impacts if just the over-estimation of suppliers' capacity have been considered running the optimization model at the brand owners' level (i.e. first scenario) and how it changes including also stochastics events, such as rush orders (i.e. second and third scenarios).

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