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A simulation optimization framework for production planning and control in the fashion industry

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Abstract

Fashion is one of the world's most important industries, driving a significant part of the global economy representing, if it were a country, the seventh-largest Gross Domestic Product (GDP) in the world in terms of market size. According to the high complexity that has to be managed by companies operating in the fashion Supply Chain (SC), Production Planning and Control (PP&C) represents a relevant issue that these companies have to face with, especially considering the dynamic context where they work and, consequently, the high occurrence of stochastic events (e.g. unexpected sample production, changes in production priority, raw material arrivals delay, rush orders) they have to manage.

Even if this is a well-debated topic both from an academic and an industrial point of view, related tools are no widely adopted along companies working along the fashion SC, especially considering Small and Medium Enterprises (SMEs). The few implementations mainly refer to their adoption by brand owners for a single-step planning on a strategic and tactical level, while SMEs are discouraged because of the related complexity and high costs.

According to this, the present work aims to present an iterative simulation-optimization framework for the fashion SC industry to be used by all the actors of the SC, both brand owners and suppliers, in order to continuously control, reallocate and optimize the production plan, considering their Critical Success Factors (CSFs) and the unexpected events that may occur.

The reason why optimization and simulation are jointly used within this framework is twofold: on the one hand, using optimization algorithms allows companies to find an optimal allocation for their production considering the parameters, constraints and objectives they have defined during the model setting; on the other hand, with simulation stochastic events, such as rush orders or delays in the expected components delivery date, are taken into account, moving the production allocation analysis from a deterministic scenario to a not-deterministic one.

Moreover, the comparison among simulated outputs coming from different scenarios, each one characterized by a specific set of input parameters (e.g. enabled resources, occurrence of stochastic events), can be conducted considering how a pre-defined set of Key Performance Indicators (KPIs), such as customers' due dates compliance, advances in production and total processing cost, varies moving from a scenario to another one.

Finally, the implementation of an iterative simulation-optimization framework into three different sectors (i.e. metal accessories, leather goods and footwear) has been presented, highlighting its relevance from an industrial perspective due to the fact that it represents a decision-support tool for production planners and managers that need to rapidly understand how evaluate the alignment between the gained PP&C performances and the company's CSFs

to, eventually, reallocate the already scheduled production to remain competitive in a such dynamic SC.

As a future step, the information needed as input for the framework implementation could be automatically gathered through several technologies, such as Internet of Things (IoT) sensors, track and trace systems, and Radio Frequency Identification (RFId). According to this, integrating the framework implementation with third part real-data acquiring sources could allow to update in real-time the inputs and, consequently, the outputs, creating a digital twin model for the operational planning within the fashion SC.

Acronyms

The Table 1 lists all the acronyms that have been used in the present work.

Table 1 - Acronyms

Acronym	**Meaning**
ABS	Agent-based Simulation
ALB	Assembly Line Balancing
APS	Advance and Planning Scheduling
CNC	Computer Numerical Control
COTS	Commercial Off-The-Shelf
CSFs	Critical Success Factors
DES	Discrete Event Simulation
EDD	Earliest Due Date
ERP	Enterprise Resources Planning
GALB	Generalized Assembly Line Balancing
GDP	Gross Domestic Product
IoT	Internet of Things
JIT	Just In Time
KPI(s)	Key Performance Indicator(s)
LSCM	Logistics and Supply Chain Management
LT	Lead Time
MALB	Mixed Assembly Line Balancing
MIS	Management Information System
MRP	Material Requirements Planning
MSP	Mixed-Model Sequencing Problem
OF(s)	Objective Function(s)
OR	Operational Research
PP&C	Production Planning and Control
RFId	Radio Frequency Identification
RQ	Research Question
SALB	Single Assembly Line Balancing
SC	Supply Chain
SCM	Supply Chain Management
SD	System Dynamics
SKU(s)	Stock Keeping Unit(s)
SMEs	Small and Medium Enterprises
TMS	Transportation Management System
VBA	Visual Basic for Application

1. Introduction

The present work aims to define a framework to improve production planning performances within companies working along the fashion industry.

In the following paragraph (see paragraph 1.1 Industrial background), an overview of the research context has been done, including both the characteristics of the market and its impact on the economics.

1.1 Industrial background

The following paragraphs give an overview on the fashion industry, the sector this work has been focused on.

Firstly, the main peculiarities related to the fashion industry have been highlighted, focusing on the characteristics of the final products and the complexity related to the market environment that companies have to face with (see paragraph 1.1.1 The Fashion Industry: a general overview).

In the last paragraph, the relevance of this industry, both in the global and local markets, has been highlighted, underlining the economics related to this sector (see paragraph 1.1.2 The Fashion Industry: the economics perspective).

1.1.1 The Fashion Industry: a general overview

Fashion industry is characterized by a complex environment, with a SC composed by several actors that differ each other in terms, for example, of company's dimension, moving from big brand owners to small-medium suppliers working along the SC.

These differences reflect into different CSFs these companies have to satisfy for being competitive on the market, such as delivery on-time or minimize production costs, that means different strategies and actions even for companies that belong to the same SC.

Moreover, within the same SC, composed by all the companies that work around a single brand owner, it is quite common that most of the included suppliers have not-exclusive labour-relationships with the brand owner itself, who has to share each supplier's available capacity with one or more other brand owners. This intricate supply base, that includes both exclusive and not-exclusive labour-relationships between brand owners and suppliers, makes managing both the information and production flows along the SC even more complex and unpredictable.

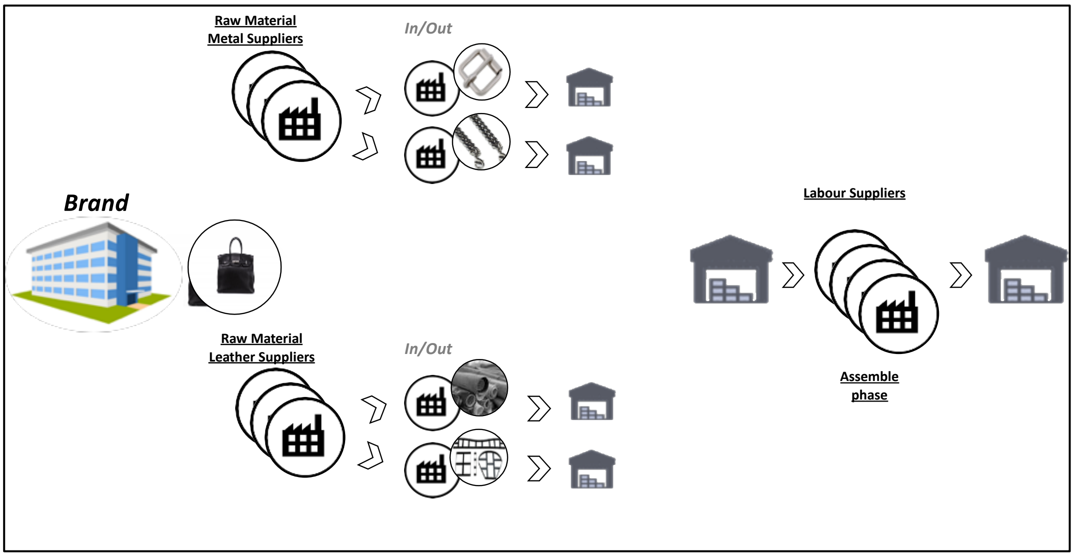

Figure 1 - Fashion SC network

Moving from the complexity related to the SC to the one referred to the product, according to the Fisher classification (Fisher, 1997) the fashion industry is mostly characterised by selling "innovative products", that are products with an unpredictable demand, a short life-cycle and a really high variety. In particular, the product life-cycle has become even shorter than the past according to the market changes in terms of increasing number of seasons and flash collections per year. The even faster rhythm of the fashion cycle, in fact, represents one of the main challenges highlighted by McKinsey & Company and The Business of Fashion in their report "State of Fashion 2017"[1], underling also that speed and flexibility bring new challenges. On the other hand, shortening Lead Time (LT) requires major changes to the traditional business model and SC setup to accelerate the time from design to shelf.

According to this, technology will also be seen as the solution to addressing sourcing and SC challenges in an effort to improve margins, considering the IT capacity as one of the main sources for value chain digitisation.

On the other hand, market itself still requires outstanding quality levels that have to be guaranteed in a shorted time to market, because higher quality in longer time means being out of the market.

These evidences, jointly with the ones related to the SC structure, represent the main issues that increase the complexity related to both the types of products to be sell and actors that work together to realize them.

1.1.2 The Fashion Industry: the economics perspective

The Fashion Industry represents one of the main industries in the global scenario, driving a significant part of the global economy. Supporting this, in 2017 it represents, if the fashion industry were a country, the seventh-largest GDP in the world in terms of market size[2].

Most of the industry value is captured by a small percentage of players, with the top 20 percent creating 100% of total economic profit.

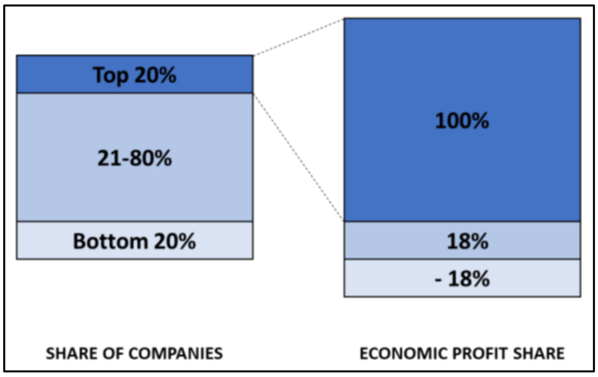

Figure 2 - Profit share for fashion industry (adapted from McKinsey Global Fashion Index 2016)

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[1] McKinsey & Company and The Business of Fashion "State of Fashion 2017".
[2] International Monetary Fund, "List of Countries by Projected GDP", October 21, 2016, http://statisticstimes.com/economy/countries-by-projected-gdp.php.

An average growth between 3.5% and 4.5% (+ 4% or 5% for the luxury segment) have been registered for a total sales volume that could reach €2,100 billion[3]. The main sources of growth have been the emerging-market countries across Asia–Pacific, Latin America, and other regions; they have been forecasted to grow at rates ranging between 5% and 7.5% in 2018. Meanwhile, the economic outlook in the mature part of Europe has been stable, and fashion-industry sales growth has been likewise expected to remain at a modest but steady 2% to 3%.

In this scenario, Italian fashion industry revenue has been grown 2.5% in 2017 for a total amount of €64.8 billion, reaching 2.8% if also the fine and costume jewellery, eyewear and cosmetics sectors are taken into account. According to the described global perspective, growth in 2017 has been mainly export-driven, with a 4.5% upturn, generating a trade surplus of €17.6 billion, €1.1 billion higher than in 2016. Including the fine and costume jewellery, eyewear and cosmetics sectors, previous upturn value moves from +4.5% to +6%, reaching a trade surplus of €27.9 billion.

Considering the market segments involved in the fashion industry, the metal accessories has covered more than €3.5 billion of revenues in 2015, including more than 250,000 companies (most of them SMEs) and occupying more than 14,000 employees[4].

Moving from the metal accessories to the Italian leather industry, it has increased about the 6.4% comparing the results of the first 10 months of the 2017 with the ones of the previous year[5]. Again, this has been mainly related to the boom of the export abroad of leather goods, with €6.1 billion (+14.1% compared to the 2016) and bags, more than others luxury bags, as best-selling category.

Considering the footwear market segment, Italy represents the first producer in the European Union and the 11th in the world, while is the 3rd in the world in term of export value. The total revenue is around €14.2billion, with 4,800 companies and 77,000 employees[6].

All the previous results related to the Italian fashion market are 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.

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[3] McKinsey & Company and The Business of Fashion "State of Fashion 2018".
[4] Italian Chamber of Commerce, www.camcom.gov.it
[5] Italian Leather Goods Association, www.aimpes.it
[6] Italian Footwear Producer Association, www.assocalzaturifici.it

In Table 2, data on the exports considering the 30 Italian districts with the higher exports' value are listed[7].

Table 2 - Exports' growth for the 30 most relevant Italian districts (2016 vs 2017, 2nd trimester)

	Billion €			**%**	
	2° trim. 2016	**2° trim. 2017**	**Δ**	**2° trim. 2017**	**1° sem. 2017**
Valenza goldsmithery	440	660	219.6	49.9	39.5
Boat district of Viareggio	158	244	85.9	54.3	59.8
Metal industry of Brescia	840	911	70.3	8.4	11.3
Leather and Footwear districts of Florence	892	949	57.1	6.4	10.4
Metalworker of Lecco	590	644	53.4	9.1	12.1
Leather and Footwear districts of Arezzo	109	157	47.8	43.8	36.6
Instrumental metalworker of Vicenza	562	608	46.1	8.2	6.9
Metalworker of the Basso Mantovano	238	280	42.1	17.7	12.5
Taps, valves and cookware from Lumezzane	822	861	39.3	4.8	4.1
Inox valley appliances	304	338	34.6	11.4	12.5
Apparel district of Empoli	284	316	32.1	11.3	9.3
Tanning of Arzignano	615	644	29.4	4.8	4.7
Taps, valves and cookware from Cusio-Valsesia	333	359	25.3	7.6	10.5
Mechatronics of Bari	279	304	25.3	9.1	22.5
Jeweler's of Arezzo	464	489	24.5	5.3	5.1
Wine from Langhe, Roero and Monferrato	307	332	24.4	7.9	9.6
Fruit and Vegetables of Bari	63	88	24.2	38.1	9.2
Wood machinery from Rimini	77	100	22.4	29	22.8
Packaging machines of Bologna	585	606	20.5	3.5	8
Textile and Apparel of Prato	498	517	19.1	3.8	3.8
Termomeccanica of Padova	265	284	18.9	7.1	8.9
Plastic materials from Treviso, Vicenza, Padova	373	391	18.2	4.9	7.1
Textile from Biella	362	380	17.7	4.9	8.7
Marble from Carrara	184	201	17.5	9.5	7.6
Termomeccanica scaligera	331	348	17.2	5.2	12.7
Textile and Apparel of Arezzo	61	78	16.5	26.9	17.7
Dairy from Parma	54	69	15.7	29.2	16.1
Meat from Verona	123	137	14.5	11.8	14.3
Mobile from Livenza and Quartieri del Piave	615	629	13.8	2.2	4.8
Meats and cured meats of Cremona-Mantova	41	55	13.3	32.1	32.9
TOTAL	**24,121**	**25,165**	**1,043.4**	**4.3**	**5.3**

[7] Intesa San Paolo "Monitor dei Distretti – Novembre 2017"

In this context, Italian districts working in the fashion SC have registered a relevant growth in terms of exports (+6.7%), leaded by the ones from Tuscany with leather goods and footwear producers from Florence and Arezzo, as shown in Figure 3. Considering data in Table 2, in fact, these districts cover the fourth and sixth positions in the Italian scenario.

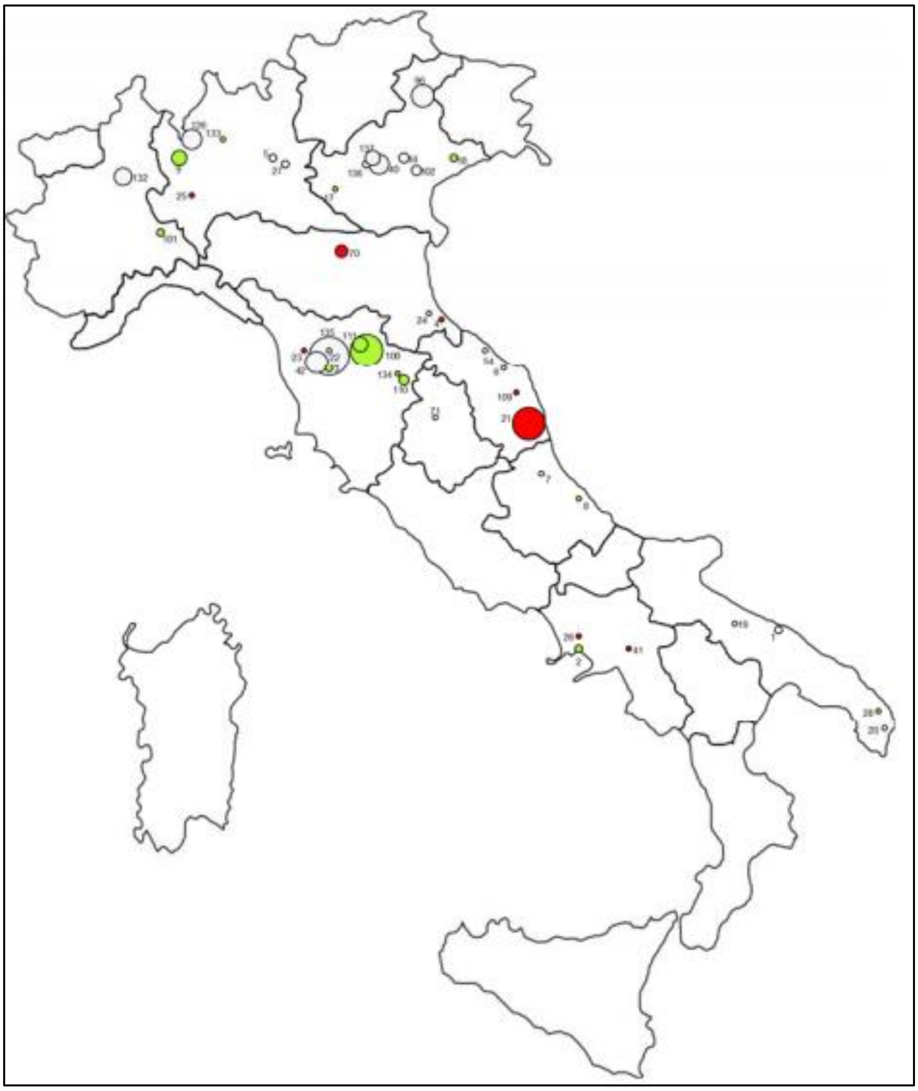

Figure 3 - Exports' growth per districts for the Italian fashion industry (2017, 2nd trimester)

2. Objective

Due to the high relevance of the fashion industry, moving from the global economics to the Italian one, manage the complexity of its SC has become a key challenge within the Italian scenario.

In the following paragraphs, the reasons why this research is focused on PP&C in the fashion SC are deeply explained (see paragraph 2.1 Motivation of the thesis), followed by their declination on the three research questions to be answered (see paragraph 2.2 Research scope).

2.1 Motivation of the thesis

The high complexity of the SC network that characterizes most of the industries, included the fashion one, makes PP&C optimization a quite known and debated topic, both from an academical and an industrial point of view.

In fact, according to the main evidences come from the industrial background, the fashion SC network collects companies that have daily to face with a high level of complexity to be managed. This evidence is also widely recognized by the literature, that confirms the high uncertainty of the demand as one of the main criticalities of the fashion industry (Ait-Alla et al., 2014; d'Avolio et al., 2015; Hu et al., 2013).

Moreover, in the recent years, fashion product lifecycle has become even shorter than in the past with a higher number of fashion season and special collections to be managed, increasing the need of quickly reacting to changes in customers' desires and, consequently, of compressing time to market for being in the right moment with the right product on this fast-changing market.

On the other hand, fashion customers ask for a higher service level, mainly in terms of outstanding quality and sustainable products (May et al., 2015), pushing brand owners to stress their suppliers, most of them SMEs with a low investment capability and consequently focused on production costs reduction, in terms of compliance with the delivery dates required for high-quality products (Brun et al. 2014).

This evidence reflects the fact that these results cannot be obtained operating at a single-company level, but considering the entire SC, because the outstanding quality of a final product is strictly linked to that one of its components and, in the same way, the delay of the final product depends on components' delays (Caniato et al. 2013). Moreover, this correlation is even more critical in industries, such as the fashion one, 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.

Finally, the high product variety and a fragmented supply base increase even more the complexity of the SC network and, consequently, the need of a structured production planning at all the supply chain levels, because all the actors should be perfectly aligned to the delivery date for fulfilling the demand on-time and this alignment should reflect the one between the physical and the information flows (Caniato et al. 2015).

Both for managing this complexity and balancing these opposite aspects (i.e. shorter time to market and higher service level), several authors have developed scheduling models for production process in the fashion SC, even if most of the cases are focused on the retail companies' perspective (Ait-Alla et al., 2014; Hu et al., 2013), highlighting the need to promote a more structured scheduling culture along these companies.

Even if the idea and needs related to an optimization tool for the fashion SC are not innovative from a research point of view, from an industrial one none of the actual solutions are quite often used by companies operating in the fashion SC.

First of all, the high number of SMEs working along this SC have a low investment capability that forces them to often implement, at least, a unique management information system that mainly covers the administrative functionalities, such as pricing and invoicing.

Secondly, most of the optimization tools allows to set input parameters and generate an optimal solution without making possible the comparison between different optimal solutions generated starting from different inputs, such as available resource capacity, or working not in a deterministic scenario but including also stochastic events, such as rush orders or delays on the delivery of critical components. The importance of including rush orders is due to the uncertainty and high variability of the brand owners' production orders, representing one of the main critical issues to be managed considering their occurrence in the fashion industry, that can reach the 20% of the total capacity. In fact, these unexpected events that characterized this industry have a high impact on being or not compliant with the requested delivery date, delaying the production of the already-scheduled items. 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 having priority on the others. 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. These unexpected phenomena are quite common along companies operating in the fashion SC because fashion brand owners, due to the high variability of the demand, are reducing the suppliers' orders visibility in a context where production time is compressed, consequently increasing the frequency of production plan re-scheduling. According to this, these events cannot be avoided because of their strict dependency on the industry nature, but have to be managed, in order to quickly readapt the production plan.

Finally, even considering available information along the fashion SC, it is needed to move from an implementation of the simulation-optimization model at the single-company level, that generates local and misaligned optimal solutions, to a wider application along the different involved SC actors, in order to define sub-optimal local solutions that guarantee higher overall SC performances. In fact, in real contexts every brand owner independently defines a production plan and communicates it to its suppliers (both exclusive or not), that collect the received production plans usually from more than one brand owner and, according to their objectives and their real production capacity, define each one its own optimized production plan. The supplier's optimized production plan can differ from the original one developed by the brand owner, mainly due to two different reasons. On the one hand, the Objective Functions (OFs) included to define the optimized production plan from the brand owner's and the supplier's perspective can be different because the CSFs related to the strategical objectives for the two SC actors cannot be equal (e.g. the brand owner may include only the minimization of delays while the supplier of both delays and advances). On the other hand, even if the OFs for brand owners and suppliers were perfectly aligned, differences between their production scheduling could be related to the influence of stochastic events (e.g. failures, rush orders) that can occur during the week. In fact, if rush orders have to be managed by the supplier or failures occur to its machines, a negative impact on the overall performances, for example in terms of delays on expected delivery dates, will probably follows. In this context, coming back to the brand owners' perspective, they know if their production plans will be respected or not only when due dates occur, with no possibility to change their production plan or re-scheduling a part of it before.

Summing up, even if PP&C for the fashion SC is a debated topic both from an academical and an industrial point of view, no optimization tools are widely applied in the industry. Due to this fact, the main challenge that this work aims to reach is to define an iterative framework enabling a set of decision-making tools to be given to all the SC actors, in order to preventively highlight the criticalities related to the feasibility of optimized production plan and the way to manage them, comparing different optimized production plans that differs each other in terms of inputs and that can be more or less influenced to the occurrence of stochastic events. Moreover, the framework implementation facilitates the interaction between the different actors, in order to achieve a global optimization performance of the entire fashion SC.

In a first scenario, the framework can be applied to a single SC level, in order to optimize the production at that level as shown in Figure 4.

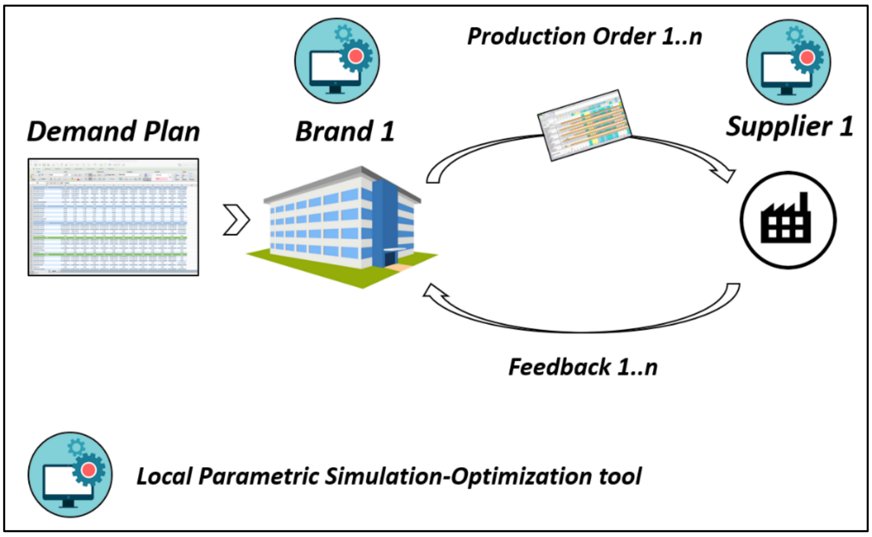

Figure 4 - Single-level iterative optimization framework

In a second scenario, the framework can be applied to the all fashion SC to determine the global optimized production plan as shown in Figure 5.

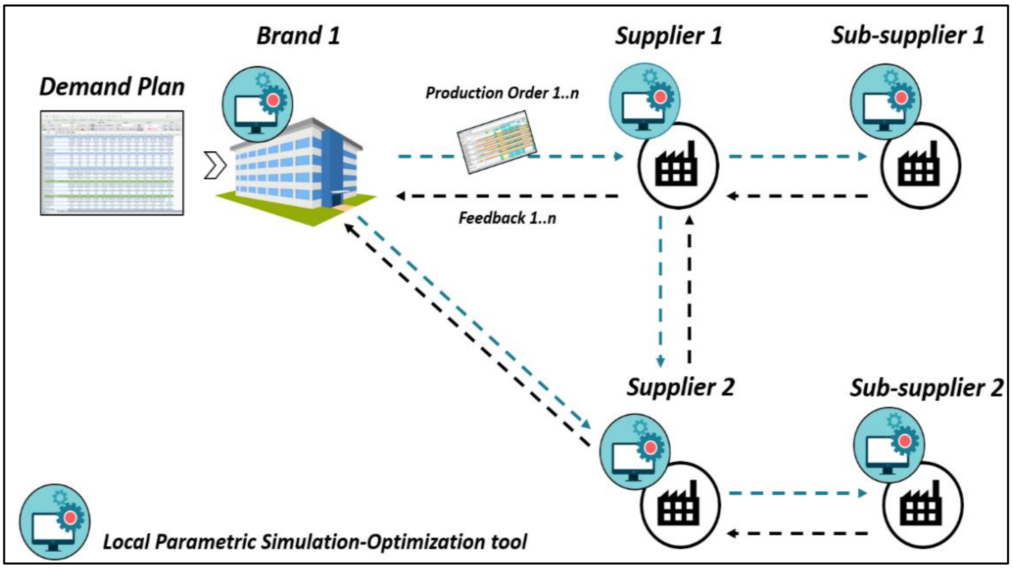

Figure 5 - Global SC iterative optimization framework

2.2 Research scope

Considering the main evidences come from the previous section, the high complexity that characterized the fashion SC requires to manage, in a very short time, the information flows exchanged between different SC actors that belong to a multiple-layers network, most of them SMEs with a low informatization level. Moreover, the even shorter lifecycle that the wide fashion products' varieties have and the high quality to be guaranteed to the final customer push these companies to be focused on how manage their own production in order to on-time deliver the required items and, on the other hand, quickly give back to their direct clients a feedback about the feasibility of the orders they received. In fact, according to the evidence that different SC actors may have different CSFs, the way each one of them defines the optimal scheduling may vary and, consequently, the scheduled orders production plans of the two suppliers may differ, even if the delivery dates requested are the same ones.

According to this, the first research question (RQ) aims to investigate how fashion companies usually manage their production planning process in order to define the optimal output in terms of production allocation that better fits their own CSFs and how this process can be improved in order to be implemented by all the SC actors, both in terms of usability and affordability.

The RQ_1 is then summed up as follows:

RQ_1: *How fashion companies may include their CSFs during the production planning process in an easy-to-use and affordable way?*

Even these companies, most of them SMEs, hypothetically had an optimizing tool, the ones commonly used run under deterministic conditions, giving as output a list of assigned quantities per item per resource and the related delivery dates starting from a list of static parameters used to configure the tool. The weakness of the on-field implementation of these models is then represented by the fact that static best-performant allocations under deterministic conditions can be rarely used due to the high-dynamicity of the context where these companies work, that requires quick responses to the frequent changes on the key production-related parameters. According to this, one of the main challenges for these companies has become to understand how stochasticity, generated by both themselves (e.g. resources' failures) and the SC actors working up- and down-stream (e.g. unexpected priority orders), can be included into the production planning process. Moreover, due to the need to be quick-respondent in a such dynamic industry, these companies should be able to rapidly compare different scenarios that vary each other in terms of input parameters, occurrence and type of stochasticity to be included or a combination of them.

The RQ_2 is then summed up as follows:

RQ_2: *How fashion companies may manage the occurrence of stochastic events during the production planning process and conduct scenario analysis to support the related decision-making process?*

Optimal production plans are usually defined at the single-companies level, mainly because the objectives for the optimization reflect the CSFs that usually change moving from one to another SC actor, even if they belong to the same SC. This evidence produces unsuitable production plans.

As a result, companies have to face with a continuous production re-scheduling from the beginning of the SC (e.g. brand owners) to the last actors (e.g. sub-suppliers), in order to fix misaligned production plans.

According to this, a challenge for a such dynamic industry, mainly characterised by a multiple-layers supply base, is not to define a unique global optimized production plan but applying local optimization models in an iteratively way, in order to include feedbacks coming from different SC actors to define sub-optimal feasible production plans.

The RQ_3 is then summed up as follows:

RQ_3: *How fashion companies may define an optimized production plan managing the feasibility feedbacks coming from all the actors in order to increase the overall SC performances?*

3. Methodology

In order to answer the three research questions listed above, different methodologies, deeply described in the following paragraphs, have been involved.

First of all, the action research methodology (see paragraph 3.1 Action research) has been used with a twofold aim: on the one hand, to identify the main issues companies working in the fashion SC have to face with in the PP&C field; on the other hand, to validate the results related to the models developed within the boundary of the present work through their on-field implementation.

Secondly, a literature review (see paragraph 3.2 Literature review) has been conducted to support and integrate the evidences came from the application of the action research methodology to identify the main issues of the analysed industry. Moreover, it has been used to understand how the identified issues have been solved, both in general and in the fashion industry.

3.1 Action research

In order to answer the research questions, the action research methodology has been followed, coherently to the fact that the starting point of this work comes from an industrial input. In fact, the main reason why the action research has been chosen in the present work is because it merges research and praxis, and several contributions about how action research can be applied in case of systems development can be found in the literature (Baskerville and Wood-Harper, 1996).

The action research method has been developed by Lewin (1951) at the Research Centre for Group Dynamics, in the University of Michigan. In his original model, six stages are included: (1) analysis, (2) fact-finding, (3) conceptualization, (4) planning, (5) implementation of action, and (6) evaluation.

Years later, Blum (1955) has explained the action research as a two-step method, with a first diagnostic stage followed by a more practical one where hypothesised changes are included and related effects studied.

In order to achieve scientific rigor, the Blum's model has been enlarged by Susman and Evered (1978) in their cyclical five-steps process, formalized in 1983 and showed in Figure 6.

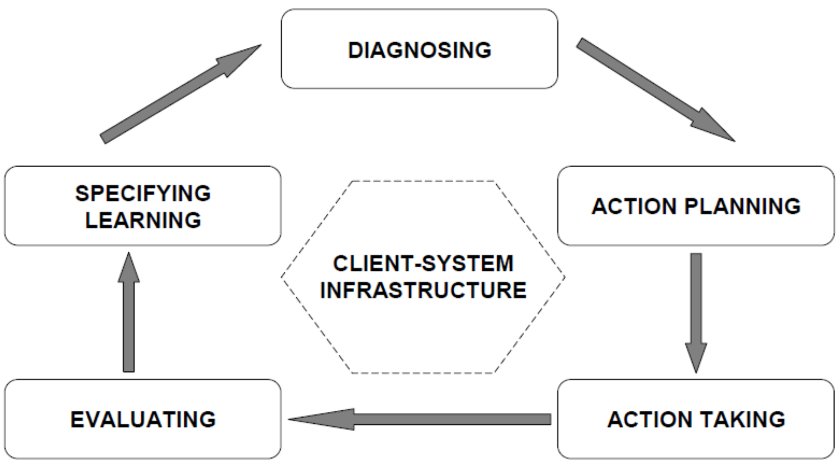

Figure 6 - The action research cycle (adapted from Susman, 1983)

As step "0", their approach requires the identification of a client-system infrastructure or research environment, that represents a sort of agreement that allows researchers to define and apply the actions they identify as beneficial to the client or host organization. At this point, the boundaries of research have to be defined and also the steps of collaboration needed between researchers and client's practitioners have to be declared.

After the client-system infrastructure has been defined, the five steps that have to be iteratively conducted are the following: (1) diagnosing, (2) action planning, (3) action taking, (4) evaluating, (5) specifying learning.

"Diagnosis" is the identification of the primary problems, strictly related to the reason why the organization looks for a change.

Starting from the identified primary problems, researchers and practitioners collaborate to define the organizational actions that should be implemented to solve or reduce them in the "Action planning" step. The definition of the planned actions is driven by the desired future state for the organization and the changes needed to achieve it.

The "Action taking" phase follows to implement the planned actions defined at the previous point. The researchers and practitioners collaborate in changing the client organization in order to improve the actual state.

When actions implementation is concluded, the researchers and practitioners evaluate its outcomes during the "Evaluating" step. This includes the comparison between the real and the expected effects of actions' implementation, considering their effectiveness in terms of problems solving. At this point, if changes are successfully made, the real actions that generate success have to be identified. On the other hand, in case of unsuccessful change adjustments and hypotheses on the implemented actions have to be established as inputs to run the next iteration of the action research cycle.

The "Specifying learning" is the activity usually represented at the end, while it is usually an ongoing process. In fact, the knowledge gained from the action research can be collected during the research and both in case of successful or unsuccessful actions implementation. Where the change is unsuccessful, what involved actors have understood from the errors in the problems analysis represents additional knowledge useful to define better bases for conducting the diagnosis step for the following iteration of the action research cycle. Finally, the results of each of these iterations provide further knowledge to both the organization and the scientific community for future researches.

Summing up, Hult and Lennung (1980) have defined action research as a methodology that simultaneously assists in practical problem solving and expands scientific knowledge, increasing competences of both researchers and practitioners through a collaborative approach that is cyclically replicated according to the feedbacks collected at the end of each iteration.

In the present work, action research has been firstly used in order to develop the optimization model, starting from the comparison between the theory on scheduling optimization in the fashion industry and the requirements gathered on-field from both the analysed brand owners and suppliers. In particular, the model has been developed integrating the evidences coming from the literature review with the analysis coming from the on-field interviews to the production manager of the companies included as pilots. Starting from the pilot on a metal accessories supplier, the list of collected requirements has been included into the optimization model and then enlarged moving the analysis to the leather suppliers and, finally, to the footwear ones, considering both the suppliers' and the brand owners' perspective for all the analysed market segments.

Moreover, the same procedure has been replicated for developing the simulation model and identifying the KPIs dashboard to allow the scenario analyses.

Finally, through the action research methodology has been tested the usability of both the proposed optimization and simulation models in a real scenario.

3.2 Literature review

During the conduction of the "Action planning" step within the action research cycle, a literature review has been done in order to support and integrate the evidences and ideas come from the analysed companies and to establish a solid theoretical basis for the present work.

As suggested by Flynn (1990), for conducting the literature review three main components has been evaluated:

- Search engines (see paragraph 3.2.1 Search engines)
- Research keywords (see paragraph 3.2.2 Research keywords)
- References overview (see paragraph 3.2.3 References overview)

3.2.1 Search engines

Looking to the search engines, several of them that are especially designed for the purpose of academic research, helping to get relevant information without going through irrelevant or low-quality pages.

Considering the industrial engineering, the most important scientific search engines available nowadays can be considered Scopus and Science Direct, both of them published by Elsevier.

On the other hand, Google Scholar has to be also mentioned due to the wide range of results obtained using it, allowing to reach a high number of scientific papers that, on the other hands, require more time to be read and then selected.

3.2.2 Research keywords

Using the research engines described above, the literature review has been conducted considering as subject areas related to the present research engineering, computer science and operations. Moreover, the literature review includes both sector-oriented papers, focused on the fashion industry, and general ones.

The selected publications refer to the last 15 years, without any constraint in terms of geographical area.

The used keywords are the following, each of them also searched adding "fashion industry" or "leather" or "apparel": Optimization, Scheduling, Simulation-Optimization, Production planning and control, Simulation, Optimization and Simulation, Balancing, Sequencing.

3.2.3 References overview

The most relevant results of papers collected using the search engines showed in paragraph 3.2.1 Search engines and inserting the keywords listed in paragraph 3.2.2 Research keywords has been classified and collected into two different states of the art. The first one, reported in 4.1.1 Literature review on scheduling model for the fashion industry, deals on the application of optimization models to the production and it has been used in order to develop the optimization tool based on OpenSolver. The second one, reported in 4.2.1 Literature on simulation model in the fashion industry, is focused on the application of the simulation in the fashion industry, distinguishing between System Dynamics (SD), Agent-based Simulation (ABS) and Discrete Event Simulation (DES), and it has been used in order to develop the simulation model, adopting AnyLogic® as commercial simulation tool.

4. Implementation

The main results of the present work aim to answer the three previously described research questions (see paragraph 2.2 Research scope).

In particular, the following section can be summed up as follows: in order to answer to RQ1, in the first paragraph (see 4.1 Scheduling model for the fashion industry) the steps for developing the proposed optimization model have been described, starting from the evidences come from the literature review followed by the validation of the proposed model through on-field implementations; in the second one (see paragraph 4.2 Simulation model for the fashion industry), the same approach has been followed to develop the proposed simulation model in order to answer the RQ2; finally, in the last section (see paragraph 4.3 Simulation-optimization framework for the fashion industry) it is illustrated how optimization and simulation models can be jointly used in an iterative way to improve the defined set of production planning KPIs, in order to answer the RQ3.

4.1 Scheduling model for the fashion industry

Optimizing production planning is a quite relevant issue especially for companies working in industries, such as the fashion one, characterised by selling a high variance of product type, with an outstanding quality level, in a really short time.

In order to answer to the RQ1, an optimization tool that enables companies operating in the fashion SC has been developed to define the optimal output in terms of production allocation. One of the critical points that had to be considered in this step has been to define model in a parametrical way, in order to be easily readapted to fit each one of the SC actors' peculiarities.

According to this, a literature review on scheduling model has been done as first step (see paragraph 4.1.1 Literature review on scheduling model for the fashion industry), in order to analyse the different approaches taken into account both in general and specifically for the fashion industry. Starting from the evidences coming from the literature review, the first draft of the proposed optimization model has been developed and then iteratively readapted until the definition of its final version, according to the feedbacks collected from its implementations (see paragraph 4.1.2 Proposed scheduling model for the fashion industry). Once the proposed optimization model had been explained, the chosen tool for the model implementation has been described in the last sections (see paragraph 4.1.3 Implementation of the proposed scheduling model in the fashion industry).

4.1.1 Literature review on scheduling model for the fashion industry

PP&C optimization of a multi-level SC, composed by several small companies, mostly SMEs, coordinated by a big company, which usually is the brand owner in the fashion industry, is a widely discussed topic, analysed by researchers from different point of view.

In the scientific literature, several different approaches in the definition of scheduling formulation can be found. Published reviewing papers on scheduling (Maravelias, 2012; Méndez et al., 2006; Phanden et al., 2011; Mula et al., 2010; 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.

Focusing on contributions regarding the fashion industry, the reviewed papers consider many different parameters, which sometimes are not calculated in the same way moving from one to another works. For example, scheduling model 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.

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

Looking at other parameters, differently from the majority of the other works, Rahmani et al. (2013) distinguish between regular-time and overtime production, having different relative capacity and costs. In their model, setup times and costs are also included, but setup times are independent from jobs sequence.

A mathematical model for production planning in the fashion industry considering the orders' allocation on different production plants, characterized by different LTs and production costs, has been presented by Ait-Alla et al. (2014). The case study they have conducted involves a fashion apparel supplier.

Guo et al. (2015) and Wong et al. (2014) have studied how to increase manufacturers' performances improving production visibility and decision-making performances by implementing effective production monitoring and scheduling through the RFId technology. The pilot manufacturing company included in the work of Guo et al. (2015) is a medium-sized clothing manufacturer producing casual wear and sportswear, while Wong et al. (2014) have collected experimental data from a Chinese labour-intensive manufacturing company producing knitwear.

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

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 labour-intensive manufacturing industry, in general (Betrand and Van Onijen, 2008; Wong et al., 2014; Wu et al., 2011) or specifically in the fashion market (Ait-Alla et al., 2014; Hu et al., 2013). The OFs included in the reviewed works are several, moving from minimize the production costs (Ait-Alla et al., 2014), to minimize the tardiness (Ait-Alla et al., 2014; Betrand and Van Onijen, 2008; Guo et al., 2015; Wong et al., 2014), the throughput and the idle time (Guo et al., 2015; Wong et al., 2014), the hiring and layoff costs associated with the change of the workforce level (Rahmani et al., 2013), and the total setup, inventory and backorder costs (Bevilacqua, 2016; Rahmani et al., 2013).

Analysing real world industrial problems, it is usual the co-existence of multiple optimization objectives (Wong et al., 2014), that can be translated into both linear and not linear OFs that include costs, time and plant performance optimization (Betrand and Van Onijen, 2008). 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 models consider the optimization of a single level of the SC, using as input the production plan received from the upper lever and producing as output the scheduling and the delivery plan for the lower level of the SC.

Considering the challenges that fashion companies have to face with, the ones that work using assembly lines have to be focused also to the relative balancing problem.

There are two different types of assembly lines. The first one requires that the product moves from one station to another, whilst the second one assume that the product is fixed and the materials move to the product. In the footwear producers, the assembly lines that will be taken into account are the first one.

Assembly lines can be single-model, multi-model and mixed-model, as shown in Figure 7.

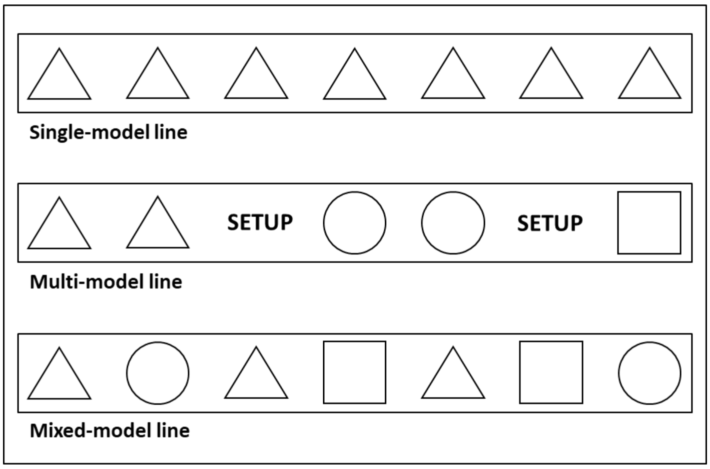

Figure 7 - Assembly lines configurations

The fashion system assembly lines are usually configured as the mixed-model one, where multiple items are alternated and have no significant setup time.

Starting from this boundary, it is possible to define the following terms:

- Task: it is a fraction of the total work needed to get a finished product.
- Station: it is a part of the assembly line, where one or more tasks are carried out.
- Cycle time: it is the total amount of time that a single item should stop into a station.
- Balancing: it represents the sub-division of the tasks among the different station, in order to maximize an objective function, that typically refers to the maximization of the production or the minimization of the costs (Sadeky et al., 2017).

Starting from the terminology describe above, the Assembly Line Balancing (ALB) problem can be summarized into the optimization of an objective function that consider all the stations of an assembly line, in order to maximize the performances according to the requirements of the production manager.

Considering, for example, an objective function referred to maximizing the total number of items produced per day, it can be translated into strategical or operative objectives (Sadeghi et al., 2018): on the one hand, in the medium or long terms it can refer to the optimization of the layout design or the tasks' allocation on the assembly line stations; on the other hand, in the short period the goal can be the optimization of the daily production scheduling, considering fixed cycle times and number of stations, in order to maximize the saturation of each station, starting from the bottle neck of the line.

The problem of the line balancing has been discussed several times in the literature. The first published paper of the ALB problem has been the one of Salveson (1955), who suggested a linear programming solution. After that, two articles by Scholl and Becker (2006) and Becker and Scholl (2006) provide the state-of-the-art about exact and heuristic solution procedures for Single

Assembly Line Balancing (SALB) problems and a survey on problems and methods in Generalized Assembly Line Balancing (GALB) respectively. Considering the schema in Figure 7, SALB problems refer to the assembly lines configured as single-model, while the GALB to the ones configured as multi- or mixed-models.

As reported by Pachghare et al. (2014), SALB problems can be divided into the following categories:

- SALBP-1: Assigning tasks to stations minimizing the number of stations themselves for a given production rate (i.e. fixed cycle time).
- SALBP-2: Minimizing the cycle time (i.e. maximizing the production rate) for a given number of stations.
- SALBP-E: Maximizing the line efficiency minimizing, at the same time, the cycle time and the number of stations, considering their interdependency.
- SALBP-F: Establishing whether or not a feasible line balancing exists for a given combination of number of stations and cycle time.
- SALBP-3: Maximising the workload smoothness for a given number of stations.
- SALBP-4: Maximising workload relatedness.
- SALBP-5: Taking into account multiple objectives.

Among the GALB problems, the leather assembly line can be described as a Mixed Assembly Line Balancing (MALB) problem.

MALB problems can be classified in the same way of the previous one, having:

- MALBP-1: Assigning tasks to stations minimizing the number of stations themselves for a given production rate (i.e. fixed cycle time).
- MALBP-2: Minimizing the cycle time (i.e. maximizing the production rate) for a given number of stations.
- MALBP-E: Maximizing the line efficiency minimizing, at the same time, the cycle time and the number of stations, considering their interdependency
- MALBP-F: Establishing whether or not a feasible line balancing exists for a given combination of number of stations and cycle time.

According to the literature, any of the GALB problems can be classified according to two dimensions: the OF that has to be optimized and the methodology used in order to solve it.

Looking at the first dimension, it is possible also to optimized more than a single OF simultaneously, moving from a single- to a multi-OFs.

The OFs that can be taken into account are:

- Minimization of the number of stations, once fixed the desired output, specifying the cycle time.
- Minimization of the cycle time, once determined the number of stations.
- Maximization of the line efficiency.
- Minimization of the costs.
- Maximization of the profit, calculated as the difference between the revenues and the costs.

- Minimization of the deviation between the production time of every different type of item for every single station (i.e. horizontal balancing).
- Minimization of the deviation of the production time in every single station (i.e. vertical balancing).
- Minimization or maximization of different scores related to line bottle necks, efficiency and quality of components.

The methodologies that can be used in order to solve ALB problems are:

- Linear optimization.
- Not linear optimization.
- Limit value.
- Heuristic procedure.
- Analytic value.
- Simulation.
- Iterative procedure.
- Metaheuristic procedure.

In Table 3 a comprehensive table of the papers approaching different OFs and methodologies in ALB problems, adapted from several authors (Battaia, 2013; Becker, 2006; Faccio, 2008; Pachghare, 2014), is reported.

Table 3 - Literature reivew on ALB problems

Authors	**Objective Function**							**Methodology**								**I***
	Min. stations	**Min cycle time**	**Max Efficiency**	**Min costs**	**Max Profit**	**Min deviation**	**Min or Max score**	**Linear model**	**Not linear model**	**Limit value**	**Heuristic**	**Analytic value**	**Simulation**	**Iterative**	**Metaheuristic**	**Fashion Specific**
Aase et al. (2003, 2004)	X							X		X		X	X			
Amen (2000, 2001, 2006)				X				X		X	X	X				
Bautista and Pereira (2002,2006)	X	X					X	X						X	X	
Boysen and Fliedner (2006)					X				X		X	X			X	
Bukchin and Rabinowitch (2005)				X				X		X		X				
Bukchin and Tzur (2000)				X				X		X		X				
Bukchin et al. (2002)							X	X			X				X	

Capacho and Pastor (2004)	X						X								
Carnahan et al. (2001)		X				X				X				X	
Chen et al. (2012)															X
Chen et al. (2014)															X
Chica et al. (2016)			X				X	X							X
Erel et al. (2001, 2005)	X			X							X				X	
Germanes et al. (2017)			X								X					X
Guimarães et al. (2014)	X												X			X
Karabati and Sayin (2003)							X	X			X					
Kucukkot et al. (2014)	X							X								X
Lapierre and Ruiz (2004)	X										X					
Lee et al. (2001)							X		X		X					
Matanachai and Yano (2001)						X					X					
Miltenburg et al. (2002)	X					X	X		X		X	X				
Nicosia et al. (2002)				X						X		X				
Pastor and Corominas (2000)							X		X	X		X				
Quyen et al. (2017)	X												X			X
Rekiek et al. (2001, 2002)				X		X									X	
Sadeghi et al. (2017)	X												X			X
Sadeghi et al. (2018)	X												X			X
Scholl and Becker (2005)				X				X		X		X				
Scholl et al. (2006)	X							X	X			X				
Ulutas and Islier (2015)	X															X
Vilarinho and Simaria (2002)	X					X		X							X	
Zamani et al. (2011)	X												X			X
Zangiacomi et al. (2004)	X												X			X

* Industry

Most of the publications in line balancing deal with SALB problems, in which only one type of product is processed in the assembly line (Sewell and Jacobson, 2012). On the other hand, as reported by Sivasankaran and Shahabudeen (2014), most of the papers dealing with MALB problems are academic, and only few deals with a real-world environment. Moreover, in order to solve MALB problems on real assembly lines they are usually translated into SALB problems, assuming a single "equivalent item" to be produced having as processing time the average value of the different processing times of the original items.

Regarding the fashion industry, the footwear market segment is the analysed one where the balancing problems are applied and, according to this, where most of the academic contribution for the fashion industry have been found. For example, in their work Guimarães et al. (2014) talk about workers' macro-ergonomic evaluation, while Zangiacomi et al. (2004) dealing with production planning and scheduling for mass customisation. Concerning the design of assembly lines, Chen et al. (2014) use simulation to configure the layouts of stitching lines, Ulutas and Islier (2015) work on the layout problem and Dang and Pham (2016) design an assembly line using simulation. Other works are the ones of Chen et al. (2012), that propose a heuristic approach for scheduling problems in parallel sewing lines, and Quyen et al. (2017), that study the resource constrained assembly line balancing problem in a single model line.

In conclusion, there is an extensive literature about ALB problems, but only few articles include applications in the fashion industry (Sadeghi et al., 2018).

Together with the long-term balancing problem, there is also the Mixed-Model Sequencing Problem (MSP) which goal is to define the better sequence of the items (Baybars, 1986; Boysen, 2006; Scholl e Becker, 2006) in order to maximize the productivity of the assembly line.

MSP regards the optimization of the sequencing of mixed-models according to a specific OF, assuming as already defined the balancing problem and the layout of the conveyors. As assumptions, jobs are considered to be equally divided among the different employees in the stations, the line is considered to move at a fixed speed and the operator is free to start a new job when it has finished the previous one if there are, otherwise he waits for the next job.

MSP solution techniques have been deeply analysed in the literature since the beginning of the study of the mixed-model balancing. According to Caridi and Sianesi (1999) it is possible to define four different eras:

- The "Optimization Era", adopted between the 1970 and the 1980, that was not able to achieve significant success in the result of such problems.
- The "Heuristic Era", widely adopted during the 1980 – 1990, where several solutions were proposed.
- The "Artificial Intelligence (AI) Era", where different approaches can be found, like the export systems, neural networks, genetic algorithms and autonomous agents.
- The "Interactive Scheduler Era", developed linked to the development of the Just In Time (JIT) theory.

In order to understand how the sequencing problem has been studied, in Table 4 is reported the number of the related papers during the last years, classified into the four previously listed different approaches.

Table 4 - Sequencing literature classified by year (adapted from Faccio, 2008)

Year	Era				Authors
1965	Optimization				Thomopoulos et al. (1967), Wester and Kilbridge (1964)
1970					Mutsimori and Takada (1972)
1975					Baker et al. (1978), Dar-El and Cother (1975), Dar-El et al. (1978), Vrat and Virani (1976)
1980		Heuristic			Monden et al. (1983), Okamura and Yamashina (1979)
1985			Artificial Intelligence		Chakravarty et al. (1985), Miltenburg et al. (1989), Shtub et al. (1986), Yano and Bolat (1989)
1990				Interactive scheduler	Bard et al. (1992), Bolat et al. (1994), Bolat et al. (1994), Decker et al. (1993), Ding and Cheng (1993), Domschke et al. (1993), Inman and Bulfin (1991), Kubiak and Sethi (1991), Ng and Mark (1994), Schneeweiß and Söhner (1991), Steiner and Yeomans (1994), Ziegler et al. (1990)
1995					Pinedo et al. (1995), Keun Kim, Hyun and Kim Y. (1995), Xiaobo and Ohno (1996), Xiaobo, Zhou and Asres (1996), Hyun et al. (1996), Korkmazel and Meral (1997), Caridi and Sianesi (1999), Zhu and Ding F.Y (1998), Xiaobo and Ohno (1998), Park and Kim Y.D. (1998), McMullen (1998), McMullen and Frazier (1998), Kurashige et al. (1999), Celano et al. (1999), Scholl (1999)
2000 - today					Celano et al. (2001), Drexl and Kimms (2001), Ventura and Radhakrishnan (2002), Ho and Ji (2003), Mansouri et al. (2004), Ding, Zhu and Sun (2004), Celano et al. (2004), Xiaobo et al. (2005), Bautista and Cano (2005), Tavakkoli-Moghaddam and Rahimi-Vahed (2006), Rahimi-Vahed et al. (2007), Kim S. et al. (2007), Fliedner and Boysen (2007), Boysen et al. (2007), Akgündüz and Tunali (2010), Zhu and Zhang (2011), Moradi and Zandleg (2011), Moradi and Zandleh (2013), Dörmer et al. (2015), Cortez and Costa (2015), Nazar and Pillari (2015), Nazar and Pillai (2018)

Independently from the techniques adopted, objective function of sequencing problems can be classified as:

- Minimization of processing time.
- Minimization of processing cost.
- Minimization of the stocks (e.g. using JIT techniques).

Within the first category (Schneeweiß and Söhner, 1991), some examples include the minimization of the number of additional resources or the minimization of the workers' free time (i.e. the time occurring when an operator is waiting for the next item after he finished to process the previous one).

In the second category, a first objective that can be defined is the total labour cost, defining a regular cost for the operators working inside their station and an extra cost for the operators that work outside their station. Costs can differ depending on the type of jobs (Ziegler, 1990), the station (Thomopoulos, 1967) or the time needed to move outside the stations (Vrat and Virani, 1976).

In the third category, the availability of the material at the station is taken into consideration, in order to quantify and reduce the relative stock per station.

According to the summary showed in Table 4, research on this topic has been increased with the development of new technologies, like the AI techniques, that enabled the possibility to solve complex problems. Nerveless, only few papers deal with the fashion industry (Sivasankaran and Shahabudeen, 2014), whilst most of them are referred to traditional industries like automotive, especially when techniques, like JIT, are applied (Inman, 1991).

4.1.2 Proposed scheduling model for the fashion industry

According to the evidences from the literature review on optimization models for the fashion industry and the on-field interviews at the production managers for the analysed companies, the boundaries of the model have been defined in terms of the development of a multi-objective integer linear optimization model with a weighted sum OF.

The linearity of the model, with a low complexity in its implementation, is due to the dimension that most of the companies working along the fashion SC have.

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 fact, the weighted sum OF reflects the commercial agreement between these companies and the brands: different weights for different sub-objectives. Moreover, a solution implementable with an open source solver and a commercial spreadsheet has been chosen according to their low IT investment capability.

The model is explained through the following sections: Indices and Parameters (see paragraph 4.1.2.1 Indices and Parameters), Decision Variables (see paragraph 4.1.2.2 Decision variables), Constraints (see paragraph 4.1.2.3 Constraints) and Objectives (see paragraph 4.1.2.4 Objectives).

First section includes the model inputs, which are the items to be scheduled that are listed in the production orders coming from fashion companies, typically characterized by short visibility and small lots with a high fragmentation. In the same section, the master data (e.g. suppliers and resources' lists) are included. Some variables (e.g. set up and LTs) are then listed but not used in the pilots, in order to simplify the first step of model implementation.

The proposed model generates a production plan that indicates the quantities for each ordered item that should be produced per period, distinguishing between regular-time and overtime hours, start and end dates for that production, and involved resources. These data are described in the Decision Variables section.

The Constraints has been grouped into the following category: demand fulfilment, available capacity, activated resources, positive and integer scheduled quantity.

The Objectives that characterized the OF are described within the last section.

4.1.2.1 Indices and Parameters

The Indices (In) and Parameters (Pn) considered in the model represent the inputs for running the model and how they are filled reflects the peculiarities of the single SC actor.

(I1) II = {1, 2, …, IIN}: the indices for the job order row. IIN is the number of the job order rows to be scheduled. The job order rows refer to a job order, that represent the single order that an upstream SC actor sends to a downstream SC actor. According to this, each job order is related to a single customer (i.e. the upstream SC actor) and usually reports, on the header, several information that are shared by the included items, known as Stock Keeping Units (SKUs) in the fashion industry and characterized by a specific combination of model, material, colour and size. Consequently, the single job order row refers to a single SKU that belongs to a specific job order and represents the elementary unit to be assigned through the optimization model.

(I2) TT = {1, 2, …, TTN}: the indices for the scheduled periods. TTN is the number of the scheduled periods to be managed.

(I3) PP = {1, 2, …, PPN}: the indices for the production phases. PPN is the number of the production phases to be managed.

(I4) RR = {1, 2, …, RRN}: the indices for the resources (i.e. the resources - machineries, personnel, …- which can process the production order). RRN is the number of the resources to be managed.

(I5) JJ = {1, 2, …, JJN}: the indices for the SKUs. JJN is the number of SKUs to be managed.

(I6) KK = {1, 2, …, KKN}: the indices for the kits. KKN is the number of kits to be managed. The concept of kit refers to the fact that some job order rows can be related one to each other, requiring to be coherently assigned. An example of kit in the fashion is a suit, a set of garments usually consisting of, at least, two different SKUs: a jacket and a pair of trousers.

(P1) $RQ_{i,p,t}$: the requested quantity of the job order row i Є II for the production phase p Є PP in t Є TT.

(P2) RDD_i: the requested delivery date of the job order row i Є II. RDD_i Є TT.

(P3) $CCDD_i$: the expected delivery date for the critical component of the job order row i Є II. If it is before the starting scheduling date it is considered equals to the first day in the plan, because that means that critical component is already available for being used on the production line.

(P4) SKU_{ji} = the SKU_j with j Є JJ to whom the job order row i Є II refers. In fact, different job orders can include the same SKU, for example in case it has been required on different deliveries or made by different suppliers.

(P5) $JORP_i$: the job order row priority of the job order row i ∈ II. This parameter refers to the fact that, even if all the job order rows should be realized on-time, delays of some of them have a worst impact on company's performances. In the same way, some customers could have a higher priority than others, that is managed considering a higher job order row priority for all the job order rows held by it.

(P6) KIT_{ki}: the KIT_k with k ∈ KK to whom the job order row i ∈ II belongs. This parameter can be null or valued, and the same KIT_k can include different job order rows that have to be scheduled together.

(P7) $LKIT_k$: the number of job order rows that belongs to the KIT_k with k ∈ KK. $LKIT_k$ ∈ II.

(P8) UC_{kji}: the using coefficient of the SKU_{ji} with j ∈ JJ for the job order row i ∈ II that belongs to the kit KIT_k with k ∈ KK. If filled, it indicates that UC_{kji} units of the SKU_{ji} need to realize one complete kit KIT_{ki}. For example, considering the three job order rows i_1, i_2, i_3 ∈ II, the kit KIT_k can be composed by 2 units of i_1, 1 of i_2 and 1 of i_3, that means that UC_{kji} is equal to 2 for i_1 and to 1 for both i_2 and i_3.

(P9) MC_{ji}: the mix coefficient of the SKU_{ji} with j ∈ JJ for the job order row i ∈ II. If filled, it indicates that MC_{ji} units of the SKU_{ji} identify its weight in the balancing mix. For example, considering the SKUs SKU_1, SKU_2 and SKU_3 ∈ SKU_{ji}, the balanced mix defined can include 2 units of SKU_1, 1 of SKU_2 and 1 of SKU_3, that means that MC_{ji} is equal to 2 for i_1 and to 1 for both i_2 and i_3. According to this, the scheduling has to allocate quantities to be produced quite closer to multiples of MC_{ji} for each SKU_{ji} with j ∈ JJ.

(P10) $PIB_{i,p}$ ∈ {0,1} is a Boolean parameter to indicate if the production phase p ∈ PP is included (i.e. $PIB_{i,p}$=1) or not (i.e. $PIB_{i,p}$=0) in the operational cycle of the job order row i ∈ II.

(P11) $RSB_{s,r,t}$ ∈ {0,1} is a Boolean parameter to indicate if the resource r ∈ RR is available (i.e. $RSB_{s,r,t}$=1) or not (i.e. $RSB_{s,r,t}$=0) for the supplier s ∈ SS in t ∈ TT.

(P12) $PIRB_{i,r,p}$ ∈ {0,1} is a Boolean parameter to indicate if the production phase p ∈ PP for the job order row i ∈ II can be processed (i.e. $PIRB_{i,r,p}$=1) or not (i.e. $PIRB_{i,r,p}$=0) by the resource r ∈ RR.

(P13) $PRI_{i,r,p}$: the value indicates if the resource r ∈ RR is preferred (≤) or not (≥) if compared to other resources for the production phase p ∈ PP of the job order row i ∈ II in t ∈ TT.

(P14) $DSC_{p,r,t}$: the daily standard-time capacity (i.e. available capacity during the regular worktime) for the production phase p ∈ PP conducted by the resource r ∈ RR in t ∈ TT.

(P15) $DOC_{p,r,t}$: the daily overtime capacity (i.e. available capacity during the overtime) for the production phase p ∈ PP conducted by the resource r ∈ RR in t ∈ TT.

(P16) $DPSQ_{p,r,i,t}$: the daily preassigned standard-time quantity (i.e. quantity assigned in the regular worktime during previous schedules) for processing the production phase p ∈ PP of the job order row i ∈ II using the resource r ∈ RR in t ∈ TT.

(P17) $DPOQ_{p,r,i,t}$: the daily preassigned overtime quantity (i.e. quantity assigned in the overtime during previous schedules) for the production phase p ∈ PP of the job order row i ∈ II using the resource r ∈ RR in t ∈ TT.

(P18) $SUC_{p,r,i}$: the standard-time unitary cost (i.e. single-item cost assigned in the regular worktime) for processing the production phase p ∈ PP of the job order row i ∈ II using the resource r ∈ RR.

(P19) $OUC_{p,r,i}$: the overtime unitary cost (i.e. single-item cost assigned in the overtime) for the production phase p ∈ PP of the job order row i ∈ II using the resource r ∈ RR. The reason why the unitary cost has been distinguished between the one related to the standard-time and the overtime production is mainly related to the fact that the overtime cost is quite often higher than the standard-time one.

(P20) $OT_{p,r,i}$: the operational time for the production phase p ∈ PP of the job order row i ∈ II using the resource r ∈ RR.

(P21) $SUT_{p,r,i,k}$: the setup time for the production phase p ∈ PP of the job order row i ∈ II, worked after k ∈ II, using the resource r ∈ RR.

(P22) $LT_{p,r,i}$: the LT for the production phase p ∈ PP of the job order row i ∈ II using the resource r ∈ RR.

(P23) dw: the delay-related weight considering the whole production plan.

(P24) aw: the advance-related weight considering the whole production plan.

(P25) cw: the cost-related weight considering the whole production plan.

(P26) ptw: the processing time-related weight considering the whole production plan.

(P27) rpbw: the resources balancing-related weight considering the whole resources pool considering the whole production plan.

(P28) rbw: the resources balancing-related weight considering the single resource r Є RR considering the whole production plan.

(P29) mbw: the mix balancing-related weight.

4.1.2.2 Decision variables

The Decision Variables (DVn) considered in the model represent the variables that have to be calculated to get the optimal solution.

(DV1) $DSSQ_{p,r,i,t}$: the daily scheduled standard quantity (i.e. quantity scheduled in the regular worktime) for processing the production phase p Є PP of the job order row i Є II using the resource r Є RR in t Є TT.

(DV2) $DSOQ_{p,r,i,t}$: the daily scheduled overtime quantity (i.e. quantity scheduled in the overtime) for the production phase p Є PP of the job order row i Є II using the resource r Є RR in t Є TT.

(DV3) $DDSSQ_{p,r,i,t}$: the delivery date for scheduled standard quantity (i.e. delivery date for quantity scheduled in the regular worktime) for processing the production phase p Є PP of the job order row i Є II using the resource r Є RR in t Є TT.

(DV4) $DDSOQ_{p,r,i,t}$: the delivery date for scheduled overtime quantity (i.e. delivery date for quantity scheduled in the overtime) for the production phase p Є PP of the job order row i Є II using the resource r Є RR in t Є TT.

(DV5) $SSPD_{p,r,i}$: the scheduled start processing date for the production phase p Є PP of the job order row i Є II using the resource r Є RR. $SSPD_{p,r,i}$ Є TT.

(DV6) $SEPD_{p,r,i}$: the scheduled end processing date for the production phase p ∈ PP of the job order row i ∈ II using the resource r ∈ RR. $SEPD_{p,r,i}$ ∈ TT.

(DV7) $SSPD_i$: the scheduled start processing date of the job order row i ∈ II. This variable is calculated as follows:

$$\mathrm{SSPD_i} \ = \ \min \{\mathrm{SSPD_{1,r,i}}\}$$

(DV8) $SEPD_i$: the scheduled end processing date of the job order row i ∈ II. This variable is calculated as follows:

$$\mathrm{SEPD_i} \ = \ \max \{\mathrm{SEPD_{PPN,r,i}}\}$$

(DV9) $DSC_{p,r,i,t}$: the daily standard-time cost per resource r ∈ RR per production process p ∈ PP of the job order row i ∈ II. This variable is calculated as follows:

∀ t ∈ TT, ∀ p ∈ PP, ∀ r ∈ RR, ∀ i ∈ II,

$$\mathrm{DSSQ_{p,r,i,t}} * \ \mathrm{SUC_{p,r,i}}$$

(DV10) $DOC_{p,r,i,t}$: the daily overtime cost per resource r ∈ RR per production process p ∈ PP of the job order row i ∈ II. This variable is calculated as follows:

∀ t ∈ TT, ∀ p ∈ PP, ∀ r ∈ RR, ∀ i ∈ II,

$$\mathrm{DSOQ_{p,r,i,t}} * \ \mathrm{OUC_{p,r,i}}$$

(DV11) $DD_{p,i,t}$: the daily delays per production process p ∈ PP of the job order row i ∈ II in t ∈ TT. According to the definition of the job order row priority $JORP_i$, its value is directly proportional with the delay value, because the impact of delays related to a job order row with a higher priority will be worse than another one with lower priority. This variable is calculated as follows:

∀ t ∈ TT, ∀ p ∈ PP, ∀ i ∈ II,

$$(\max \{0; \mathrm{DD_{p,i,t-1}} + \sum_{r=1}^{RR} (\mathrm{DSSQ}_{p,r,i,t} + \mathrm{DSOQ}_{p,r,i,t}) \ - \mathrm{RQ_{i,p,t}}\}) * \ \mathrm{JORP_i}$$

(DV12) $DA_{p,i,t}$: the daily advances of the job order row i ∈ II. This variable is calculated as follows:

∀ t ∈ TT, ∀ p ∈ PP, ∀ i ∈ II,

$$(\min \{0; \mathrm{DA_{p,i,t-1}} + \sum_{r=1}^{RR} (\mathrm{DSSQ}_{p,r,i,t} + \mathrm{DSOQ}_{p,r,i,t}) \ - \mathrm{RQ_{i,p,t}}\})$$

(DV13) PT_i: the processing time of the job order row i Є II. This variable is calculated as follows:

∀ i Є II,

$$\mathrm{SEPD_i} - \mathrm{SSPD_i}$$

(DV14) $SSAT_{r,t}$: the saturation for the resource r Є RR in the period t Є TT considering standard-time production. This variable is calculated as follows:

∀ t Є TT, ∀ r Є RR,

$$\frac{\sum_{i=1}^{II} \mathrm{DSSQ}_{p,r,i,t}}{\mathrm{DSC}_{p,r,t}}$$

(DV15) $OSAT_{r,t}$: the saturation for the resource r Є RR in the period t Є TT considering overtime production. This variable is calculated as follows:

∀ t Є TT, ∀ r Є RR,

$$\frac{\sum_{i=1}^{II} \mathrm{DSOQ}_{p,r,i,t}}{\mathrm{DOC}_{p,r,t}}$$

(DV16) RPB: the overall saturation balancing is the standard deviation between the average saturation for the single resource r Є RR and the overall average saturation in the period TT. This variable is calculated as follows:

$$\sqrt{\frac{\sum_{r=1}^{RR}(\mu_{sat\_r\_TT} - \mu_{sat\_RR\_TT})^2}{RR}}$$

Having:

$$\mu_{sat\_r\_TT} = \frac{\sum_{t=1}^{TT}(\mathrm{SSAT_{r,t}} + \mathrm{OSAT_{r,t}})}{TT}$$

And

$$\mu_{sat\_RR\_TT} = \frac{\sum_{r=1}^{RR}(\mu_{sat\_r\_TT})}{RR}$$

(DV17) RB_r: the saturation balancing is the standard deviation between the average saturation for the resource r Є RR considering both the standard-time and the overtime scheduled production in the period t Є TT and the overall average saturation for the resource r Є RR. This variable is calculated as follows:

∀ r Є RR,

$$\sqrt{\frac{\sum_{t=1}^{TT}((\mathrm{SSAT_{r,t}} + \mathrm{OSAT_{r,t}}) - \mu_{sat\_r\_TT})^2}{TT}}$$

(DV18) MB: the mix balancing is the standard deviation between the quantity assigned per job order row i normalized according the mix coefficient MC_{ji} and its average value considering the single resource r ∈ RR in the period t ∈ TT. This variable is calculated as follows:

∀ t ∈ TT, ∀ p ∈ PP, ∀ r ∈ RR,

$$\sqrt{\frac{\sum_{\mathrm{i}=1}^{II}(\beta_{itr} - \mu_{Itr})^2}{II}} = 0$$

Having:

$$\beta_{itr} = \frac{DSSQ_{p,r,i,t} + DSOQ_{p,r,i,t}}{MC_{ji}}$$

And:

$$\mu_{Itr} = \frac{\sum_{\mathrm{i}\in II}\beta_{itr}}{II}$$

4.1.2.3 Constraints

The Constraints (Cn) considered in the model represent the conditions that the optimization model's solution has to satisfy.

(C1) Demand fulfilment: the total scheduled quantity per job order row i ∈ II along the whole scheduling period has to be equal to the related required quantity included in the production plan as input. This constraint is expressed as follows:

∀ p ∈ PP, ∀ i ∈ II,

$$\sum_{r=1}^{RR}\sum_{t=1}^{TT}(\mathrm{DSSQ}_{p,r,i,t} + \mathrm{DSOQ}_{p,r,i,t}) = \sum_{t=1}^{TT}\mathrm{RQ}_{i,p,t}$$

(C2) Available standard-time capacity: the scheduled quantity during the standard-time per resource r ∈ RR in the period t ∈ TT has to be lower or, at least, equal to the available standard-time capacity per resource r ∈ RR in the period t ∈ TT. This constraint is expressed as follows:

∀ t ∈ TT, ∀ p ∈ PP, ∀ r ∈ RR,

$$\sum_{i=1}^{II}(\mathrm{DSSQ}_{p,r,i,t} + \mathrm{OT}_{p,r,i}) \le \mathrm{DSC}_{p,r,t} + \sum_{i=1}^{II}(\mathrm{DPSQ}_{p,r,i,t} + \mathrm{OT}_{p,r,i})$$

(C3) Available overtime capacity: the scheduled quantity during the overtime per resource r Є RR in the period t Є TT has to be lower or, at least, equal to the available overtime capacity per resource r Є RR in the period t Є TT. This constraint is expressed as follows:

∀ t Є TT, ∀ p Є PP, ∀ r Є RR,

$$\sum_{i=1}^{II}(\mathrm{DSOQ}_{p,r,i,t} + \mathrm{OT}_{p,r,i}) \leq \mathrm{DOC}_{p,r,t} + \sum_{i=1}^{II}(\mathrm{DPOQ}_{p,r,i,t} + \mathrm{OT}_{p,r,i})$$

(C4) Activated resources: the job order rows have to be produced only by the resources enabled to do it, considering both the standard-time and overtime scheduled capacity. This constraint is expressed as follows:

∀ t Є TT, ∀ p Є PP, ∀ r Є RR, ∀ i Є II,

$$\mathrm{DSSQ}_{\mathrm{p,r,i,t}} * \mathrm{PIRB}_{\mathrm{i,r,p}} = \mathrm{DSSQ}_{\mathrm{p,r,i,t}}$$

$$\mathrm{DSOQ}_{\mathrm{p,r,i,t}} * \mathrm{PIRB}_{\mathrm{i,r,p}} = \mathrm{DSOQ}_{\mathrm{p,r,i,t}}$$

(C5) Positive scheduled standard-time quantity: the scheduled quantity during the standard-time related to the job order row i Є II per resource r Є RR in the period t Є TT has to be positive. This constraint is expressed as follows:

∀ t Є TT, ∀ p Є PP, ∀ r Є RR, ∀ i Є II,

$$\mathrm{DSSQ}_{\mathrm{p,r,i,t}} \geq 0$$

(C6) Positive scheduled overtime quantity: the scheduled quantity during the overtime related to the job order row i Є II per resource r Є RR in the period t Є TT has to be positive. This constraint is expressed as follows:

∀ t Є TT, ∀ p Є PP, ∀ r Є RR, ∀ i Є II,

$$\mathrm{DSOQ}_{\mathrm{p,r,i,t}} \geq 0$$

(C7) Integer scheduled standard-time quantity: the scheduled quantity during the standard-time related to the job order row i Є II per resource r Є RR in the period t Є TT has to be integer. This constraint is expressed as follows:

∀ t Є TT, ∀ p Є PP, ∀ r Є RR, ∀ i Є II,

$$\mathrm{DSSQ}_{\mathrm{p,r,i,t}} = int$$

(C8) Integer scheduled overtime quantity: the scheduled quantity during the overtime related to the job order row i ∈ II per resource r ∈ RR in the period t ∈ TT has to be integer. This constraint is expressed as follows:

∀ t ∈ TT, ∀ p ∈ PP, ∀ r ∈ RR, ∀ i ∈ II,

$$\mathrm{DSOQ}_{\mathrm{p,r,i,t}} = int$$

(C9) Available critical component for the scheduled delivery date: the delivery date for scheduled quantity related to the job order row i ∈ II per resource r ∈ RR in the period t ∈ TT has to be later or, at least, equal to the expected delivery date of the critical component. This constraint is expressed as follows:

∀ t ∈ TT, ∀ p ∈ PP, ∀ r ∈ RR, ∀ i ∈ II,

$$\left(\min\left\{\mathrm{DDSSQ}_{p,r,i,t}; \mathrm{DDSOQ}_{p,r,i,t} - \mathrm{CCDD}_i\right\}\right) * \left(\mathrm{DSSQ}_{p,r,i,t} + \mathrm{DSOQ}_{p,r,i,t}\right) \geq 0$$

(C10) Assignment of complete kits: the quantity of job order row i ∈ II belonged to the kit KIT_{ji} with j ∈ JJ have to be scheduled considering the schedulable quantity of the other job order rows belonged to the same kit, according to the fact that complete kit has to be delivered in the same date t ∈ TT. This constraint is expressed as follows:

∀ t ∈ TT, ∀ p ∈ PP, ∀ k ∈ KK,

$$\sqrt{\frac{\sum_{\mathrm{i} \in \mathrm{KIT}_{ji}} (\propto_{it} - \mu_{\propto\_KIT_{k\_}t})^2}{LKIT_k}} = 0$$

Having:

$$\propto_{it} = \frac{\sum_{r=1}^{RR} DSSQ_{p,r,i,t} + DSOQ_{p,r,i,t}}{UC_{kji}}$$

And:

$$\mu_{\propto\_KIT_{k\_}t} = \frac{\sum_{\mathrm{i} \in \mathrm{KIT}_{ji}} \propto_{it}}{LKIT_k}$$

This constraint has been linearized substituting the formula above with a series of constraints equal to zero between each job order row i ∈ II belonging to the KIT_{ji}.

$$\frac{\sum_{r=1}^{RR} DSSQ_{p,r,\beta,t} + DSOQ_{p,r,\beta,t}}{UC_{kj\beta}} = \frac{\sum_{r=1}^{RR} DSSQ_{p,r,\pi,t} + DSOQ_{p,r,\pi,t}}{UC_{kj\pi}}$$

∀ β, π ∈ II belonging to the KIT_{ji}.

4.1.2.4 Objectives

The Objectives (OBJn) considered in the model can be summed up as follows:

(OBJ1) Minimize the costs, referring to both the ones related to the standard-time and overtime scheduling:

$$\min\{C\} = \min\left\{\sum_{i=1}^{II}\sum_{p=1}^{PP}\sum_{r=1}^{RR}\sum_{t=1}^{TT}(\mathrm{DSC}_{p,r,i,t} + \mathrm{DOC}_{p,r,\mathrm{i},\mathrm{t}})\right\}$$

(OBJ2) Minimize the delays:

$$\min\{D\} = \min\left\{\sum_{i=1}^{II}\sum_{p=1}^{PP}\sum_{t=1}^{TT}(\mathrm{DD}_{p,i,t})\right\}$$

(OBJ3) Minimize the advances:

$$\min\{A\} = \min\left\{\sum_{i=1}^{II}\sum_{p=1}^{PP}\sum_{t=1}^{TT}(\mathrm{DA}_{p,i,t})\right\}$$

(OBJ4) Minimize the processing time:

$$\min\{PT\} = \min\left\{\sum_{i=1}^{II}(\mathrm{PT}_{i})\right\}$$

(OBJ5) Maximize the saturation balancing per resource pool:

$$\min\{RPB\}$$

(OBJ6) Maximize the saturation balancing per resource:

$$\min\{RB\} = \min\left\{\sum_{i=1}^{II}(\mathrm{RB}_{i})\right\}$$

(OBJ7) Maximize the mix balancing:

$$\min\{MB\} = \min\left\{\sum_{i=1}^{II}(\mathrm{MB}_{i})\right\}$$

As previously anticipated, the OF is a mix of the previous functions that, according to Guo et al. (2008), can be correlated using the weights defined in the Indices and Parameters section (i.e. cw, dw, aw, ptw, rpbw, rbw, mbw). According to this, the overall OF can be obtained giving different weights for each one of the elementary objectives (i.e. OBJn): if the given weight is equals to 0, it means that the related OBJn is not considered during the model implementation.

$$\mathrm{OF} =$$

$$\min \{\mathrm{cw} * \mathrm{C} + \mathrm{dw} * \mathrm{D} + \mathrm{aw} * \mathrm{A} + \mathrm{ptw} * \mathrm{PT} + \mathrm{rpbw} * \mathrm{RPB} + \mathrm{rbw} * \mathrm{RB} + \mathrm{mbw} * \mathrm{MB}\}$$

4.1.3 Implementation of the proposed scheduling model in the fashion industry

The proposed scheduling model described in the previous paragraph has been on-field implemented in real companies using an open-source solver optimization tool, OpenSolver (www.opensolver.org, version 2.8.6), integrated on Microsoft Excel®.

Even if in the literature more complex solvers (i.e. CPLEX® for AMPL or MATLAB®) have been used (Ait-Alla et al., 2014; May et al., 2015), OpenSolver has been chosen considering the restricted financial resources of the addressed companies working within the fashion SC, most of them SMEs with a low informatization level and investment capabilities in IT solution.

According to this, the natively integration between OpenSolver and the most commonly used commercial spreadsheet Microsoft Excel® represents the key value to enable these companies to easily-insert the input data required for configuring the proposed scheduling model and to easily-understand the output of model’s runs, because both the inputs and the outputs are managed and shown on an Microsoft Excel® file.

Moreover, the parameters, constraints, decision variables and objective functions previously described (see paragraph 4.1.2 Proposed scheduling model for the fashion industry) can be modeled in OpenSolver both using its own model editor (see Figure 8) and Visual Basic for Application (VBA) code, an implementation of Microsoft's event-driven programming language Visual Basic.

In the proposed model implementation, all the data have been configured using VBA code in order to automatically define themselves according to the exported data from the supplier’s Enterprise Resources Planning (ERP). In fact, changes on the model inputs, for example in terms of number of resources or job order rows, require manual inserting using the OpenSolver model editor while, using VBA code, the model constraints and decision variables are automatically updated.

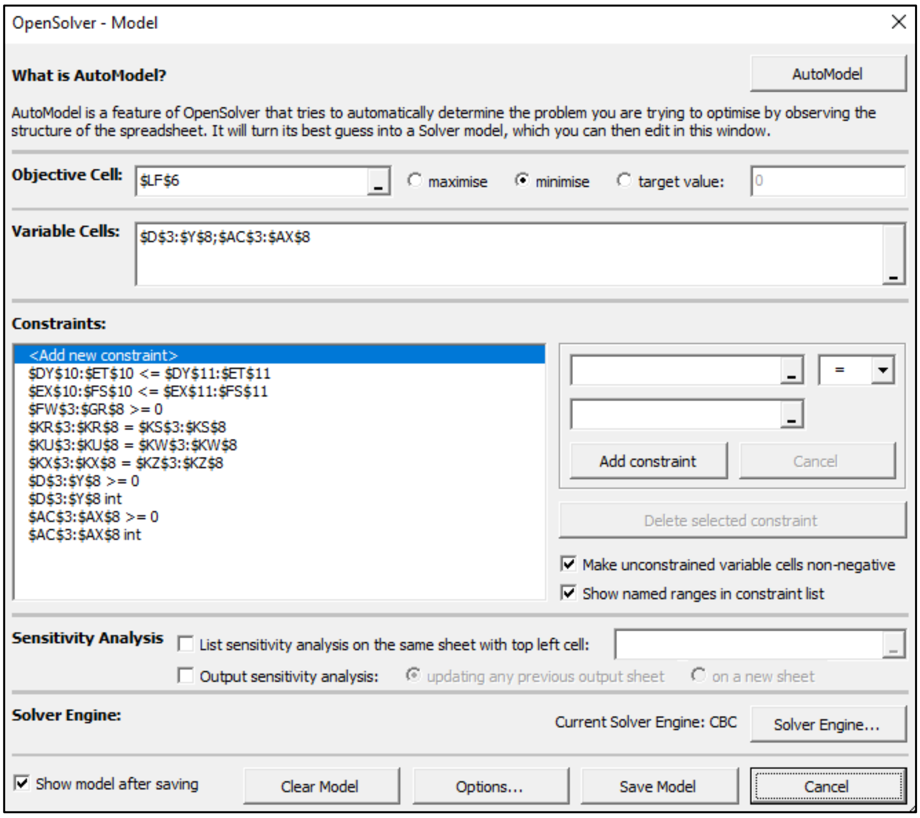

Figure 8 - OpenSolver model editor

As anticipated, the data in Figure 8 have not been manually inputted but generated running the developed VBA code and then only visualized on the OpenSolver's model editor.

In addition, once the model has been built on OpenSolver, it allows to easily-check if all data have been correctly configured through clicking on the button "Show/Hide Model", that displays directly on the Microsoft Excel® spreadsheet the resulting configuration. As shown in Figure 9 and Figure 10, the left-hand side and right-hand side of each constraint included in the model are boxed with the same colour and joined, and the constraint sense indicated (e.g. "<", "≤", "=", "≥", ">"). For example, in Figure 9 is graphically shown the constraint for the demand fulfilment, with the cells related to the required quantity and the assigned quantity per SKU brown-circled and marked with an "=", highlighting that assigned quantities have to be equal to the required ones. In the same way, Figure 10 shows the constraint related to the fact that the daily assigned capacity per resource has not to overcome the available one.

C_DemandFulfilment	
RequiredQty	**AssignedQty**
212	212
307	307
712	712
750	750
532	532
336	336

Figure 9 – Graphical explaination of constraints on OpenSolver (1)

C_SaturationResource1

skuCode	10/08/2018	11/08/2018	12/08/2018	13/08/2018	14/08/2018	15/08/2018	16/08/2018	17/08/2018
skuCode_1	0	0	0	0	14484	0	28764	0
skuCode_2	0	0	0	0	2244	2856	0	28764
skuCode_3	0	0	0	0	0	25908	0	0
skuCode_4	0	0	0	0	9180	0	0	0
skuCode_5	0	0	0	0	0	0	0	0
skuCode_6	28800	0	0	28800	2880	0	0	0
AssignedQty	28800	0	0	28800	28788	28764	28764	28764
AvailableCapacity	≤ 28800	0	0	28800	28800	28800	28800	28800
Saturation	100%	---	---	100%	100%	100%	100%	100%

Figure 10 - Graphical explaination of constraints on OpenSolver (2)

Moreover, the cell involved for the definition of the model's objective is highlighted and tagged with "min" or "max" if the goal is to minimize or maximise the cell respectively (see Figure 11), while the decision variables are shade, with integer variables tagged with "I" and binary variables with "b" (see Figure 12).

OF_ObjectiveFunction

Objective	Value	Weight	WeightedValue
Costs	2849	0	0
Delays	309	100	30900
Advances	13037	1	13037
			min 43937

Figure 11 – Graphical explaination of objective functions on OpenSolver

DV_AssignedQtyperResource1

skuCode	10/08/2018	11/08/2018	12/08/2018	13/08/2018	14/08/2018	15/08/2018
skuCode_1	integer 0	0	0	0	71	0
skuCode_2	0	0	0	0	11	14
skuCode_3	0	0	0	0	0	127
skuCode_4	0≤ 0	0	0	0	45	0
skuCode_5	0	0	0	0	0	0
skuCode_6	60	0	0	60	6	0

Figure 12 - Graphical explaination of decision variables on OpenSolver

Finally, OpenSolver has been chosen also because its versatility in terms of the wide range of "solvers" that can be select according to their suitability with different types of optimization problems. For example, for the implementation of the proposed linear and integer scheduling model in the analysed scenario, the local version of the linear solver CBC has been used, running on a personal computer with 8GB RAM and a CPU Intel Core I7 third generation and an SSD hard disk.

4.2 Simulation model for the fashion industry

Optimization models cannot be used by themselves to improve production planning performances. This evidence, also confirmed by the on-field implementations, is due to the fact that companies work in a really complex and quite dynamic scenario, especially in the fashion industry where customers require due dates each other even closer than the past pushing brand owners to frequently have to manage stochastic events such as unexpected orders and delays in raw materials' and components' deliveries. In other words, it is needed to move from static optimized plans to simulated ones, that include the effects of stochasticity.

After the optimization one, in order to answer to the RQ2, a simulation model has to be developed as second step of research. In the same way of the optimization model, the structure and logics of the simulation model had to be defined in order to apply the model itself on different SC actors. The simulation model has to allow the scenario analysis, in order to compare different outputs that come running the model considering different inputs (such as a decreased resource capacity) and/or under different deterministic and/or stochastic conditions (such as an increased occurrence of rush orders). The comparison has to be done through a gap analysis referred to a specific set of KPIs that has to be defined, studying how these KPIs' values change moving from a scenario to another one.

According to this, the followed approach has been the same of the one used for answering RQ1. First of all, a literature review on simulation model has been done as first step (see paragraph 4.2.1 Literature on simulation model in the fashion industry), in order to analyse the different approaches taken into account both in general and specifically for the fashion industry. Starting from the evidences coming from the literature review, the first draft of the proposed simulation model has been developed and then iteratively readapted until the definition of its final version according to the feedback from its implementations (see paragraph 4.2.2 Proposed simulation model for the fashion industry). Using the action research methodology, the proposed simulation model has been validated through on-field implementations on companies working in the 3 analysed market segments (i.e. metal accessories, leather goods, footwear) comparing simulation model's outputs with the optimized plan in input, both run under deterministic conditions (see paragraph 4.2.3 Implementation of the proposed simulation model in the fashion industry).

4.2.1 Literature on simulation model in the fashion industry

Considering the approaches to simulation modeling in Operational Research (OR), DES and SD are both widely used within business contexts especially for supporting the decision-making process, even if they are quite different one to each other, according to several contributions in literature (Brailsford and Hilton, 2001; Sweetser, 1999).

DES models systems as networks of queue and activities, characterized by state changes that occurs at discrete points of time in the system. Each modeled object has some parameters that characterize itself and determine its behaviour in the system, such as the probability distributions to define the activity duration.

Using accurate historical and actual operating data as input, DES model can replicate the performance of an existing system and provide decision maker insights about how the modeled system might perform changing the input parameters or the configuration of the system itself. Moreover, the simulated model can be represented using computer animation, that provides an even more tangible support in the decision-making process giving an excellent overview of how a process operates, in the actual or prospect scenario, where backlogs and queues form, and how system's performances change implementing the proposed improvements to the system. In other words, this means that DES allows companies to conduct scenario analysis to compare how system's performances change moving from a scenario, characterized by a specific set of inputs, parameters and process configuration, to another one.

Considering the implementation on a real-context, DES is more appropriate to analyse well-defined systems or linear processes, such as a production line. In fact, this kind of systems can be modeled considering state changes at specific instants: resources fail, operators take breaks, shifts change, and so on. According to this, DES can provide statistically valid estimates of performance measures associated with these systems, such as number of entities waiting in a specific queue.

On the other hand, SD models a system as a collection of elements that continually interact over time to form a unified whole, a series of stocks and flows where state continuously changes. According to this, SD is a methodology to understand how systems change over time, being more suitable to model continuous processes instead of discrete ones. In SD three main objects are considered: (i) stocks, that are basic stores of objects, (ii) flows, that define the movement of items between different stocks in the system and out/into the system itself, and lastly (iii) delays, that are the delay between the system measuring something and then acting upon that measurement.

Moreover, in SD one of the key concepts is the "structure", that refers to the components and relationships among the components of a system and represents what determines performance. In fact, having a clear understanding of the linkages between people, processes and resources, the structure of a system can be optimized to improve performance These links should be explicitly modeled by feedback loops that represent how a change in one variable affects other variables in the system, so how the whole system consequently performs over time. On the other hand, these linkages may be not so easy to be empirically quantify, and their evaluation can be based not only on real data but on estimates coming from experts.

In contrast, modeling according to a DES approach requires a great effort on data analysis and distribution fitting based on accurate historical data or estimates of future performance to ensure the model is statistically valid.

Summing up it is possible to say that DES tends to look at the smaller detail of a system (microscopic), whereas SD tends to take a more overall perspective (macroscopic). Moreover, a key difference between DES and SD is the intrinsic nature of the two approaches: on the one hand, DES is stochastic in nature and therefore will give different results on different runs; on the other hand, SD model is deterministic in nature, producing the same results run after run and consequently needing to be run once.

Another approach included in the literature as one of the three major paradigms in simulation modeling is the ABS, a relatively new simulation method especially in the field of OR, where the already described DES and SD methods have been widely applied.

ABS models systems as being made up of autonomous (self-directed) agents which follow a series of predefined rules to achieve their objectives whilst interacting with each other and their environment. One of the strengths of this approach is its versatility, because modeled agents could be completely different things.

On the other hand, the reason why this recent approach is rarely implemented in the OR field can be related to the fact that, while DES is built around networks of queues, in an ABS system there is no concept of queues (Siebers et al., 2010). Moreover, the agents in an ABS model have their own behaviour, while in a DES model their behaviour depends on the system, and this is the reason why their attitude can be classified as "active" for the ABS and "passive" for the DES.

A comparison between the three described simulation approaches have been done by Behdani in 2012 and summarized it the following table (see Table 5).

Table 5 - Summary of main characteristics of three simulation paradigms (Behdani, 2012)

System Dynamics (SD)	**Discrete Event Simulation (DES)**	**Agent-based Simulation (ABS)**
System-oriented; focus is on modeling the system observables.	Process-oriented; focus is on modeling the system in detail.	Individual-oriented; focus is on modeling the entities and interactions between them.
Homogenized entities; all entities are assumed have similar features; working with average value.	Heterogeneous entities.	Heterogeneous entities.
No representation of micro-level entities.	Micro-level entities are passive "objects" (with no intelligence or decision-making capability) that move through a system in a pre-specified process.	Micro-level entities are active entities ("agent") that can make sense the environment, interact with others and make autonomous decisions.
Driver for dynamic behaviour of system is "feedback loops".	Driver for dynamic behaviour of system is "event occurrence".	Driver for dynamic behaviour of system is "agent's decision and interaction".
Mathematical formalization of system is in "Stock and Flow".	Mathematical formalization of system is with "Event, Activity and Process".	Mathematical formalization of system is by "Agent and Environment".
Handling of time is continuous (and discrete).	Handling of time is discrete.	Handling of time is discrete.
Experimentation by changing the system structure.	Experimentation by changing the process structure.	Experimentation by changing the agent rules (internal/interaction rules) and system structure.
System structure is fixed.	Process is fixed.	System structure is not fixed.

According to several works, such as the ones of Tako and Robinson (2012) and Terzi and Cavalieri (2004), simulation modeling approaches are widely used as decision support tools in Logistics and Supply Chain Management (LSCM), enabling to reproduce and test different alternatives between possible scenarios, in order to define in advance the performances related to each one of the analysed strategies. Considering DES an SD as modeling approaches, the second one is mostly used to model problems at a strategical level, while DES at an operational/tactical one (Jahangirian et al., 2010; Tako and Robinson, 2012; Terzi and Cavalieri, 2004). In fact, starting from the classification they did for ordering LSCM issues into strategic and operational/tactical (see Figure 13), DES is mostly used in literature to solve problems related to the "System performance" and "Production planning and scheduling" issues, while the SD the ones for "Information sharing" and "Bullwhip effect". Moreover, even if they have different goals, DES-related contributions are widely found in their literature review.

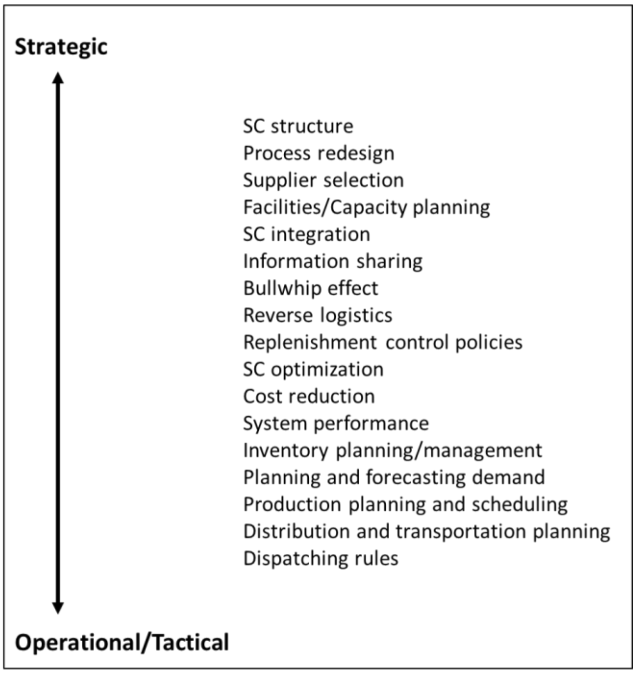

Figure 13 - Classification of LSCM issues (adapted from Tako and Robinson, 2012)

According to this, DES better fits with the aim of the present work, above all for providing "what-if" analysis that quantitatively evaluates benefits and issues related to different operational scenarios, allowing this comparison without interrupting the real system. The direct consequence is a strong time compression that permits to make on-time decisions (Chang and Makatsoris, 2001), representing a CSF especially for companies operating in high-competitive and time-stressed industries, such as the fashion one.

Due to its relevance, a deeper analysis on DES modeling in SC and its application in real scenarios has been conducted.

One of the main results is that, looking at the application areas, the main one where simulation modeling implementations have been found is on the scheduling topic, followed by production planning and inventory control, process engineering and inventory management (Jahangirian et al., 2010). Moreover, another evidence is that DES seems to be convenient for detailed process analyses, resource utilisation, queuing, and relatively shorter-term analyses, that can all be summarized as operational/tactical performances assessment.

On the other hand, moving to the industries application, the healthcare has been identified as the one where the wider range of works can be found, especially focused on the need of tools to improve efficiency (Taylor and Robinson, 2006).

Looking at the fashion industry, very few works have been found in the literature.

In Mazziotti and Horne (1997), a review on the Commercial Off-The-Shelf (COTS) scheduling packages has been done, with an analysis of the critical system characteristics that are often ignored in commercial packages. Then, a simulation-based scheduler for the textile and clothing industry is proposed.

Al-Zubidi and Tyler (2004) develop stochastic simulation models for the clothing SC to be applied for the retail inventory control. In particular, the developed models are designed to investigate the effects of improved retailing and supply procedures on a pre-defined KPIs dashboard using two supply strategies: fixed quantity and fixed interval re-ordering. In other words, simulation has been used to conduct scenario analyses, in order to evaluate which one of the two strategies has a better impact on the company's performances, such as the replenishment time and the potential lost sales.

Lo et al. (2008) present an integration of a Management Information System (MIS) development procedure with an e-fashion Supply Chain Management (SCM) multi-agent system by adopting the techniques of the Semantic Web and multiple agents. The proposed system integrates different information technologies in order to catch more information from customers. Its implementation also considers some practical issues in the fashion retailing SCM.

A case study on a fast-fashion retailer's distribution centre has been studied by Cagliano et al. (2011), using SD to solve issues related to the warehouse management. As the previous one, also in this case study simulation has been used to conduct scenario analyses, but to understand how different sourcing policies and resource usage influence the operational performances related to warehouse processes.

Considering the same topic of the previous work, Mehrjoo (2014) presents the results of a simulation model using the SD technique for the fast-fashion apparel industry, in order to evaluate the impact of product variety on the SC. The average cost, revenue and profit of each stage along the SC have been used as the performance metrics. The results show a trade-off between cost and revenue when the level of variety increases.

According to the evidence that the MSP (see paragraph 4.1.1 Literature review on scheduling model for the fashion industry) represents one of the main challenges companies working using assembly line, such as the ones in the footwear SC, the work of Jayaprakash et al. (2015) has been taken into account. More in detail, the objective of the study is to maximize percentage of utilization and minimize makespan to improve productivity in an assembly line, considering four different methods of line sequencing and modeling them through the DES software PRO-Model. Again, the simulation has been used to conduct scenario analyses, in order to evaluate the best sequence, in terms of related performances, moving from one to the other method of line sequencing. In this work, the KPIs dashboard used to compare different scenarios includes the makespan time, the percentage of utilisation and the number of setups. Moreover, the simulation model's implementation allows also to obtain feasible and acceptable solution.

Some of the evidences highlighted in the literature review in terms of DES implementation have been collected starting from the survey dispatched by Taylor and Robinson (2006), that shows how building sufficiently credible simulations is crucial to push the decision makers toward considering the simulation itself as useful solution methodology from an industrial point of view.

Moreover, the data collection and analysis has been defined as a priority, reflecting to the evidence that often the 30-70% of the simulation project time should be spent on collecting model input data.

Finally, looking at possible opportunities in the near future, the integration of simulation with real-time systems is a quite innovative way to build simulation models that use the latest state of real system as the starting point, populating then the model through a warm-up period when real data are constantly updated using the available advanced technologies, such as IoT sensors, track and trace systems, and RFId. According to this, integrating the simulation modeling with third part real-data acquiring sources allows to update in real-time the inputs and, consequently, the outputs, creating a fashion SC digital twin model for the operational planning.

4.2.2 Proposed simulation model for the fashion industry

After a literature review on simulation models for the fashion industry and on-field interviews at the production managers for the analysed companies, the boundaries of the model have been identified, defining the inputs and outputs to be included.

According to the premises done for developing the proposed optimization model, also the simulation model has been developed in order to fit companies' peculiarities and to represent the real system in an easy-to-understand way, using computer animation to help decision-makers to have a clear overview of how a process operates.

The model is explained through the following sections: Parameters (see paragraph 4.2.2.1 Parameters), KPIs (see paragraph 4.2.2.2 KPIs dashboard) and Stochastic events (see paragraph 4.2.2.3 Stochastic events).

First section includes the model inputs, which are the items scheduled through runs of optimization model, having as parameters the assigned quantity per assigned delivery date and the resource that processes the specific item. Moreover, master data such as cost and processing time per resource scheduled considering finite capacity and LTs related to the ones scheduled with infinite capacity are included.

As outputs of the model's run, a set of KPIs has been defined and modeled with a twofold aim: on the one hand, the validation of the proposed simulation model checking the alignment between KPIs' values related to the optimized plan in input and the ones to the simulated plan run under deterministic condition in output; on the other hand, the KPIs dashboard supports final users in the scenario analysis, enabling them to easily-compare different simulated plans generate through runs of models with changes in the input parameters or moving from a deterministic scenario to another one where stochastic events are included. The set of KPIs and how to calculate them have been described in the second paragraph of the chapter.

Once the simulation model has been defined and validate under deterministic condition, stochasticity has to be included in order to understand how the different simulated plans are influenced by the occurrence of stochastic events. According to this, in the last paragraph of the chapter the stochastic events included in the proposed simulation model have been described.

4.2.2.1 Parameters

The parameters included in the configuration of the simulation model represent the inputs for running the model itself and the way they are filled reflects the peculiarities of the single SC actor.

In particular, the information needed to set the simulation model can be summed up as follows.

The assumption is using simulation to conduct a scenario analysis on optimized plans, so the first input for the simulation model is represented by the assigned quantity per assigned delivery date related to a specific job order row.

The assigned quantity per job order row has been scheduled for being processed by a specific resource, so the information related to the processing cost and time per assigned resource represents another parameter for running the simulation model.

Considering the involved resources, these can be divided between ones scheduled with finite or infinite available capacity. In particular, in the model it has been considered a single resource type with finite capacity, while the others have infinite available capacity. In order to simulate a resource with an infinite capacity, using the LT as processing time, a generic parallel resource has been used.

The selected single finite-capacity resource type changes moving from a fashion industry's market segment to another one, but the approach followed to manage these two resource types (i.e. the one with finite and the others with infinity available capacity) is the same one.

More in detail, all the resources with infinite capacity have been modeled as black boxes that can be positioned before (i.e. "Pre-processing" block) or after (i.e. "Post-processing" block) the single finite-capacity resource type. While for "Pre-processing" and "Post-processing" blocks the information needed as input for the simulation model is the LT associated to these blocks, usually expressed in days/item, for the SKU belonged to a specific job order row, considering the finite-capacity resource type the related input is the processing time per article, expressed in minutes/item. The main differences in their modeling is the fact that no queues have been considered for "Pre-processing" and "Post-processing" blocks, according to the fact that the finite-capacity resource type are the ones that, without an optimal production scheduling, represent the bottleneck of the entire production process.

The processing cost is another input parameter, associated to both these resource types, usually included to make a difference between processing items during the standard-time or the overtime.

The described parameters for running the simulation model are the ones necessary for enabling the final user to compare different optimized production plans (see paragraph 4.2.2.2 KPIs dashboard) under deterministic condition. On the other hand, when stochasticity is included, other parameters have to be defined as inputs for the simulation model, according to the chosen stochastic events (see paragraph 4.2.2.3 Stochastic events).

4.2.2.2 KPIs dashboard

As outputs of the simulation model's run, a set of KPIs has been defined and modeled with a twofold aim: on the one hand, the validation of the proposed simulation model; on the other hand, the KPIs dashboard supports final users in the scenario analysis.

Considering the first goal, the validation of the proposed simulation model has been conducted checking the alignment between the KPIs' values related to the optimized plan in input and the ones for the simulated plan run under deterministic condition in output. This comparison has been done for evaluating if, including the same inputs in the optimization model, the simulation model generates the same outputs in terms of assigned quantity per assigned day on a specific resource, considering each job order row included in the analysed production plan and, consequently, the same KPIs' values.

In addition, considering the second purpose of developing a set of KPIs implemented on the simulation model, the different optimized production plans can be compared through the KPIs' values themselves, calculated for each simulated production plan. In particular, the KPIs dashboard supports final users in the scenario analysis, enabling them to easily-compare different simulated plans generate through runs of models with changes in the input parameters (see paragraph 4.2.2.1 Parameters) or moving from a deterministic scenario to another one where stochastic events are included (see paragraph 4.2.2.3 Stochastic events).

For example, considering deterministic scenarios it is possible to estimate the gap between the KPIs values related to simulated production plans that differ in terms of changes in input parameters, such as the enabled resources to process each SKU or the total number of resources and the related available capacity. On the other hand, considering the same modeled deterministic scenario, changes can be done in terms of different optimization criteria including, for example, only the minimization of the delays instead of both delays and advances.

According to the evidences from the literature review and the on-field experience of interviewed production managers, the main KPIs included as output of the simulation model implementation to evaluate performances of production plans can be grouped as shown in Table 6.

Table 6 - KPIs groups

	Granularity		**Formula**				
KPIs group	**Whole process**	**Single resource**	**Sum**	**Avg**	**Min**	**Max**	**%**
Delays	X	X	X	X	X	X	X
Advances	X	X	X	X	X	X	X
On-time	X	X	X				X
Absolute time gap	X	X	X	X	X	X	X
Costs	X	X	X	X	X	X	X
Productivity	X	X	X	X	X	X	X
Makespan	X		X				
Saturation	X	X		X	X	X	

In Table 6, the identified KPIs groups have been listed and their detail level of implementation (see “Granularity” column) and the way they can be calculated (see “Formula” column) have been explicated filling the table with “X”.

Looking at the “Granularity” column, it distinguishes between “Whole process” and “Single resource”, considering as reference system, on the one hand, the whole process that starts from the “source” block and ends at the “sink” block and, on the other hand, the one that ends when item exits from the “processing” block, that represents the resource having finite-capacity.

For example, looking to both the “Delays” and “Advances” in production, they can include (i.e. “Whole process”) or not (i.e. “Single resource”) the “Post-processing” block, in order to take or not into account if post-processing activities, modeled as a LT, impact on the amount of delays and advances.

Summing up the main evidences from Table 6 in terms of “Granularity”, it shows how all the identified KPIs groups can be defined considering the whole process, while at the single resource level only the makespan cannot be explained. In fact, by definition the makespan is the time difference between the start and finish of the all jobs or tasks included in the system and not of only one of them.

The way the KPIs group on row can be calculated are listed in the “Formula” column, that includes the total (“Sum”), the average (“Avg”), the minimum (“Min”), the maximum (“Max”) and the percentage (“%”).

Again, looking to both the “Delays” and “Advances” in production, they can be calculated considering the total quantity per day scheduled after and before the requested delivery date respectively (i.e. column “Sum”), but can be highlighted also the minimum (i.e. column “Min”) and the maximum (i.e. column “Max”) values in order to make the company aware about the worst and the best value they reach within a specific scenario. To evaluate how many items have been processed later or sooner than the expected date, the “Delays” and “Advances” KPIs can be expressed as percentage of the total number of items (i.e. column “%”). The percentage can be also used to evaluate how many items overcome the average value (i.e. column “Avg”) of days in delays and advances respectively.

In the same way, the KPIs groups “Absolute time gap”, “Costs” and “Productivity” can be calculated considering all of the formula, defining an overall value for the not-on time items, total costs and number of items respectively (i.e. column “Sum”), the minimum (i.e. column “Min”) and the maximum (i.e. column “Max”) values for all of them, and the average considering their daily values (i.e. “Avg”).

Summing up the main evidences from Table 6 in terms of “Formula”, it shows how for almost all the identified KPIs groups can be calculated a global value (i.e. “Sum”) that cannot be representative of the KPI itself for the managers but help them to easily compare different scenarios. The only exception is the “Saturation”, calculated only as average value (i.e. “Avg”), in order to understand the residual capacity available for guaranteeing flexibility and reactivity in case of extra-orders made by the customers, but also in terms of the minimum (“Min”) and the maximum (“Max”) values, to highlight the criticalities associated to the sub- and over-saturation.

On the other hand, “On-time” and “Makespan” cannot be calculated in terms of average, minimum and maximum values by definition.

In fact, “On-time” refers to the number of on-time items, that can be considered as overall value (i.e. “Sum”) or compared to the total number of items to get a percentage (i.e. “%”), while the “Makespan” KPIs group does not have neither the “%” column, according to the fact that it is an overall parameter of the whole production process.

The previously described intersections between the KPIs groups on rows and the objectives expressed in the “Granularity” and “Formula” columns (see Table 6), have been explained in Table 7, identifying a specific KPI for each intersection.

Table 7 - KPIs dashboard

KPIs Group	KPIs Type	KPIs Description	Granularity	Formula
Delays	Del_W_Sum	Number of items or days in delay at the exit of the "sink" block	Whole process	Sum
	Del_W_Avg	Average number of items per day or days in delay at the exit of the "sink" block	Whole process	Avg
	Del_W_Min	Minimum number of items per day or days in delay at the exit of the "sink" block	Whole process	Min
	Del_W_Max	Maximum number of items per day or days in delay at the exit of the "sink" block	Whole process	Max
	Del_W_Prc	Ratio between number of items or days in delay at the exit of the "sink" block and the number of items to be delivered	Whole process	%
	Del_S_Sum	Number of items or days in delay at the exit of the "processing" block	Single resource	Sum
	Del_S_Avg	Average number of items per days or days in delay at the exit of the "processing" block	Single resource	Avg
	Del_S_Min	Minimum number of items per day or days in delay at the exit of the "processing" block	Single resource	Min
	Del_S_Max	Maximum number of items per day or days in delay at the exit of the "processing" block	Single resource	Max
	Del_S_Prc	Ratio between number of items or days in delay at the exit of the "processing" block and the number of items to be processed	Single resource	%
Advances	Adv_W_Sum	Number of items or days in advance at the exit of the "sink" block	Whole process	Sum

	Adv_W_Avg	Average number of items per day or days in advance at the exit of the "sink" block	Whole process	Avg
	Adv_W_Min	Minimum number of items per day or days in advance at the exit of the "sink" block	Whole process	Min
	Adv_W_Max	Maximum number of items per day or days in advance at the exit of the "sink" block	Whole process	Max
	Adv_W_Prc	Ratio between number of items or days in advance at the exit of the "sink" block and the number of items to be delivered	Whole process	%
	Adv_S_Sum	Number of items or days in advance at the exit of the "processing" block	Single resource	Sum
	Adv_S_Avg	Average number of items per day or days in advance at the exit of the "processing" block	Single resource	Avg
	Adv_S_Min	Minimum number of items per day or days in advance at the exit of the "processing" block	Single resource	Min
	Adv_S_Max	Maximum number of items per day or days in advance at the exit of the "processing" block	Single resource	Max
	Adv_S_Prc	Ratio between number of items or days in advance at the exit of the "processing" block and the number of items to be processed	Single resource	%
On-time	Otm_W_Sum	Number of on-time items at the exit of the "sink" block	Whole process	Sum
	Otm_W_Prc	Ratio between number of on-time items at the exit of the "sink" block and the number of items to be delivered	Whole process	%
	Otm_S_Sum	Number of on-time items at the exit of the "processing" block	Single resource	Sum
	Otm_S_Prc	Ratio between number of on-time items at the exit of the "processing" block and the number of items to be processed	Single resource	%
Absolute time gap	Atg_W_Sum	Number of not on-time items or days (delays + advances) at the exit of the "sink" block	Whole process	Sum
	Atg_W_Avg	Average number of not on-time items per day or days (delays + advances) at the exit of the "sink" block	Whole process	Avg
	Atg_W_Min	Minimum number of not on-time items per day or days (delays + advances) at the exit of the "sink" block	Whole process	Min
	Atg_W_Max	Maximum number of not on-time items per day or days (delays + advances) at the exit of the "sink" block	Whole process	Max
	Atg_W_Prc	Ratio between number of not on-time items at the exit of the "sink" block and the number of items to be delivered	Whole process	%
	Atg_S_Sum	Number of not on-time items (delays + advances) at the exit of the "processing" block	Single resource	Sum
	Atg_S_Avg	Average number of not on-time items per day or days (delays + advances) at the exit of the "processing" block	Single resource	Avg
	Atg_S_Min	Minimum number of not on-time items per day or days (delays + advances) at the exit of the "processing" block	Single resource	Min

	Atg_S_Max	Maximum number of not on-time items per day or days (delays + advances) at the exit of the "processing" block	Single resource	Max
	Atg_S_Prc	Ratio between number of not on-time items at the exit of the "processing" block and the number of items to be processed	Single resource	%
Costs	Cst_W_Sum	Total production cost at the exit of the "sink" block	Whole process	Sum
	Cst_W_Avg	Average production cost per day at the exit of the "sink" block	Whole process	Avg
	Cst_W_Min	Minimum production cost per day at the exit of the "sink" block	Whole process	Min
	Cst_W_Max	Maximum production cost per day at the exit of the "sink" block	Whole process	Max
	Cst_W_Prc	Ratio between production cost per day and total production cost at the exit of the "sink" block	Whole process	%
	Cst_S_Sum	Total production cost at the exit of the "processing" block	Single resource	Sum
	Cst_S_Avg	Average production cost per day at the exit of the "processing" block	Single resource	Avg
	Cst_S_Min	Minimum production cost per day at the exit of the "processing" block	Single resource	Min
	Cst_S_Max	Maximum production cost per day at the exit of the "processing" block	Single resource	Max
	Cst_S_Prc	Ratio between production cost per day and total production cost at the exit of the "processing" block	Single resource	%
Productivity	Prd_W_Sum	Number of items exiting from the system at the "sink" block	Whole process	Sum
	Prd_W_Avg	Average number of items per day exiting from the system at the "sink" block	Whole process	Avg
	Prd_W_Min	Minimum number of items per day exiting from the system at the "sink" block	Whole process	Min
	Prd_W_Max	Maximum number of items per day exiting from the system at the "sink" block	Whole process	Max
	Prd_W_Prc	Ratio between number of items exiting from the system at the "sink" block and the number of items to be delivered	Whole process	%
	Prd_S_Sum	Number of items exiting from the system at the "processing" block	Single resource	Sum
	Prd_S_Avg	Average number of items per day exiting from the system at the "processing" block	Single resource	Avg
	Prd_S_Min	Minimum number of items per day exiting from the system at the "processing" block	Single resource	Min
	Prd_S_Max	Maximum number of items per day exiting from the system at the "processing" block	Single resource	Max
	Prd_S_Prc	Ratio between number of items exiting from the system at the "processing" block and the number of items to be processed	Single resource	%
Makespan	Mks_W_Sum	Time between first item entering and last item exiting from the system	Whole process	Sum

Saturation	Sat_W_Avg	Average ratio per day between assigned quantity and available capacity for all the involved resources	Whole process	Avg
	Sat_W_Min	Minimum ratio per day between assigned quantity and available capacity for all the involved resource	Whole process	Min
	Sat_W_Max	Maximum ratio per day between assigned quantity and available capacity for all the involved resource	Whole process	Max
	Sat_S_Avg	Average ratio per day between assigned quantity and available capacity for the single involved resource	Single resource	Avg
	Sat_S_Min	Minimum ratio per day between assigned quantity and available capacity for the single involved resource	Single resource	Min
	Sat_S_Max	Maximum ratio per day between assigned quantity and available capacity for the single involved resource	Single resource	Max

The KPIs list in Table 7 represents the starting point for conducting scenario analyses in the pilots' implementation, due to the fact that a selection of those KPIs has been made by the analysed companies to compare different scenarios and their strategical impacts (see paragraph 5 Results).

4.2.2.3 Stochastic events

Once the simulation model has been defined and validate under deterministic condition through the definition of a set of KPIs, stochasticity has to be included in order to understand how the different simulated plans are influenced by the occurrence of stochastic events.

The reason why stochasticity should be included in the simulation model is related to the fact that, especially in a very dynamic context such as the one where fashion companies work, unexpected events often occur and their impact on production performances should be preventively estimated, because managing their effect when they occur doesn't allow to readapt the production scheduling guaranteeing, at the same time, the performance level the brand owners require.

According to this, the implementation of the proposed simulation model including stochasticity can be used to conduct a scenario analysis that compares not only the KPIs' values changing model inputs (e.g. changes in number of available resources per SKU) under deterministic condition, but also considering different occurrence 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 occurrence of each combination of them produces a huge decrease of KPIs value).

The stochastic events included in the simulation model have been chosen according to the evidences come from the interview conducted to production managers working within companies operating in the fashion industry. In particular, the most relevant stochastic events within the analysed industry can be summed up in (i) rush orders and (ii) delays in critical components' delivery date.

Rush orders are additional orders that brand owners require and that have to be priority processed if compared with the standard orders, that are the ones previously sent and already scheduled. Rush orders can be generated by several type of events, like unexpected changes in the quantity of already-confirmed orders, new items to be processed or orders deriving from the sampling process.

On the other hand, unexpected events to be managed can be related to delays that can occur on the expected delivery date of critical components. In fact, even if the optimization model should include their expected delivery date per SKU in order to schedule its processing starting from that date, the realization of the SKU in that date is not guaranteed because quite often some of the components needed to complete the item are still not sent by suppliers or stocked.

While KPIs dashboard does not have to be changed when stochasticity is included, other parameters have to be defined as inputs for the simulation model in addition to the ones previously listed (see paragraph 4.2.2.1 Parameters), as described in the paragraph 4.2.3 Implementation of the proposed simulation model in the fashion industry.

4.2.3 Implementation of the proposed simulation model in the fashion industry

The proposed simulation model described in the previous paragraph has been on-field implemented in real companies using AnyLogic® as simulator.

AnyLogic® has been chosen firstly because it is the one that better fits the need to manage each one of the three different simulation modeling approaches (previously described in paragraph 4.2.1 Literature on simulation model in the fashion industry) and any combination of them within a single model.

Secondly, the integration between models developed on AnyLogic® and other tools or IT-infrastructure represents the key value to enable the analysed companies to easily-insert the input data required for configuring the proposed simulation model and to easily-understand the output of model's runs, because both the inputs and the outputs can be managed and shown starting from data on the company's management system's database or on an Microsoft Excel® file.

In fact, an AnyLogic® model can be exported as a Java application, that can be run separately, or integrated with other software. As an option, an exported AnyLogic® model can be built into other pieces of software and work as an additional module to ERP, Material Requirements Planning (MRP) and Transportation Management System (TMS). Another typical use is integration of an AnyLogic® model with TXT, Microsoft Excel®, or Microsoft Access® files and databases (MS SQL, MySQL, Oracle, etc.). In the proposed model implementation, all the data have been configured using a Microsoft Excel® file as input and output.

Moreover, AnyLogic® models include their own databases based on HSQLDB, that can be used to trace parameters of the simulation model such as the birth and death dates for each generated agent.

In addition, AnyLogic® allows users to import CAD drawings as DXF files, and then visualize models on top of them. This feature, mostly used in Discrete Event (process-based) models in manufacturing, can be used for animating processes inside objects like factories or warehouses.

AnyLogic® software also supports interactive 2D and 3D animation and includes a collection of ready-to-use 3D objects for animation related to different industries, including buildings and warehouse. This point represents another one of the main reasons to choose AnyLogic® as simulation tool, because this way to show the output of model's runs makes more understandable the output itself.

Considering the implementation of the proposed simulation model included in this work, the DES is the one that has been chosen because it better fits a context, such as the fashion industry's one, mostly characterised by job shops and production lines with several activities that follow one the other through queues and state changes, such as resources available or used, materials in stock or not and so on.

In fact, typical output expected from a DES model includes utilization of resources, time spent in the system by an agent, waiting times, queue lengths, system throughput and bottlenecks, that represent key values for analysis performances related to PP&C issues.

Discrete event modeling requires to think about the system to be modeled as a sequence of operations that agents perform. These operations can include delays, service by various resources, splits and many others. As long as agents compete for limited resources and can be delayed, queues will be part of nearly all discrete event models. According to this, the 2D and 3D animation for the model's output allows the final user to have a tangible perception about where queues and, consequently, bottlenecks are generated.

The model is graphically defined as a process flowchart where blocks represent operations. The flowchart usually starts with "source" blocks that generate agents and inject them into the process and ends with "sink" blocks that remove them.

Considering the implementation of the simulation model within this work under deterministic condition, the intermediate modeled blocks are alternate queues and processing that identify respectively pre-processing, processing and post-processing operations, where the first and last ones have infinite capacity while the processing block works at finite capacity (see Figure 14).

The graphical representation of the "Processing" block has to be customized according to the peculiarities of the analysed company. For example, in the pilots for the metal accessories and the leather goods market segments (see paragraphs 5.2.3 Simulation model in a metal accessories company and 5.3.3 Simulation model in a leather goods company), it has been detailed as a group of parallel services, while as a conveyor with an estimated number of stations in the footwear case (see paragraph 5.4.3 Simulation model in a footwear company).

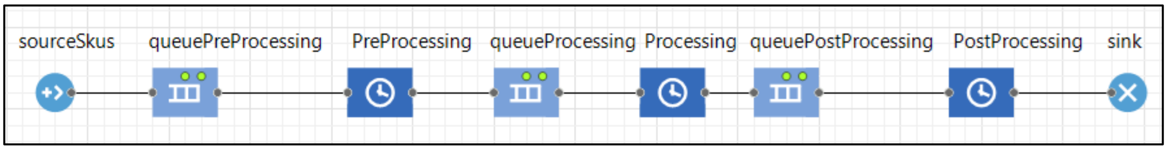

Figure 14 - Simulation model with no stochasticity

Including rush orders as stochastic events has been modeled adding a second "Source" block that generate them according a statistical distribution defined starting from historical data (see "sourceRushOrders" in Figure 15). The order by in the pre-processing queue is defined by the SKU type: in fact, the SKU having "true" has value for the related Boolean parameter "skuRushOrder" has to be priority processed, overtaking the other SKUs already waiting in the queue (see 4.2.2.3 Stochastic events).

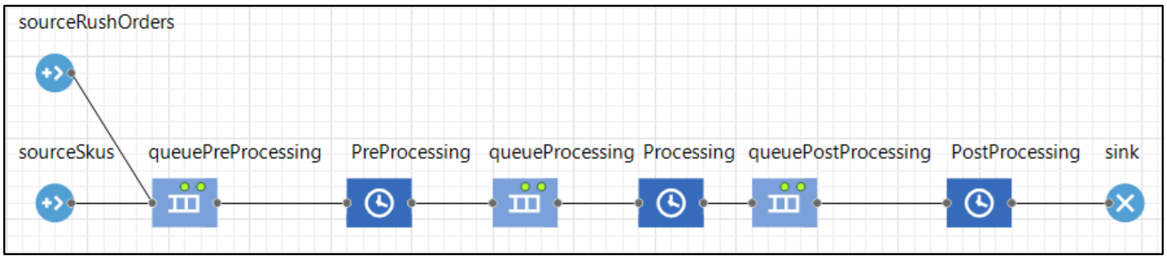

Figure 15 - Simulation model with rush orders

In order to add delays on expected delivery date of critical components as other type of stochastic events, changes on the simulation model have to be done. Firstly, the critical component (also called "material") has to be generated through a new "Source" block considering the delivery date defined as model's input, and delays have to be included introducing a statistical distribution of delays on the critical components' delivery date imported (see 4.2.2.3 Stochastic events).

In order to synchronize the two streams of agents (materials and SKUs), the "Match" block has been included to match items according to a given criteria. The way this block works is the following: the agents that have not yet been matched are stored in two queues (one for each stream); once the new agent arrives at either of the input ports, it is checked if matching criteria against all agents in the queue for the other stream are satisfied. If the match is found, both agents exit the "Match" block at the same time. The queues can be fully customized, for example, in terms of timeout, priorities or pre-emption. To reunite the two flows into only one of them (i.e. to define the single agent that exits from the block instead of the two entering in it), the block "Combine" has been added in the simulation model after the block "Match". The new agent may be a completely new one (i.e. a new object whose properties may depend on the original agents) or it may be one of the original agents, again, possibly modified in terms of related parameters.

In the analysed case, on the block "Combine" will enter both materials and SKUs that pass the required criteria in the "Match" block and will exit only SKUs. Once the two agents are ready to enter in the "Combine" block, the operation takes zero time and they immediately exit.

The described model has been shown in Figure 16.

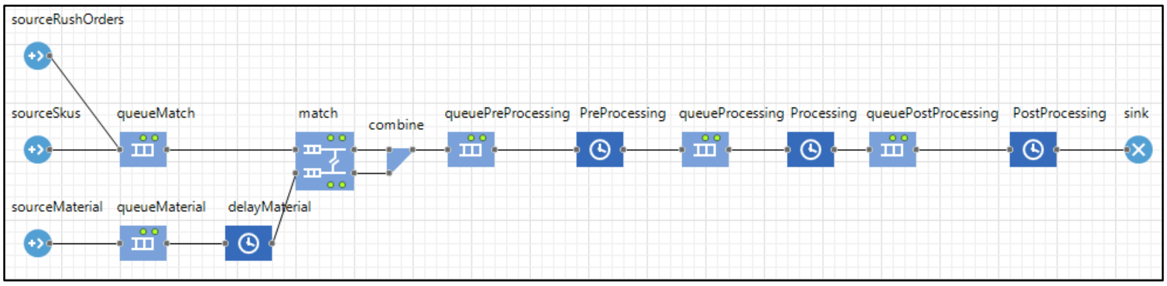

Figure 16 - Simulation model with rush orders and delays in expected critical components' delivery date

Independently from the modeled blocks, the architecture defined for its implementation at the single-company level has been summed up in Figure 17.

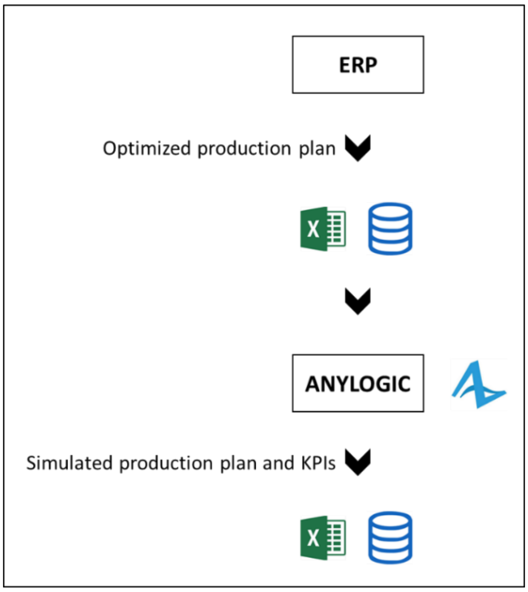

Figure 17 - Simulation model implementation

More in detail, the starting point for the simulation model implementation is the export of the production plan from the company's ERP, eventually optimized with external software like an Advance and Planning Scheduling (APS), to a Microsoft Excel® file or directly on the AnyLogic® database. The exported data includes all the parameters needed for setting the simulation model, such as the assigned quantities per resource and delivery dates per single job order row.

In particular, the following figures show an example of the data format for the Microsoft Excel® file used for running the simulation model that has been automatically create and filled using VBA commands at the end of the optimization model's run using OpenSolver on Microsoft Excel® (see paragraph 4.1.3 Implementation of the proposed scheduling model in the fashion industry).

	A	B	C	D	E	F	G	H
1	**skuCode**	**skuRushOrder**	**agentType**	**agentToService1**	**agentToService2**	**agentToService3**	**agentToService4**	**agentToService5**
2	4_skuCode_6	false	AgentToBeProcessed	true	false	false	false	false
3	29_skuCode_3	false	AgentToBeProcessed	false	true	false	false	false
4	29_skuCode_5	false	AgentToBeProcessed	false	true	false	false	false
5	29_skuCode_6	false	AgentToBeProcessed	false	true	false	false	false
6	7_skuCode_6	false	AgentToBeProcessed	true	false	false	false	false
7	32_skuCode_3	false	AgentToBeProcessed	false	true	false	false	false
8	32_skuCode_5	false	AgentToBeProcessed	false	true	false	false	false
9	8_skuCode_1	false	AgentToBeProcessed	true	false	false	false	false
10	8_skuCode_2	false	AgentToBeProcessed	true	false	false	false	false
11	8_skuCode_4	false	AgentToBeProcessed	true	false	false	false	false
12	8_skuCode_6	false	AgentToBeProcessed	true	false	false	false	false
13	33_skuCode_3	false	AgentToBeProcessed	false	true	false	false	false
14	33_skuCode_5	false	AgentToBeProcessed	false	true	false	false	false
15	9_skuCode_2	false	AgentToBeProcessed	true	false	false	false	false
16	9_skuCode_3	false	AgentToBeProcessed	true	false	false	false	false
17	34_skuCode_3	false	AgentToBeProcessed	false	true	false	false	false
18	34_skuCode_5	false	AgentToBeProcessed	false	true	false	false	false
19	10_skuCode_1	false	AgentToBeProcessed	true	false	false	false	false
20	35_skuCode_3	false	AgentToBeProcessed	false	true	false	false	false
21	35_skuCode_5	false	AgentToBeProcessed	false	true	false	false	false

Figure 18 - Input data for simulation model (1)

	A	I	J	K	L	M	N
1	skuCode	requestedQty	assignedQty	customerRequestedDate	requestedDate	customerAssignedDate	assignedDate
2	4_skuCode_6	336	60	27/8/18 0.00	27/8/18 0.00	10/8/18 0.00	10/8/18 9.00
3	29_skuCode_3	712	5	20/8/18 0.00	20/8/18 0.00	10/8/18 0.00	10/8/18 9.00
4	29_skuCode_5	532	71	27/8/18 0.00	27/8/18 0.00	10/8/18 0.00	10/8/18 9.00
5	29_skuCode_6	336	3	27/8/18 0.00	27/8/18 0.00	10/8/18 0.00	10/8/18 9.00
6	7_skuCode_6	336	60	27/8/18 0.00	27/8/18 0.00	13/8/18 0.00	13/8/18 9.00
7	32_skuCode_3	712	40	20/8/18 0.00	20/8/18 0.00	13/8/18 0.00	13/8/18 9.00
8	32_skuCode_5	532	51	27/8/18 0.00	27/8/18 0.00	13/8/18 0.00	13/8/18 9.00
9	8_skuCode_1	212	71	20/8/18 0.00	20/8/18 0.00	14/8/18 0.00	14/8/18 9.00
10	8_skuCode_2	307	11	20/8/18 0.00	20/8/18 0.00	14/8/18 0.00	14/8/18 9.00
11	8_skuCode_4	750	45	27/8/18 0.00	27/8/18 0.00	14/8/18 0.00	14/8/18 9.00
12	8_skuCode_6	336	6	27/8/18 0.00	27/8/18 0.00	14/8/18 0.00	14/8/18 9.00
13	33_skuCode_3	712	108	20/8/18 0.00	20/8/18 0.00	14/8/18 0.00	14/8/18 9.00
14	33_skuCode_5	532	2	27/8/18 0.00	27/8/18 0.00	14/8/18 0.00	14/8/18 9.00
15	9_skuCode_2	307	14	20/8/18 0.00	20/8/18 0.00	15/8/18 0.00	15/8/18 9.00
16	9_skuCode_3	712	127	20/8/18 0.00	20/8/18 0.00	15/8/18 0.00	15/8/18 9.00
17	34_skuCode_3	712	108	20/8/18 0.00	20/8/18 0.00	15/8/18 0.00	15/8/18 9.00
18	34_skuCode_5	532	2	27/8/18 0.00	27/8/18 0.00	15/8/18 0.00	15/8/18 9.00
19	10_skuCode_1	212	141	20/8/18 0.00	20/8/18 0.00	16/8/18 0.00	16/8/18 9.00
20	35_skuCode_3	712	108	20/8/18 0.00	20/8/18 0.00	16/8/18 0.00	16/8/18 9.00
21	35_skuCode_5	532	2	27/8/18 0.00	27/8/18 0.00	16/8/18 0.00	16/8/18 9.00

Figure 19 - Input data for simulation model (2)

	A	O	P	Q	R	S	T	U
1	skuCode	assignedService	processingTimeService1	processingTimeService2	processingTimeService3	processingTimeService4	processingTimeService5	postprocessingLeadtime
2	4_skuCode_6	1	480	0	0	0	0	0
3	29_skuCode_3	2	0	260	0	0	0	0
4	29_skuCode_5	2	0	360	0	0	0	0
5	29_skuCode_6	2	0	640	0	0	0	0
6	7_skuCode_6	1	480	0	0	0	0	0
7	32_skuCode_3	2	0	260	0	0	0	0
8	32_skuCode_5	2	0	360	0	0	0	0
9	8_skuCode_1	1	204	0	0	0	0	0
10	8_skuCode_2	1	204	0	0	0	0	0
11	8_skuCode_4	1	204	0	0	0	0	0
12	8_skuCode_6	1	480	0	0	0	0	0
13	33_skuCode_3	2	0	260	0	0	0	0
14	33_skuCode_5	2	0	360	0	0	0	0
15	9_skuCode_2	1	204	0	0	0	0	0
16	9_skuCode_3	1	204	0	0	0	0	0
17	34_skuCode_3	2	0	260	0	0	0	0
18	34_skuCode_5	2	0	360	0	0	0	0
19	10_skuCode_1	1	204	0	0	0	0	0
20	35_skuCode_3	2	0	260	0	0	0	0
21	35_skuCode_5	2	0	360	0	0	0	0

Figure 20 - Input data for simulation model (3)

	A	V	W	X	Y	Z	AA
1	skuCode	costService1	costService2	costService3	costService4	costService5	postprocessingCost
2	4_skuCode_6	1	0	0	0	0	0
3	29_skuCode_3	0	1	0	0	0	0
4	29_skuCode_5	0	1	0	0	0	0
5	29_skuCode_6	0	1	0	0	0	0
6	7_skuCode_6	1	0	0	0	0	0
7	32_skuCode_3	0	1	0	0	0	0
8	32_skuCode_5	0	1	0	0	0	0
9	8_skuCode_1	1	0	0	0	0	0
10	8_skuCode_2	1	0	0	0	0	0
11	8_skuCode_4	1	0	0	0	0	0
12	8_skuCode_6	1	0	0	0	0	0
13	33_skuCode_3	0	1	0	0	0	0
14	33_skuCode_5	0	1	0	0	0	0
15	9_skuCode_2	1	0	0	0	0	0
16	9_skuCode_3	1	0	0	0	0	0
17	34_skuCode_3	0	1	0	0	0	0
18	34_skuCode_5	0	1	0	0	0	0
19	10_skuCode_1	1	0	0	0	0	0
20	35_skuCode_3	0	1	0	0	0	0
21	35_skuCode_5	0	1	0	0	0	0

Figure 21 - Input data for simulation model (4)

	A	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK
1	skuCode	Customer	Brand	Season	Event	ArticleLine	Article	Category	Subcategory	AvailableTimeService	CriticalComponentCode
2	4_skuCode_6	C_2	B_2	183	7	AL_1	skuCode_6	Cat_1	SubCat_1	28800	e
3	29_skuCode_3	C_1	B_1	183	7	AL_2	skuCode_3	Cat_1	SubCat_1	28800	b
4	29_skuCode_5	C_1	B_1	183	7	AL_3	skuCode_5	Cat_1	SubCat_2	28800	d
5	29_skuCode_6	C_2	B_2	183	7	AL_1	skuCode_6	Cat_1	SubCat_1	28800	e
6	7_skuCode_6	C_2	B_2	183	7	AL_1	skuCode_6	Cat_1	SubCat_1	28800	e
7	32_skuCode_3	C_1	B_1	183	7	AL_2	skuCode_3	Cat_1	SubCat_1	28800	b
8	32_skuCode_5	C_1	B_1	183	7	AL_3	skuCode_5	Cat_1	SubCat_2	28800	d
9	8_skuCode_1	C_1	B_1	183	7	AL_2	skuCode_1	Cat_1	SubCat_1	28800	a
10	8_skuCode_2	C_1	B_1	183	7	AL_2	skuCode_2	Cat_1	SubCat_1	28800	a
11	8_skuCode_4	C_1	B_1	183	7	AL_3	skuCode_4	Cat_1	SubCat_2	28800	c
12	8_skuCode_6	C_2	B_2	183	7	AL_1	skuCode_6	Cat_1	SubCat_1	28800	e
13	33_skuCode_3	C_1	B_1	183	7	AL_2	skuCode_3	Cat_1	SubCat_1	28800	b
14	33_skuCode_5	C_1	B_1	183	7	AL_3	skuCode_5	Cat_1	SubCat_2	28800	d
15	9_skuCode_2	C_1	B_1	183	7	AL_2	skuCode_2	Cat_1	SubCat_1	28800	a
16	9_skuCode_3	C_1	B_1	183	7	AL_2	skuCode_3	Cat_1	SubCat_1	28800	b
17	34_skuCode_3	C_1	B_1	183	7	AL_2	skuCode_3	Cat_1	SubCat_1	28800	b
18	34_skuCode_5	C_1	B_1	183	7	AL_3	skuCode_5	Cat_1	SubCat_2	28800	d
19	10_skuCode_1	C_1	B_1	183	7	AL_2	skuCode_1	Cat_1	SubCat_1	28800	a
20	35_skuCode_3	C_1	B_1	183	7	AL_2	skuCode_3	Cat_1	SubCat_1	28800	b
21	35_skuCode_5	C_1	B_1	183	7	AL_3	skuCode_5	Cat_1	SubCat_2	28800	d

Figure 22 - Input data for simulation model (5)

	A	B	C
1	criticalComponentCode	expectedCriticalComponentDeliveryDate	criticalComponentQty
2	e	9/8/18 9.00	60
3	b	9/8/18 9.00	5
4	d	9/8/18 9.00	71
5	e	9/8/18 9.00	3
6	e	12/8/18 9.00	60
7	b	12/8/18 9.00	40
8	d	12/8/18 9.00	51
9	a	13/8/18 9.00	71
10	a	13/8/18 9.00	11
11	c	13/8/18 9.00	45
12	e	13/8/18 9.00	6
13	b	13/8/18 9.00	108
14	d	13/8/18 9.00	2
15	a	14/8/18 9.00	14
16	b	14/8/18 9.00	127
17	b	14/8/18 9.00	108
18	d	14/8/18 9.00	2
19	a	15/8/18 9.00	141
20	b	15/8/18 9.00	108

Figure 23 - Input data for simulation model (6)

The set of information used as inputs for the simulation model basically refers to the scheduled SKU code included in a specific job order (see “skuCode” in Figure 18), that represents the elementary unit managed by the simulator.

More in detail, for each one of the “skuCode” has been associated the resource that has been assigned by the optimization model to process it, using a Boolean per resource that will be equal to “true” if the resource is the one assigned to the “skuCode”, otherwise “false”. In the example in Figure 18, 5 resources have been modeled and, consequently, five Booleans have been exported on the Microsoft Excel® file (see “agentToService1”, “agentToService2”, “agentToService3”, “agentToService4”, “agentToService5” in Figure 18). In other words, the number of columns used to identify the resource that processes the “skuCode” on row will change from a model’s configuration to another one according to the enabled number of resources.

In Figure 19 is shown the quantity per “skuCode” that has to be produced and the date when it has to be assigned to the resource, named “assignedQty” and “assignedDate” respectively, but also the date when it will be delivered to the final customer, calculated by the optimization model adding the post-processing LT to the “assignedDate” (see “customerAssignedDate” in Figure 19). In addition, also the quantity and date required by the customer, that represent the input for running the optimization model, have been imported into the simulation model (see “requestedQty”, “requestedDate” and “customerRequestedDate” in Figure 19), in order to evaluate eventual gaps between the customer’s requirements and the simulated results.

The assigned resource (see “assignedService” in Figure 20) and the LT to be considered for the post-processing activities (see “postprocessingLeadtime” in Figure 20) are listed. Looking at the unitary processing time per resource, as described above the modeled resources in the sampled

Microsoft Excel® file are 5, such as the fields “processingTimeService1”, “processingTimeService2”, “processingTimeService3”, “processingTimeService4”, “processingTimeService5” in Figure 20.

In the same way, the unitary costs per resource have been shown, named “costService1”, “costService2”, “costService3”, “costService4”, “costService5” in Figure 21, such as the one related to the post-processing activities (see “postprocessingCost” in Figure 21).

In Figure 22 is listed a set of parameters of the “skuCode” that have not to be used for running the optimization and the simulation models, but for clustering the final results within the KPIs’ dashboard, allowing the filtering and drilling-down functionalities. In detail, that fields are named “Customer”, “Brand”, “Season”, “Event”, “ArticleLine”, “Article”, “Category” and “Subcategory”. For example, considering the KPIs value related to the delays on the customer requested delivery date resulting from the implementation of the simulation model, it can be splitted into the delays referred to different customers to evaluate which are the best-served ones.

The available capacity in seconds per each resource is also included (see “AvailableTimeService” in Figure 22), in order to evaluate the resource saturation in the KPIs dashboard at the end of the simulation run.

The previously listed fields are all the one used for running the simulation model considering a deterministic scenario. Due to the stochastic events to be included, other fields are filled on the Microsoft Excel® file.

In particular, managing rush orders in the simulation model requires to include in the input also the field “skuRushOrder” as a Boolean (see Figure 18), exported from the optimization model as equals to “false” because all the SKUs resulting from that implementation refer to a deterministic scenario where no rush orders are included.

In the configuration of the simulation model, considering for example the rush orders related to the fact that customers require an extra-quantity for the already-confirmed orders, the field “skuCode” has then been used to generate SKUs having the same parameters of the scheduled ones, such as times and costs per resource, excepting for the “skuRushOrder” and “assignedQty” ones: on the one hand, the value of the “skuRushOrder” field is set as “true”, in order to separate the impacts on the KPIs related to scheduled SKUs and rush orders; on the other hand, the number of items generated as extra-orders reflects a statistical distribution calculated starting from the analysis of historical data.

The information related to the delays on the expected delivery date of critical components has been included adding in the model input the fields “criticalComponentCode”, “assignedCriticalComponentQty” and “expectedCriticalComponentDeliveryDate”, that indicate that a number equals to “assignedCriticalComponentQty” units of a critical component named “criticalComponentCode” has to be generated at the “expectedCriticalComponentDeliveryDate” from the “sourceMaterial” block (see Figure 16).

The link between the SKU and its critical component is explained through the field “CriticalComponentCode” in Figure 22, and this relation is the one verified in the block “Match” of the simulation model: a specific “skuCode” exits from the “Match” block only when the related “CriticalComponentCode” enters in the same block.

Stochasticity has been introduced in the model associating a statistical distribution of delay calculated starting from the analysis of historical data and expressed in the “Delay” block (see Figure 16), that forced the critical components to enter in the system having a delay despite the “expectedCriticalComponentDeliveryDate”.

As previously described, while the optimized production plan represents the optimal solution under deterministic condition and according to a pre-defined set of objective functions as input, the simulated production plans have been run including stochastic events and their effects on the performances related to the scheduled production are evaluated and reported on Microsoft Excel® files or directly on the company’s ERP database, using a set of KPIs selected by the companies starting from the previously defined KPIs dashboard (see Table 7).

After each simulation run, in fact, the outputs and related KPIs will be saved on the AnyLogic® database and can be exported, again, on a Microsoft Excel® file in order to compare the deterministic with the stochastic scenario, highlighting how performances vary introducing stochasticity.

To validate the statistical significance of the impact of each stochastic event on the KPIs, the one-way analysis of variance (ANOVA) has been conducted after each one of the simulation tool’s implementation within the analysed companies. More in detail, the two factors separately included in each test have been the rush orders and delays on the expected critical components’ delivery date. Three levels for each factor have been defined according to the collected data and their relevance for the companies. For each factor, the simulation model has been run including 10 replications and the resulting KPIs have been used as response variables.

According to this, the conduction of the ANOVA test aims to determine if each one of the selected factors impacts (i.e. rush orders or delays on the expected critical components’ delivery date) on one of the response variables (i.e. advances or delays in production), as shown in Figure 24.

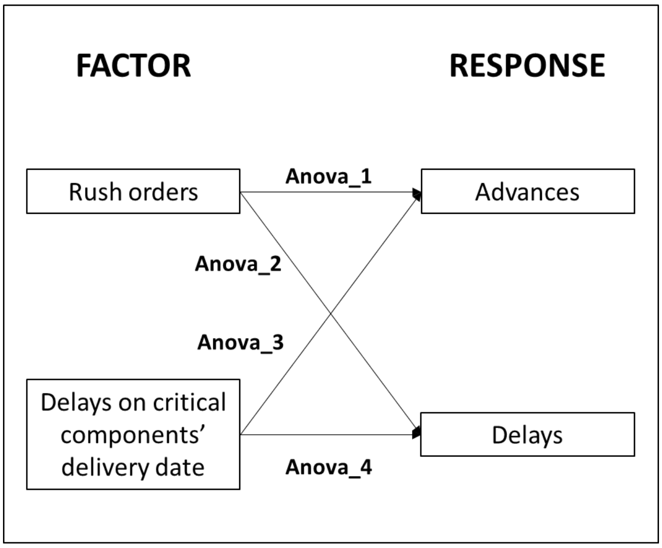

Figure 24 - Factors and responses included in the ANOVA

For example, considering the “Anova_1” test in Figure 24 (i.e. rush orders vs advances), non-significance of the test statistic would imply that the occurrence of rush orders has no effect on advances in production. On the other hand, significance would imply that advances afflict different rush orders’ groups differently.

In order to determine the statistical significance of a factor’s group on a response variable, the one-way ANOVA compares the means of the independent groups. The null hypothesis (i.e. H_0) for the test is that all the means are equal. On the other hand, a significant result means that at least a mean differs from the others, that represents the alternative hypothesis (i.e. H_1).

Rejecting or not H_0, that means that results are or not statistically significant respectively, depends on the p-value compared to the significance level: when the p-value is less than the significance level, H_0 is rejected.

During the simulation model implementation, the one-way ANOVA has been conducted using Minitab® 17.

In Figure 25 is shown an example of the inputs used to conduct the “Anova_1” and “Anova_2” tests in Figure 24 (i.e. rush orders as factor), while Figure 26 shows the ones for the “Anova_3” and “Anova_4” tests in Figure 24 (i.e. delays on the expected critical components’ delivery date as factor).

↓	C1	C2	C3
	RO	delays	advances
1	30	7083	6024
2	30	7420	5703
3	30	7859	5672
4	30	8214	5587
5	30	8256	5856
6	30	8459	5410
7	30	8565	5647
8	30	8604	5175
9	30	9540	5114
10	30	9770	4694
11	50	15361	3982
12	50	15818	4036
13	50	16584	3910
14	50	16880	4051
15	50	17237	3968
16	50	17378	3761
17	50	17392	4042
18	50	17538	3882
19	50	17670	3802
20	50	17722	3739
21	70	24911	3561
22	70	25662	3456
23	70	25855	3441
24	70	26223	3529
25	70	26283	3504
26	70	26523	3481
27	70	26601	3492
28	70	27006	3479
29	70	27023	3491
30	70	27218	3471

Figure 25 - Input for ANOVA test (factor: rush orders)

↓	C1	C2	C3
	CCD	delays	advances
1	2	7652	6811
2	2	7656	6815
3	2	7670	6669
4	2	7694	6361
5	2	7699	6653
6	2	7723	6643
7	2	7775	6727
8	2	7791	6536
9	2	7801	6578
10	2	7871	6228
11	5	12482	3182
12	5	12606	3147
13	5	12679	3135
14	5	12679	3134
15	5	12692	3105
16	5	12795	3078
17	5	12850	3078
18	5	12941	3028
19	5	13155	2929
20	5	13189	2944
21	8	21054	1163
22	8	21107	1141
23	8	21109	1138
24	8	21146	1149
25	8	21253	1111
26	8	21257	1103
27	8	21282	1107
28	8	21322	1114
29	8	21335	1118
30	8	21394	1100

Figure 26 - Input for ANOVA test (factor: delays on expected critical components' delivery date)

As shown in Figure 25, the levels used for the rush orders factor have been 30, 50 and 70 and 10 replications of simulation model's runs have been conducted for each of them to evaluate the values for the "delays" and "advances" KPIs.

10 replications have been conducted also using only delays on expected critical components' delivery date as stochastic event, considering 2, 5 and 8 as the three levels of this factor in the "Anova_3" and "Anova_4" tests shown in Figure 24.

In Figure 27, Figure 28, Figure 29 and Figure 30 are respectively shown the results of the "Anova_1", "Anova_2", "Anova_3" and "Anova_4" tests (see Figure 24), all confirming the rejection of the null hypothesis due to the fact that the p-value is less than a significance level of 0.05.

One-way ANOVA: delays versus RO

Method

Null hypothesis	All means are equal
Alternative hypothesis	At least one mean is different
Significance level	α = 0,05

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
RO	3	30; 50; 70

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
RO	2	1612684932	806342466	1304,64	0,000
Error	27	16687564	618058		
Total	29	1629372496			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
786,167	98,98%	98,90%	98,74%

Means

RO	N	Mean	StDev	95% CI
30	10	8377	836	(7867; 8887)
50	10	16958	807	(16448; 17468)
70	10	26331	710	(25820; 26841)

Pooled StDev = 786,167

Figure 27 - One-way ANOVA delays vs rush orders

One-way ANOVA: advances versus RO

Method

Null hypothesis	All means are equal
Alternative hypothesis	At least one mean is different
Significance level	α = 0,05

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
RO	3	30; 50; 70

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
RO	2	22135634	11067817	193,02	0,000
Error	27	1548214	57341		
Total	29	23683849			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
239,460	93,46%	92,98%	91,93%

Means

RO	N	Mean	StDev	95% CI
30	10	5488	396	(5333; 5644)
50	10	3917,3	117,9	(3761,9; 4072,7)
70	10	3490,5	34,8	(3335,1; 3645,9)

Pooled StDev = 239,460

Figure 28 - One-way ANOVA advances vs rush orders

One-way ANOVA: delays versus CCD

Method

Null hypothesis	All means are equal
Alternative hypothesis	At least one mean is different
Significance level	α = 0,05

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
CCD	3	2; 5; 8

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
CCD	2	928918717	464459358	19442,24	0,000
Error	27	645008	23889		
Total	29	929563725			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
154,561	99,93%	99,93%	99,91%

Means

CCD	N	Mean	StDev	95% CI
2	10	7733,2	73,1	(7632,9; 7833,5)
5	10	12806,8	230,7	(12706,5; 12907,1)
8	10	21225,9	114,5	(21125,6; 21326,2)

Pooled StDev = 154,561

Figure 29 - One-way ANOVA delays vs delays on expected critical components' delivery date

```
One-way ANOVA: advances versus CCD

Method

Null hypothesis         All means are equal
Alternative hypothesis  At least one mean is different
Significance level      α = 0,05

Equal variances were assumed for the analysis.


Factor Information

Factor  Levels  Values
CCD          3  2; 5; 8


Analysis of Variance

Source  DF     Adj SS    Adj MS  F-Value  P-Value
CCD      2  154157737  77078868  5393,16    0,000
Error   27     385883     14292
Total   29  154543620


Model Summary

      S    R-sq  R-sq(adj)  R-sq(pred)
119,549  99,75%     99,73%      99,69%


Means

CCD   N     Mean  StDev         95% CI
2    10   6602,1  187,5  ( 6524,5;  6679,7)
5    10   3076,0   85,2  ( 2998,4;  3153,6)
8    10  1124,40  21,71  (1046,83; 1201,97)

Pooled StDev = 119,549
```

Figure 30 - One-way ANOVA advances vs delays on expected critical components' delivery date

The Tukey's range test has been jointly used with the ANOVA test as post-hoc analysis to find means that are significantly different from each other, comparing all the possible pairs of means.

Such as the ANOVA, the Tukey's method has been implemented using Minitab ® 17 and the main results are shown in the following figures. In particular, the results considering rush orders as factor and the response variables (i.e. delays and advances) are shown in Figure 31 and Figure 32 respectively, while for delays in the expected critical components' delivery date in Figure 33 and Figure 34. All of them show that means significantly differ one to each other.

```
Tukey Pairwise Comparisons

Grouping Information Using the Tukey Method and 95% Confidence

RO   N   Mean  Grouping
70  10  26331  A
50  10  16958    B
30  10   8377      C

Means that do not share a letter are significantly different.
```

Figure 31 - Tukey's method delays vs rush orders

Tukey Pairwise Comparisons

Grouping Information Using the Tukey Method and 95% Confidence

RO	N	Mean	Grouping
30	10	5488	A
50	10	3917,3	B
70	10	3490,5	C

Means that do not share a letter are significantly different.

Figure 32 - Tukey’s method advances vs rush orders

Tukey Pairwise Comparisons

Grouping Information Using the Tukey Method and 95% Confidence

CCD	N	Mean	Grouping
8	10	21225,9	A
5	10	12806,8	B
2	10	7733,2	C

Means that do not share a letter are significantly different.

Figure 33 - Tukey’s method delays vs delays on expected critical components' delivery date

Tukey Pairwise Comparisons

Grouping Information Using the Tukey Method and 95% Confidence

CCD	N	Mean	Grouping
2	10	6602,1	A
5	10	3076,0	B
8	10	1124,40	C

Means that do not share a letter are significantly different.

Figure 34 - Tukey’s method advances vs delays on expected critical components' delivery date

The statistical analyses conducted on the inputs and outputs coming from the simulation model implementation increase the consistency of the results achievable through scenario analyses focused on evaluating the impacts of the occurrence of stochastic events on the main PP&C KPIs.

According to this, once the statistical analyses have been concluded, the scenario analyses can be conducted considering a sub-set of the KPIs dashboard defined in Table 7 and evaluating how changes in strategical objectives (i.e. OFs) and/or input configuration and/or stochasticity type and occurrence impact on them.

The scenario analyses conducted on the KPIs groups selected by the analysed company result in a set of graphs that give to the business a tangible measure of how KPIs vary according to one or more changes in the input parameters.

The tool used to create reports for the selected KPIs dashboard has been Microsoft Power BI®, a business analytics service by Microsoft to provide interactive visualizations and business intelligence capabilities through an easy-to use interface that enable final users to create by themselves their own reports and dashboards.

In order to populate the database used by Microsoft Power BI® as starting point for the reporting activities, several database views have been created on the AnyLogic® database, including information resulting from both the optimization and the simulation models. For example, all the information related to the attributes that are included in the job order rows imported from the company's ERP as inputs of the optimization model, such as related customer, article line and season, have to be imported on Microsoft Power BI® in order to conduct statistics on, for example, who is the best-served customer per season. Moving to the data coming from the simulation model, they represent the real assigned dates and quantities per job order row specifying the resource that processes them enabling, for example, statistics about average daily or monthly resources' saturation.

Starting from the analysed data and considering a scenario where no stochastic events are included, the KPIs related to the time dimension can be represented as shown in Figure 35.

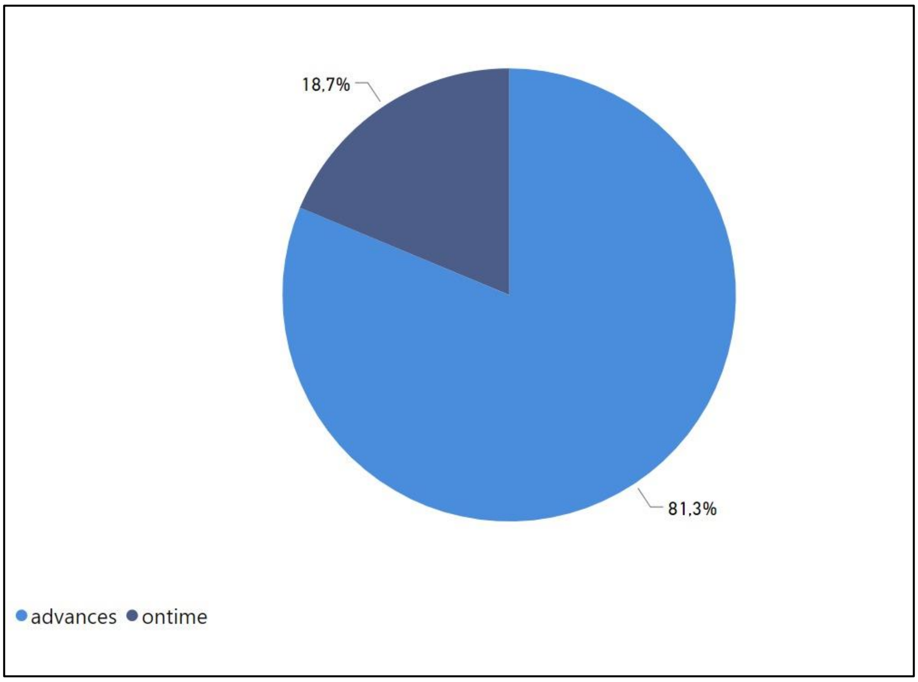

Figure 35 - KPIs dashboard: Time (deterministic scenario)

Looking at the graph in Figure 35, even if the selected KPIs for the time dimension include on-time, advances and delays, only the first two sections have been displayed. This evidence is aligned to the fact that the OF in the optimization model includes both delays and advances, but the weight of the first one in the OF far exceeds the one of the advances, resulting on an Earliest Due Date (EDD) strategy that sequences the job order rows starting from their due date.

Moving from a deterministic to a scenario where stochasticity is included, both considering the occurrence of rush orders (i.e. 50) and delays on critical components' delivery date (i.e. 3), the KPIs values related to the time dimension, represented using the same graph, highlight how stochastic events negatively impact the company's compliance to the delivery date. In fact, the on-time and the advances decrease while, on the other hand, delays exponentially grow (see Figure 36).

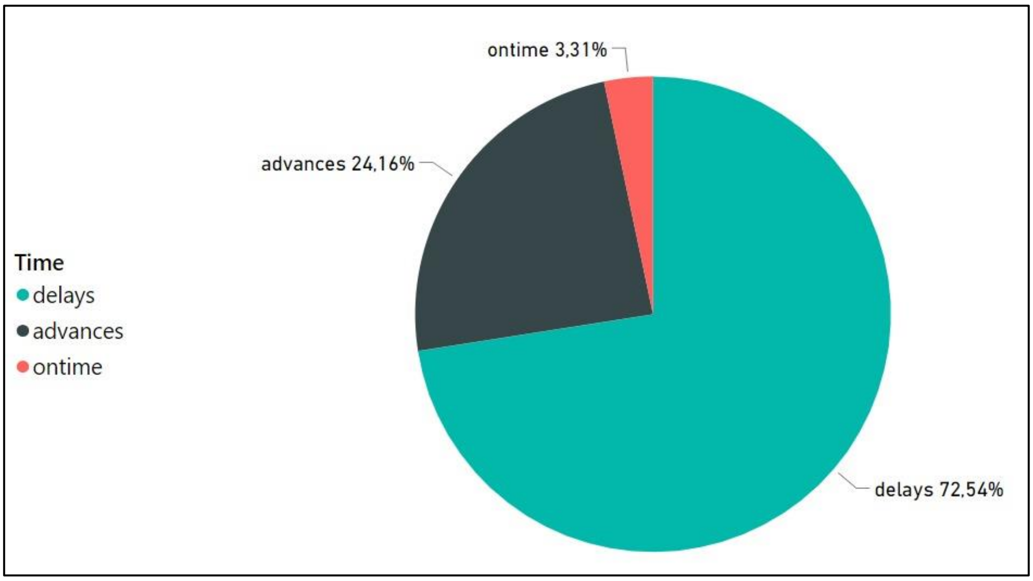

Figure 36 - KPIs dashboard: Time (stochastic scenario)

Through the Microsoft Power BI® reporting tool, the final user has been also enabled to execute filtering, drill-down and drill-up operations in order to navigate data and gain relevant evidences.

The way to execute these operations are strictly dependent to the information collected in the Microsoft Power BI® database and, consequently, to the AnyLogic® database views that, for example, include the classification of advances and delays in terms of the time window they cover, enabling the final user to create statistics that segment data that have delays or advances included in pre-established ranges (e.g. from 1 to 5 days, from 6 to 10 days and higher than 10 days).

In the analysed example, drilling-down the delays section on the graph in Figure 35 it is possible to investigate the percentage of advances lower and higher than a week, such as in in Figure 36 where it is detailed the same time segmentation but referred to the delays.

According to the fact that the OF has been defined to represent an EDD strategy and no stochastic events are included in the scenario represented by the Figure 35, in Figure 37 the percentage of advances lower than a week far exceeds the one higher.

On the other hand, Figure 38 shows the results of the same scenario after the stochasticity has been included, splitting the delays between the ones lower and higher one week.

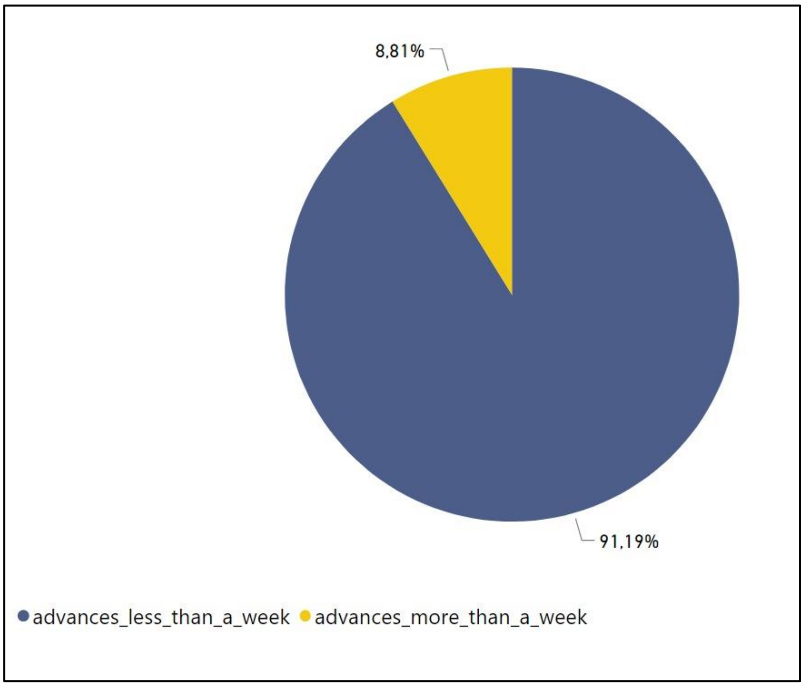

Figure 37 - KPIs dashboard: Time detail (deterministic scenario)

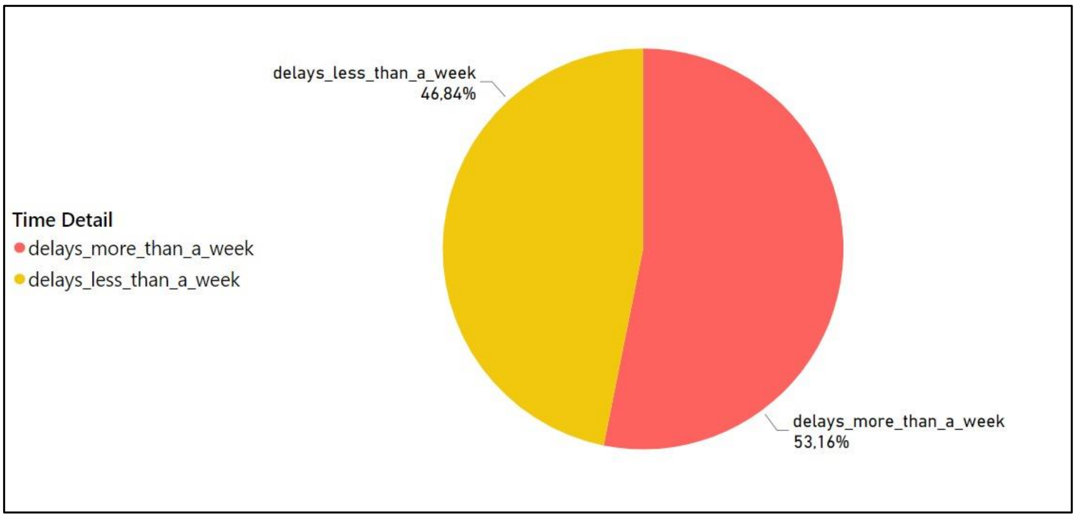

Figure 38 - KPIs dashboard: Time detail (stochastic scenario)

Analysing the stochastic scenario represented in Figure 38, another drill-down operation can be executed investigating, for example, which are the articles that have a certain percentage of delays, as shown in Figure 39, enabling the final user to give back to the customer a more detailed information about the relevance of the expected delay.

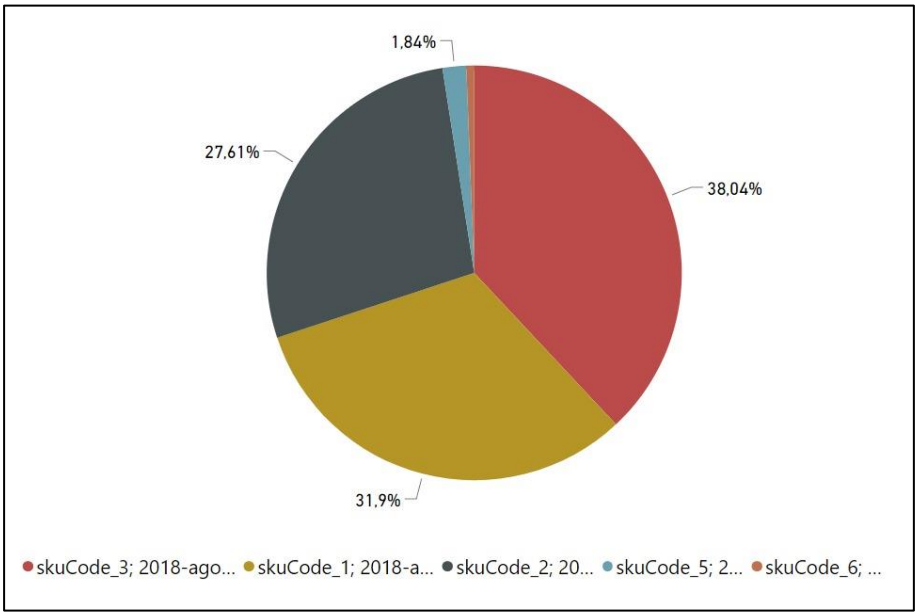

Figure 39 - KPIs dashboard: Article per soft delays (stochastic scenario)

Coming back to Figure 36, the KPIs dashboard that shows the percentage of delayed, advanced and on-time items can be drilled-down also considering the customers, in order to enable the final user to identify the best-served customer, as shown in Figure 40.

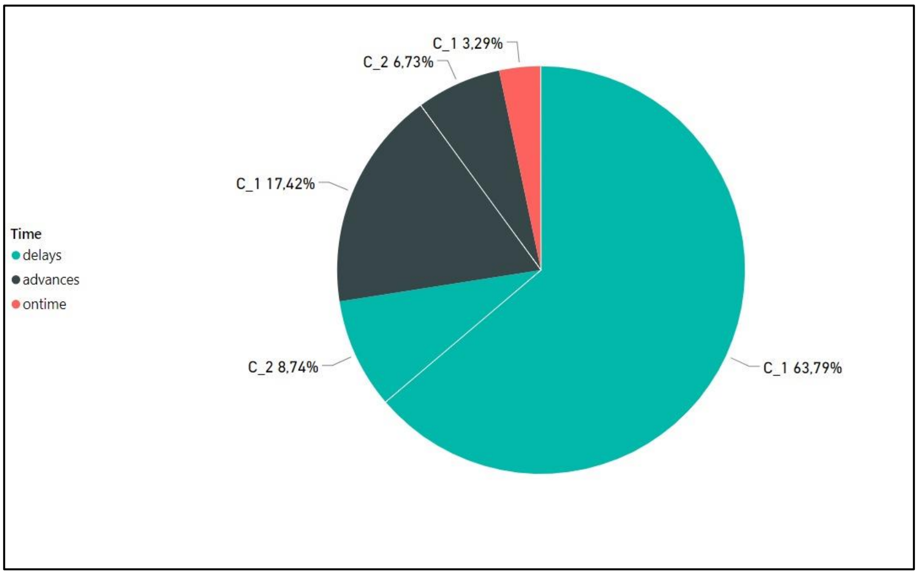

Figure 40 - KPIs dashboard: Time per customers (stochastic scenario)

Moreover, starting from the graph in Figure 40 it is possible to filter data in order to analyse only one of the two displayed customers (see Figure 41), defining a report for each one of them that can be directly sent to the customer itself as proof of the service level guaranteed.

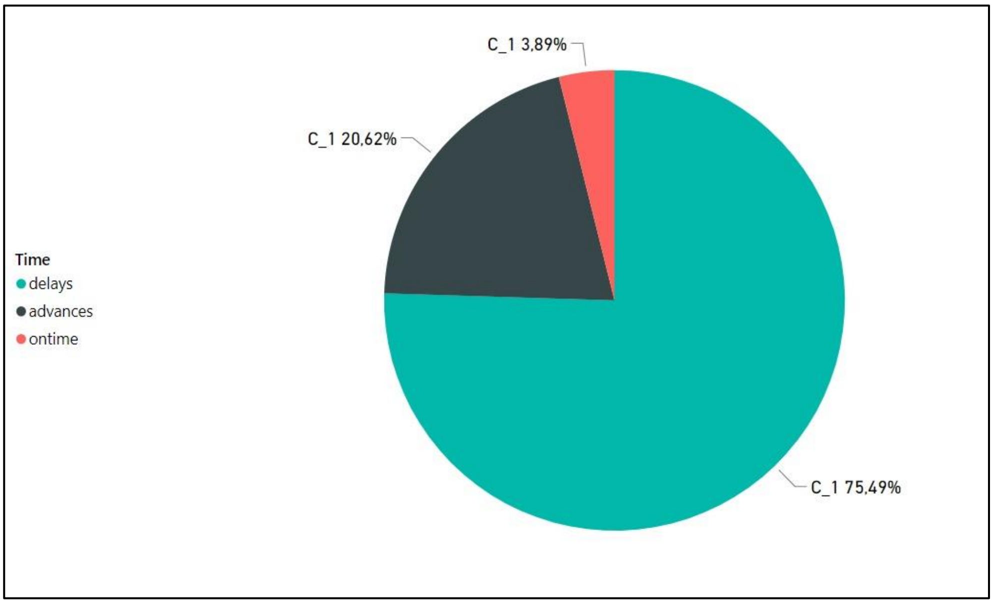

Figure 41 - KPIs dashboard: Time per customer (stochastic scenario)

A second level of drill-down can be done, for example, on the graph in Figure 41 in order to investigate, considering the items expected to be delivered later than the requested date, the percentage of “soft” and “hard” delays, referred to the ones lower and higher than one week respectively (see Figure 42).

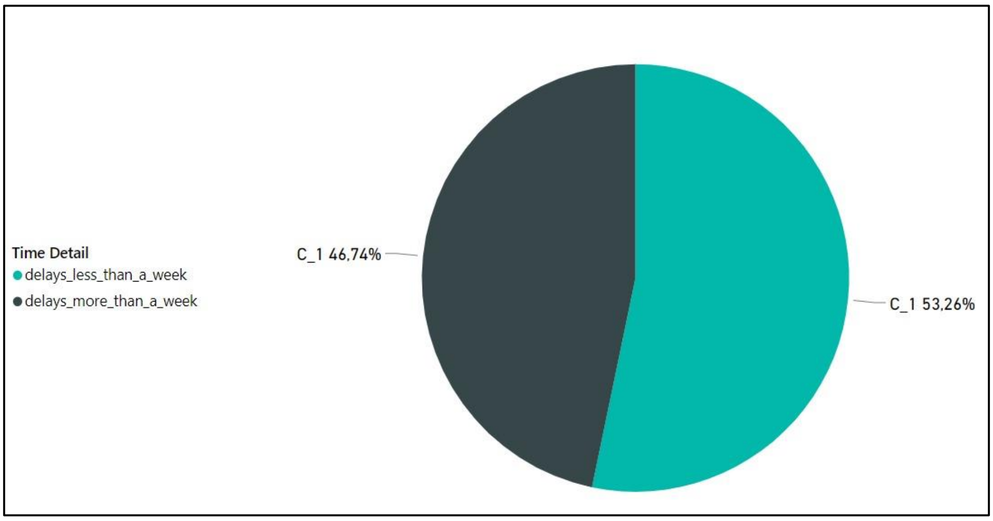

Figure 42 - KPIs dashboard: Time detail per customer (stochastic scenario)

After the exploration of the percentage of delayed, advanced and on-time job orders, their segmentation for customer (i.e. first frill-down level) and the analysis of the “hard” delays filtering for one of the customers (i.e. second frill-down level), a third level of drill-down can be done, for example, to investigate which are the more delayed (i.e. delays higher than one week) articles for the customer filtered in Figure 42, as shown in Figure 43.

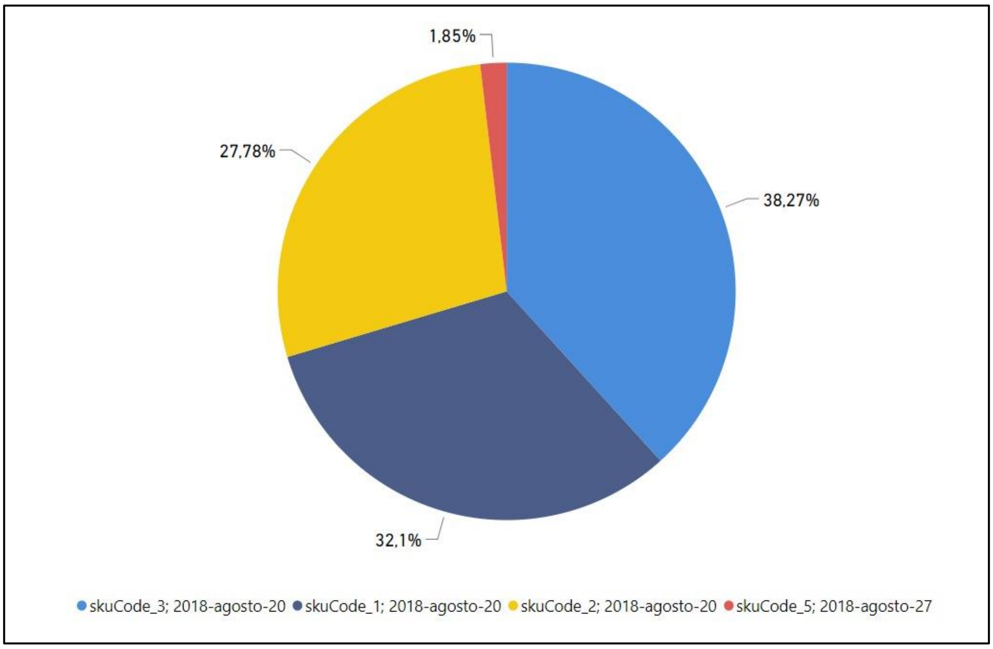

Figure 43 - KPIs dashboard: Time detail per customer per article (stochastic scenario)

The KPIs dashboard related to the time dimension is not the only one that can be created to support managers in the decision-making processes. In fact, another graph that can be realized is the one in Figure 44, that shows the behaviour of the saturation of the two analysed resources (i.e. “Service 1” and “Service 2”) over time, in order to identify, for example, which are its minimum, average and maximum values, when each of them occur, and if the resources are well-balanced or not. Moreover, moving the cursor along the graph it will show the value of the saturation per resource on the Y axis for the specific date on the X axis, enabling the final user to deeply investigate a specific behaviour or the outliers that occur on the graph.

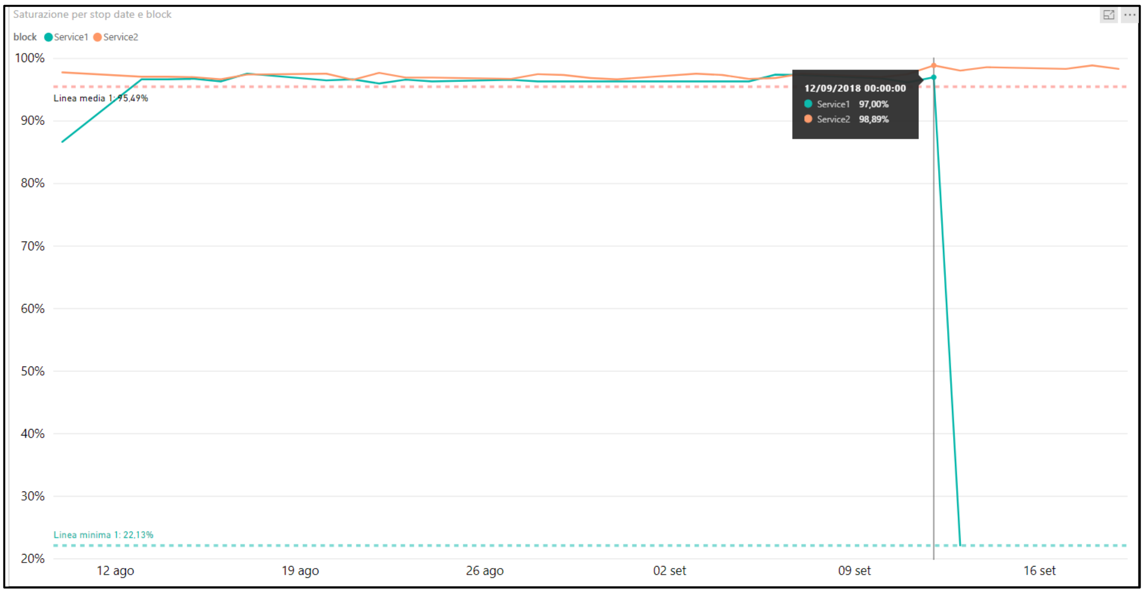

Figure 44 - KPIs dashboard: Saturation

The outputs of the simulation model that can be analysed through a reporting tool are not limited to a single scenario that managers decide to investigate in detail, such as the previously explained KPIs dashboards. In fact, another analysis that can be managed is the sensitivity analysis, an experiment to explore how sensitive are the simulation results to changes of the model parameters. In particular, according to the results of the ANOVA tests, the investigated parameters could be the occurrences of rush orders and delays on the critical components delivery date, while the monitored outputs the delays and advances.

This kind of experiment has then been conducted on the AnyLogic® tool running the model 10 times for each one of the variations of the rush orders' occurrence, that moves from 30 to 70 with 20 as step (i.e. values equal to 30, 50 and 70). Due to the fact that the resulted delays have been expressed as a dataset and exported as database view to the Microsoft Power BI® database, a series of curves represent the results of the sensitivity analysis, shown on the chart in Figure 45 for allowing a comparison that reflects how the simulation output depends on the rush orders' occurrence.

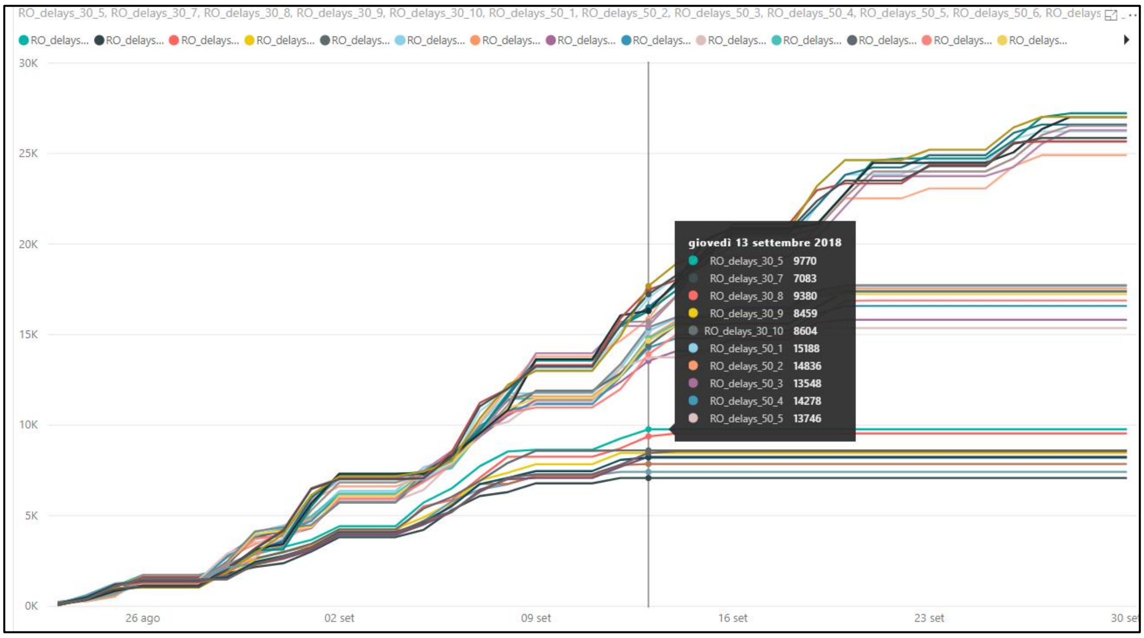

Figure 45 - Sensitivity analysis: rush orders

Starting from the analysis shown in Figure 45, that involves all the 10 replications per occurrence of rush orders, another analysis can be conducted comparing only the daily average output per occurrence. Looking at the chart in Figure 46, it shows how the higher is the occurrence of rush orders, the greater is the output value. Consequently, the date when all the requested SKUs have been processed (i.e. the date when the graph becomes stable) become higher moving from the graph having occurrence equals to 30 (i.e. 12 September 2018), to 50 (i.e. 20 September 2018), to 70 (i.e. 28 September 2018), as shown in Figure 46.

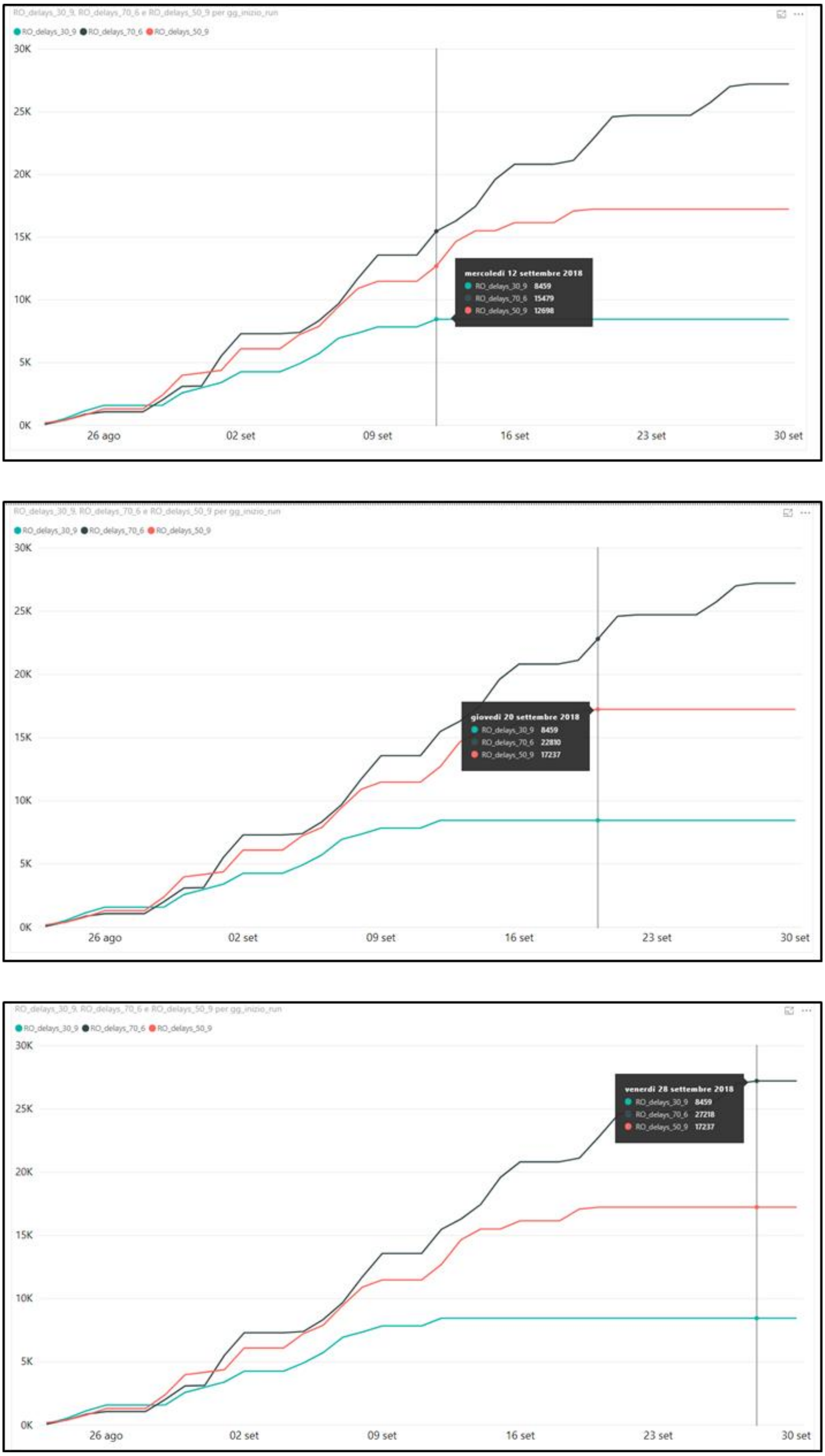

Figure 46 - Sensitivity analysis: rush orders (average)

4.3 Simulation-optimization framework for the fashion industry

The implementation of both the optimization and simulation models previously described (see paragraphs 4.1.3 Implementation of the proposed scheduling model in the fashion industry and 4.2.3 Implementation of the proposed simulation model in the fashion industry) refers to a single-company that, in a real context, work within a SC network composed by several actors that exchange each other information and material flows.

Once both the optimization and the simulation have been developed, in order to answer to the RQ3, they have to be jointly used considering that outputs of the optimization model represent the inputs for running the simulation model. The reason why optimization and simulation are jointly used within this framework is twofold: on the one hand, using optimization algorithms allows companies to find an optimal allocation for their production considering the parameters, constraints and objectives they have defined during the model setting, according to their own CSFs; on the other hand, with simulation stochastic events, such as rush orders or delays in the components delivery, are taken into account, moving the production allocation analysis from a deterministic scenario to a not-deterministic one.

Moreover, this two-step implementation has to be repeated in an iterative way, varying the simulation-optimization model input based on the outputs per iteration (i.e. including new constraints, such as available capacity), in order to evaluate if changes result into improvement in the overall SC KPIs values.

According to this an iterative simulation-optimization framework for improving the global SC PP&C performances has been developed, in order to include the effects that the feedbacks coming from the implementation of simulation-optimization models at the single-companies level may have on the overall SC performances.

Starting from the evidences coming from the literature review, the first draft of the proposed iterative simulation-optimization framework has been developed and then readapted until the definition of its final version according to the feedback from its implementations (see paragraph 4.3.1 Proposed iterative simulation-optimization model). Using the action research methodology, the proposed tool has been validated through on-field implementations on companies working in the 3 analysed market segments (i.e. metal accessories, leather goods, footwear) in terms of usability and effectiveness (see paragraph 4.3.2 Implementation of the proposed iterative simulation-optimization model in the fashion industry).

4.3.1 Proposed iterative simulation-optimization model

Once the optimization and the simulation models have been separately developed and tested (see paragraphs 4.1 Scheduling model for the fashion industry and 4.2 Simulation model for the fashion industry respectively), they have to be jointly implemented into a simulation optimization decision-support tool to be iteratively run on companies working along the fashion SC.

According to this, in the first paragraph of this chapter the general scenario considered for developing the proposed iterative simulation-optimization framework has been described (see paragraph 4.3.1.1 Simulation-optimization model description). More in detail, the analysed context includes an interdependent environment composed by a group of focal companies that work with both exclusive and not-exclusive suppliers.

Secondly, the steps of implementation for applying the proposed model to a real context have been listed in the paragraph 4.3.1.2 Simulation-optimization model architecture. In particular, the framework includes the proposed discrete-event simulator, linked together with the multi-objective, integer linear-optimization scheduler previously described through an import-export routine, and has been developed in a parametrical way, in order to fit the peculiarities of the different actors operating along the fashion SC.

The tool aims to enable the comparison among scheduling algorithms in order to optimize the overall performances in terms of customers' due dates compliance and costs and processing times reduction.

4.3.1.1 Simulation-optimization model description

The proposed optimization and simulation models described in the previous paragraphs (see paragraphs 4.1 Scheduling model for the fashion industry and 4.2 Simulation model for the fashion industry respectively) have been developed and implemented considering the single-company level instead of the whole context where these companies work.

In fact, starting from the boundaries described above, the simulation-optimization framework proposed in this work aims to define the optimal production plan not at the single-company level, but considering the performances of the whole SC according to a pre-defined set of KPIs and the influence of stochastic events.

More in detail, the framework includes the implementation of the proposed discrete-event simulator linked together with the previously described multi-objective, integer linear-optimization scheduler through an import-export routine. As already declared, both the optimization and simulation models have been developed in order to be suitable by the different actors that belong to the fashion SC, such as brand owners and suppliers, parametrically defining those models in order to configure themselves fitting each one of the SC actors' peculiarities.

The analysed scenario for the description of the proposed framework includes a SC network composed by more than one brand owners and several suppliers, both exclusive and not, that work together. In order to simplify the graphical representation, the context chosen to explain the proposed framework is the one described in Figure 17, where "Supplier_1" and "Supplier_3" are exclusive suppliers for brand owners "Brand_1" and "Brand_2" respectively, while "Supplier_2" works for both of them.

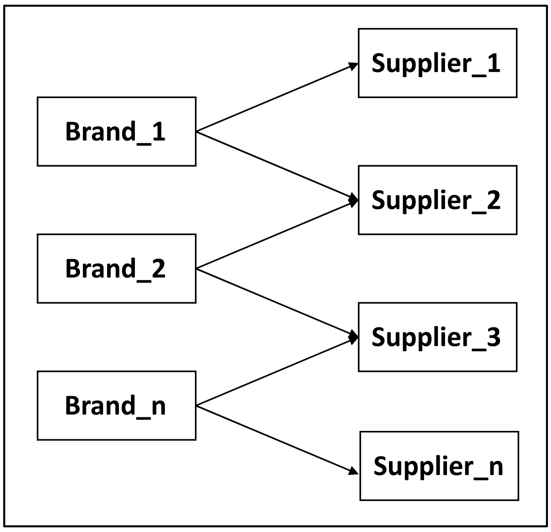

Figure 47 - General SC network included in the proposed framework

The general SC network showed in Figure 47 can be used to understand why it is needed to move from an implementation of the simulation-optimization model at the single-company level to a wider application along the different involved SC actors.

In fact, in real contexts 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 units that can be produced per week or per day.

According to the main evidences highlighted from the on-field interview, 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. Looking at the Figure 47, considering the supplier "Supplier_2" that works for both the brand owners "Brand_1" and "Brand_2", it is a common practice that it declares a higher available capacity to both of them.

Moving to the suppliers' perspective, each of them collects the received production plans and, according to its objectives and its real production capacity, defines a personal production plan. In order to verify if the expected delivery dates will be reached, brand owners periodically (usually weekly) ask suppliers to confirm them or give back the updated delivery dates considering the orders which production has already started and the re-scheduling of the others.

The actual production plan of the suppliers can differ from the optimized production plan, developed according to the brand owners' CSFs, mainly due to two different reasons.

Firstly, as anticipated above, the OFs included for optimizing the production plan from the brand owner's perspective and from the supplier's one can be different, because the CSFs for the two SC actors cannot be equal (e.g. the brand owner may include only the minimization of delays while the supplier of both delays and advances).

On the other hand, even if OFs of brand owners and suppliers were perfectly aligned, differences between the related production scheduling could be related to the influences of the occurrence of stochastic events (e.g. failures, rush orders). In fact, if rush orders have to be managed by the supplier or failures occur to its machines, a negative impact on the overall performances, for example in terms of delays on expected delivery dates, will probably follows.

Coming back to the brand owners' perspective, they 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.

Starting from the boundaries described above, the simulation-optimization framework proposed in this work has the objective to overcome these limits, giving to all the SC actors a decision-making tool that enables them to preventively highlights the criticalities and the way to manage them, through the iterative procedure described in the next paragraph (see paragraph 4.3.1.2 Simulation-optimization model architecture).

According to this, the scenario moves from the identification of the optimal solutions for each one of the SC actors to provide the sub-optimal brand owners' and suppliers' production plans that guarantee the best overall SC performances, and the proposed simulation-optimization framework is shown in Figure 48.

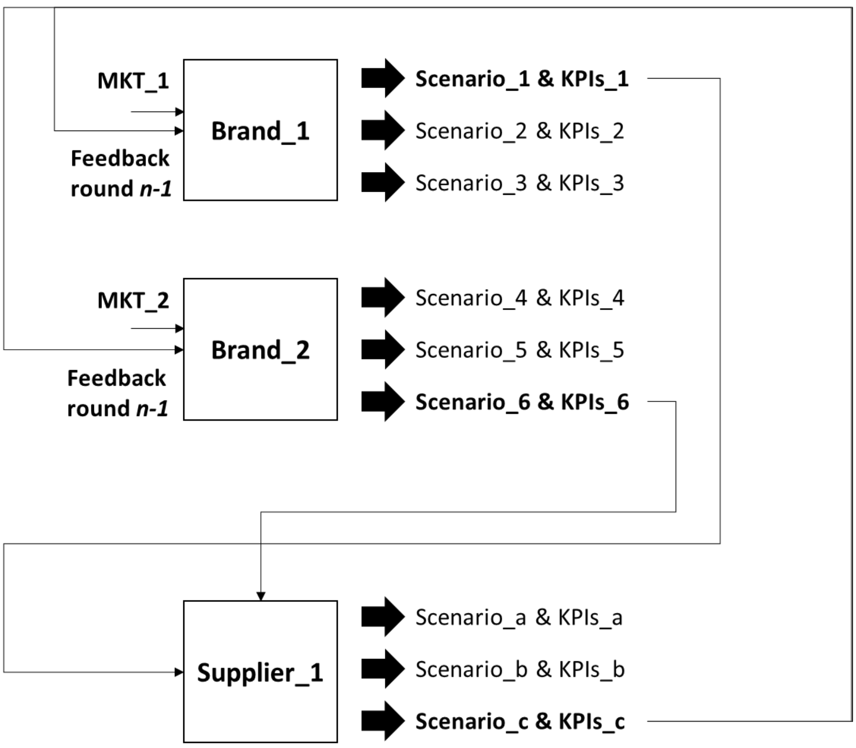

Figure 48 - Iterative simulation-optimization framework

In the proposed framework showed in Figure 48, the brand owners “Brand_1” and “Brand_2” are represented, each one of them receiving a demand plan that collects quantities per SKUs to be produced by due dates defined in order to be on-time on the market (“MKT_1” and “MKT_2” in Figure 48). Using that plan as input for its optimization and adequately setting the other parameters needed, the optimization model, before, and the simulation one, after, will be run, showing at the end several scenarios according to the changes each brand owner has made to the inputs of both the models, such as changing the optimization model inputs in terms of different number of available resources or changing the simulation model inputs in terms of different type of stochastic events, such as rush orders instead of delays on expected arrival date for critical components, or their statistical distribution.

Once the scenarios are displayed, each one of the brand owners may select the preferable one according to the related KPIs’ values, resulting on a specific set of quantities per SKUs assigned to one or more suppliers by an assigned delivery date. In the framework, the selected optimized plans (“Scenario_1 & KPIs_1” and “Scenario_6 & KPIs_6” in Figure 48) include the assigned quantities and delivery date for the SKUs to be produced by the common supplier “Supplier_1”, that will receive them from both the brand owners and use them as input for running the optimization and then the simulation model to optimize its own production performances. In the same way of brand owners, “Supplier_1” will compare the different possible scenarios coming from the models implementation and give back to the brand owners the optimized production plans he is able to guarantee (“Feedback round n-1” in Figure 48), with the related KPIs that may include delays or advances on the resulting production scheduling if compared to the brand owners’ ones. If brand owners agree with these, no more iteration is needed and the best solution for the whole SC is gathered.

Otherwise, each one of the brand owners has to run again the optimization and the simulation models including as input not only the demand plan but also the evidences coming from the received feedback. For example, if the KPIs’ values related to the optimized production plan came from the “Supplier_1” shows that he is over-saturated and this results on high delays on the overall required due dates, each one of the brand owners may decide to allocate some quantities to be processed to other suppliers that belong to their supply base that, for example, can be not taken into account in the previous iteration because more expensive or less compliant than “Supplier_1”.

Going deeper from the boundaries described above, the simulation-optimization model applied at the single-company level includes the application of the proposed optimization model (see paragraph 4.1 Scheduling model for the fashion industry) followed by a “what-if” simulation analysis conducted through the implementation of the proposed simulation model (see paragraph 4.2 Simulation model for the fashion industry). This two-steps implementation conducted for both brand owners and suppliers underlines also how the optimized results and the related KPIs can differ moving from the brand owner to the supplier perspective, especially considering a scenario where multiple brand-supplier relationships exist and the uncertainty due to both internal (e.g. machine failures, reworks, employees unavailability) and external stochastic events (e.g. rush orders) that often characterises a dynamic context such as the one of fashion SC.

4.3.1.2 Simulation-optimization model architecture

Starting from the framework previously described, the architecture of the model applied at the single-company level is showed in Figure 49.

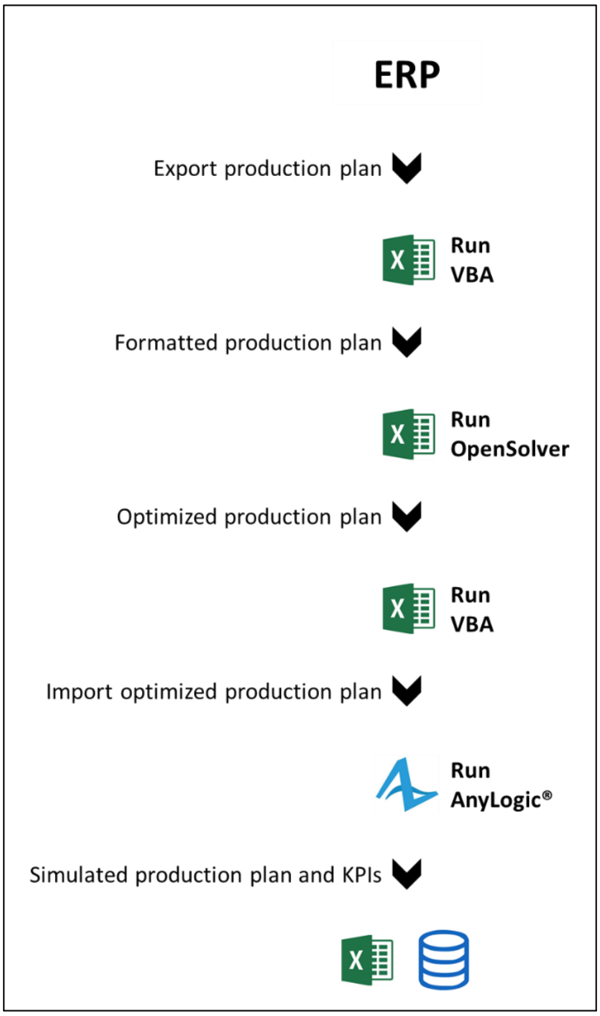

Figure 49 - Simulation-optimization model general architecture at the single-company level

More in detail, the first step is the export of the production plan from the company's ERP on a Microsoft Excel® file. The data includes required quantities and delivery dates per single SKU but also all the other parameters needed for setting the model. In fact, this Microsoft Excel® file, elaborated using VBA code, is used as input for running the proposed optimization model using OpenSolver as optimization tool (see paragraph 4.1 Scheduling model for the fashion industry). The results, in terms of assigned quantities per resource and delivery dates, represent the optimal solution under deterministic conditions and according to the selected parameters, constraints and weighted OF set as input.

In order to compare different optimized plans and move from a deterministic scenario to another one that includes stochastic events, the optimized production plan has to be reformatted on another Microsoft Excel® file in order to resume all the information needed for running the simulation model and then imported into the simulator's database, such as the ones related to the occurrence of stochastic events. This procedure, that readapts the information resulting from running the optimization model, has been automatize developing a specific VBA code.

In fact, according to the proposed simulation model (see paragraph 4.2 Simulation model for the fashion industry), stochastic events have to be included at this point, for example inserting a percentage of unexpected orders to be generated with priority on the planned ones, representing the production of rush orders that fashion companies usually have to manage.

The introduction of stochastic events may impact on the output coming from the simulator, that can differ in terms of performances from the one came from the optimization model used as input for simulation. Running the simulation model, in fact, data referred to the simulated quantities and delivery dates per SKU are exported on an Microsoft Excel® file, used to compare the deterministic with the stochastic scenario, highlighting how performances vary introducing stochasticity through a pre-defined set of KPIs (see paragraph 4.2.2.2 KPIs dashboard). In particular, the KPIs dashboard allows to conduct a scenario analysis based on structured data focused, on the one hand, on how optimized production plans vary changing model inputs, such as available resource capacity and enabled suppliers per SKU or weights in the OF, and, on the other hand, on how the simulated scenarios are differently stressed by stochastic events, changing the percentage of that kind of events.

According to this, the architecture shown in Figure 49 has to be implemented for each combination of parameters, constraints, OFs and stochastic events to be compared, and the detailed architecture of the model is represented in Figure 50, including three scenarios that can be compared for supporting SC actors in the decision-making process.

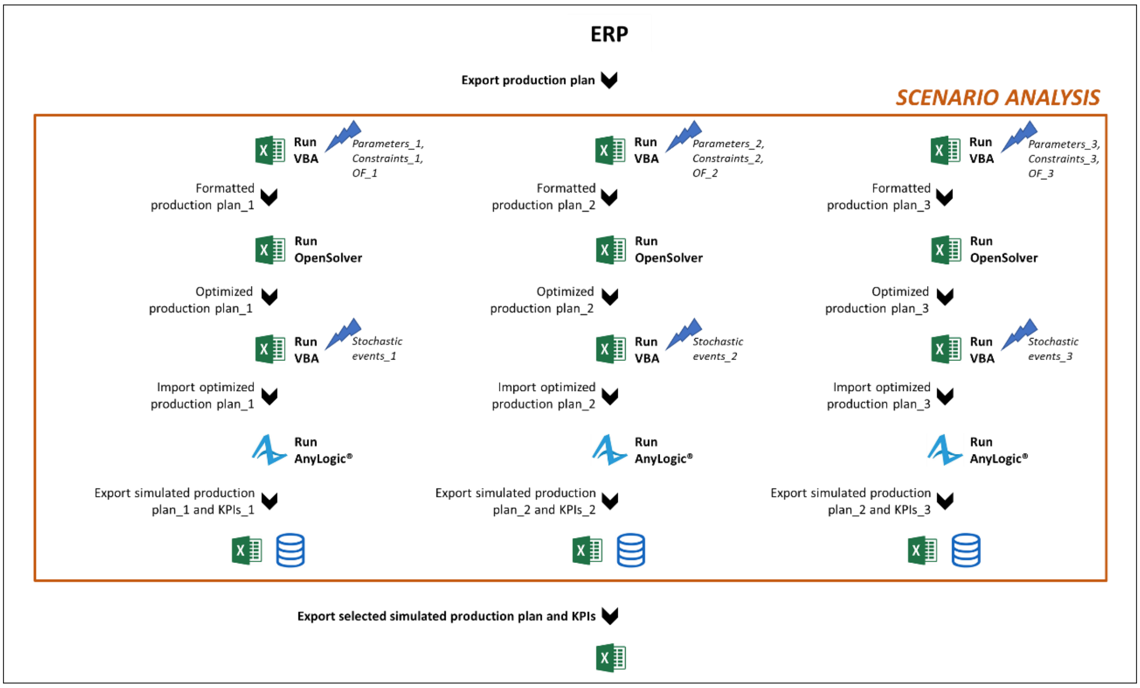

Figure 50 - Simulation-optimization model detailed architecture at the single-company level

According to the simulation-optimization framework previously proposed (see paragraph 4.3.1.1 Simulation-optimization model description), the procedure in Figure 50 can be applied both to brand owners and suppliers operating in the fashion SC. In particular, it includes the iterative implementation of the procedure above, considering a SC network composed by more than one brand owners and several suppliers, both exclusive and not, that work together.

In this way, the iterative procedure for the application of the proposed framework (see Figure 48) is shown in Figure 51.

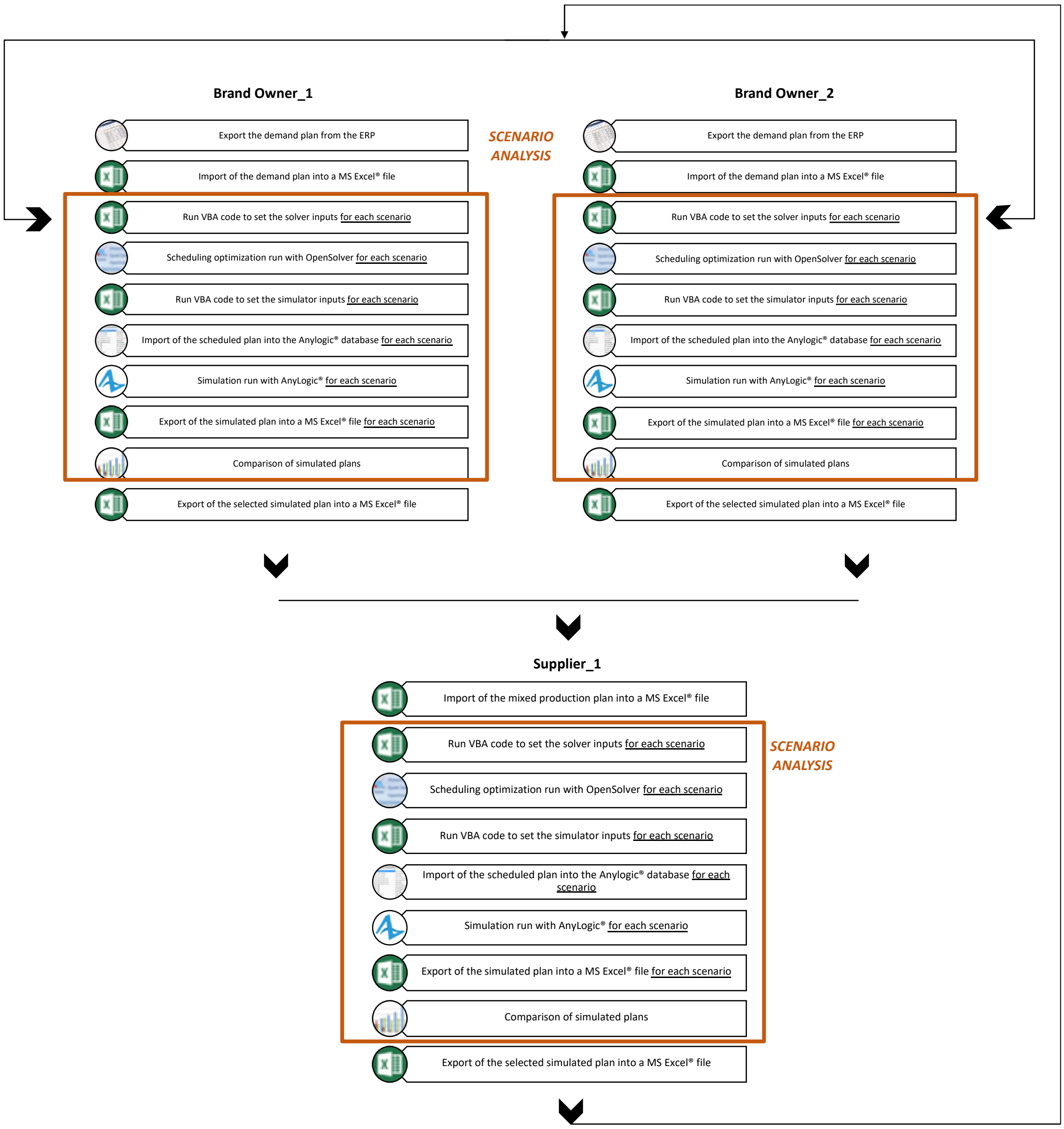

Figure 51 - Iterative simulation-optimization procedure

4.3.2 Implementation of the proposed iterative simulation-optimization model in the fashion industry

Starting from the procedure for the iterative implementation of the simulation-optimization model (see Figure 51), different scenario analysis can be conducted.

First of all, according to the evidences coming from the description of the implementation procedure for the simulation model (see paragraph 4.2.3 Implementation of the proposed simulation model in the fashion industry), a scenario analysis can be conducted at the single-company level. On the one hand, an analysis can be done comparing deterministic scenarios, considering the impacts on KPIs resulted from the implementation of optimization model with different inputs, such as OFs' weights or suppliers' production capacity. On the other hand, another type of KPIs' values comparison can be done making no changes on the optimization model inputs but only in the simulation model ones, for example varying the occurrence of stochastic events or including more than one stochasticity. Moreover, a combination of the described changes (i.e. both on optimization and simulation model inputs) can be done.

Moving from a single-company level to a SC network, the scenario analysis can be conducted comparing the gap between the demand planning and the brand owner's simulated production plan (see "ProcessingDate_gap_A" in Figure 52) and the gap between the demand planning and the supplier's simulated production plan (see "ProcessingDate_gap_B" in Figure 52), both in terms of delays and advances related to the required quantities and delivery date per SKU and the average saturation per available resource.

Looking at the KPIs in Figure 52, both of them refer to the KPIs "Otm_W_Sum" and "Atg_W_Sum" listed in Table 7, representing the number of on-time and not ot-time items respectively, that have to be calculated, on the one hand, at the brand owner's level and, on the other hand, from the supplier's perspective.

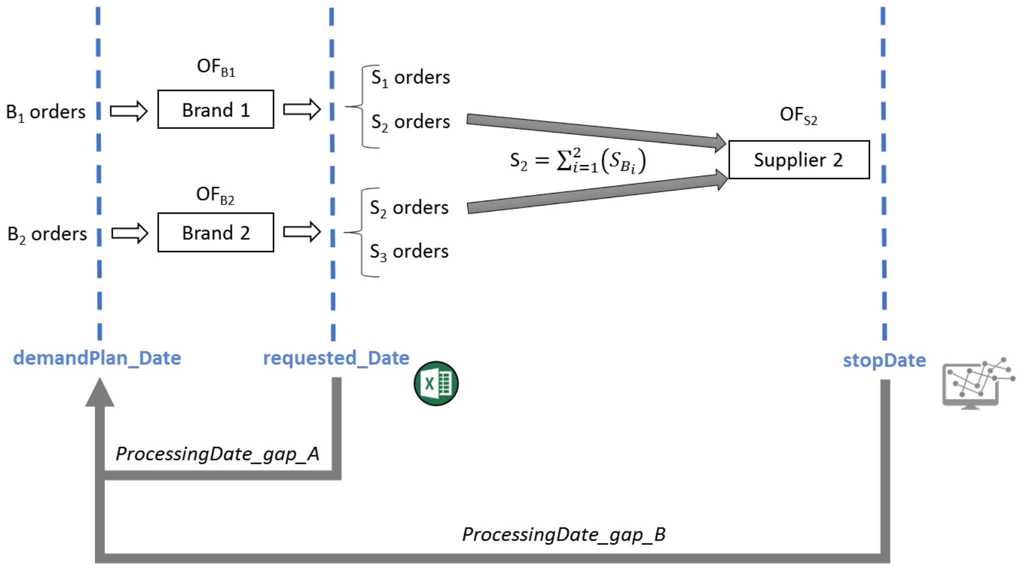

Figure 52 - Scenario analysis at the SC network level

The comparison between “ProcessingDate_gap_A” and “ProcessingDate_gap_B” considering different scenarios at the single-company level makes easier to identify the combination of brand owner’s one and supplier’s simulated plans that have the best impact on the overall SC network performances.

Finally, the general framework can be applied into different SC network configuration (for example 1:1, 1:N, M:1, M:N brand-supplier relationships) but also into different market segments, such as metal accessories, leather goods and footwear, readapting the parameters of single models to the peculiarities of each company. This is allowed by the development of both the optimization and simulation model in a parametrical way, for example enabling to include or not some parameters in the OF, giving a weight equals or not to zero, and expressing same parameters in a different way (e.g. resource capacity in terms of quantity per day or minutes per day moving from a brand owner to a supplier perspective).

5 Results

According the Action Research methodology, the framework has been developed in order to collect the requirements and validate the usability of a general production planning simulation-optimization model in the leather industry. In particular, the on-field implementations have been conducted on companies working in the 3 analysed market segments comparing model's outputs with the production planner's evaluations.

First of all, a brief overview of the pilots' implementation has been detailed (see 5.1 Pilots overview).

After that, the results of the metal accessories (see paragraph 5.2 Metal accessories), leather goods (see paragraph 5.3 Leather goods) and footwear (see paragraph 5.4 Footwear) pilots' implementation have been reported.

5.1 Pilots overview

According to Hu et al. (2013), model validation has to be conducted starting with a pilot implementation, where the model is tested with a small-scale problem, assuming a single resource at finite capacity and a production plan for a limited sample of products that covers one month and a half, which represents the orders visibility that these companies usually have from the fashion brands. All the processes included into the production cycle of the item, before and after the only job scheduled at finite capacity, has been modelled using the LT as the processing time.

The simulation-optimization model has been applied to real companies working along the fashion SC, where costs, delay, and advances have been considered in order to define the OF for the optimization model and, on the other hand, the type if stochasticity to be included have been chosen according to the challenges each SC actor in the analysed market segment has to face with.

The empirical implementation of the framework has been done using data coming from fashion companies belonged to the same SC network, considering rush orders and delays on critical components' delivery date as stochastic events for the scenario analysis and the KPIs assessment.

According to the previous paragraph (see paragraph 4.3.2 Implementation of the proposed iterative simulation-optimization model in the fashion industry), the procedure followed for implementing the proposed models along the fashion SC, especially in SMEs with a low informatization level and investment capabilities in IT solution, includes, on the one hand, using a commercial spreadsheet and OpenSolver as an open source CBC optimization solver and, on the other hand, AnyLogic® for the DES modeling.

In the following paragraphs it is detailed the conduction of three pilots: the first one on a metal accessories supplier, the second one on a leather goods producer and the last one on a footwear company.

Even if the main purpose for all the pilots is to validate the results and the usability of the models' implementation, each one of them has specific goals according to the peculiarities of the analysed companies and, consequently, requires the conduction of different type of scenario analysis. In fact, even if the starting point is represented by the previously explained KPIs dashboard (see the paragraph 4.2.2.2 KPIs dashboard), each company can select the set of KPIs groups to be analysed (see Table 6) and choose the subset of KPIs from the ones listed in Table 7: this selection will be graphically shown at the beginning of each pilot, filling the framework in Figure 53 with the KPIs to be evaluated and the input parameters selected for the conduction of the scenario analyses.

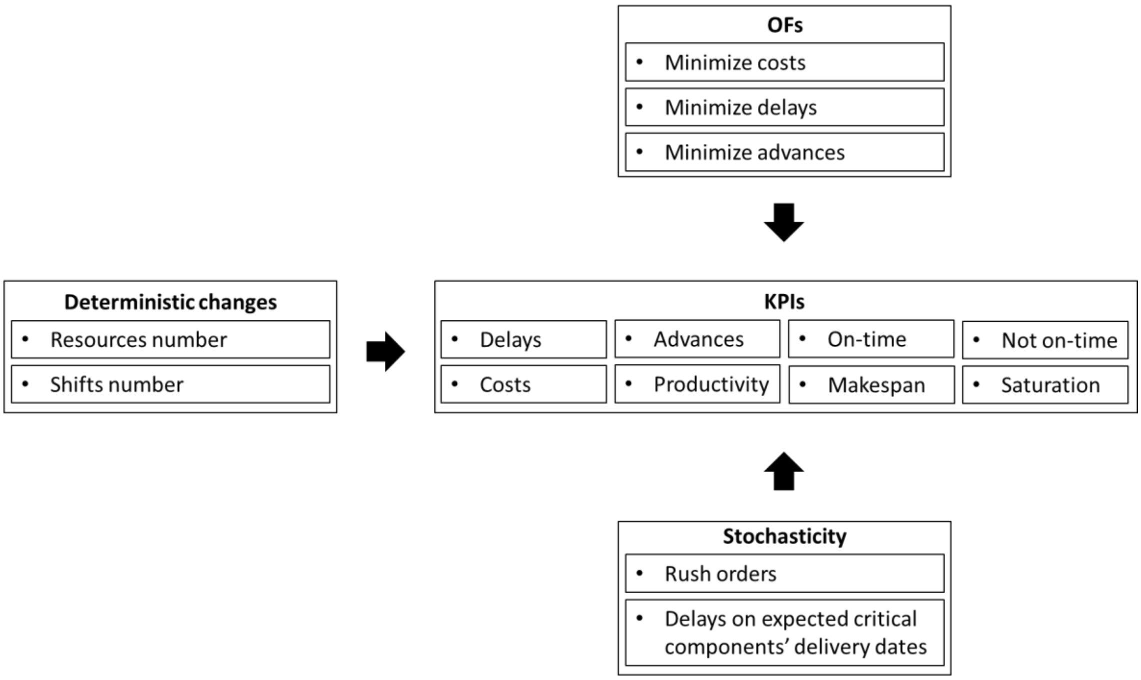

Figure 53 - Pilots' implementation framework

The pilot on a metal accessories supplier (see paragraph 5.2 Metal accessories) shows, as first result, how the optimization model can be applied and how the relative results change moving from one scenario to another one, characterized each one by a different combination of elementary objectives in the OF. Secondly, the simulation has been used to both validate the optimization model results and to evaluate how stochasticity impacts on the PP&C performances considering the different deterministic scenarios coming from the optimization model's implementation.

Moving from the metal accessories to the leather goods market segment (see paragraph 5.3 Leather goods), the validation of the models' implementation has been done for both brand owners and suppliers, highlighting the differences in the configuration of the same parametrical model. Moreover, two different gap analyses have been done through simulation, to compare deterministic and stochastic scenarios including only rush orders and both them and delays in the delivery of critical components.

Finally, the footwear industry has been analysed (see paragraph 5.4 Footwear) and the model implementation has been done starting from a balanced production plan and validated according to the managers' experience. The sequencing problem has been analysed through simulation, and several scenario analyses have been conducted in order to evaluate the best sequencing empirical rule in terms of daily productivity, resources saturation and makespan.

5.2 Metal accessories

The first pilot has been conducted on a metal accessories' supplier, using a data set acquired from the real experience of an Italian fashion company.

The following paragraphs describe the implementation of both the proposed optimization and simulation model, in order to on-field validate their results and usability and to conduct scenario analysis.

The implementation of the proposed optimization model (see paragraph 5.2.2 Optimization model in a metal accessories company) has been used to generate different optimized plans changing the combination of elementary objectives in the OF. They are then compared using the proposed simulation model (see paragraph 5.2.3 Simulation model in a metal accessories company) in both deterministic and stochastic conditions, in order to evaluate the impacts on the PP&C performances.

In particular, the production phase chosen as having finite capacity is the machine shop, where Computer Numerical Control (CNC) machines are used to produce semi-finished items, starting from raw materials or molded items. All the steps after this phase have been considered working at infinite capacity and have been modelled with a generic processor having a LT as processing time, in the same way as sub-suppliers' external jobs. The model has been implemented considering a production plan of 40 days to be processed by a production plant operating 24 hours per day, 7 days per week.

In order to summing up, the framework in Figure 53 has been filled, highlighting the configuration of the input and output parameters that have been used for the conduction of the scenario analyses in the metal accessories pilot, as exemplified in Figure 54.

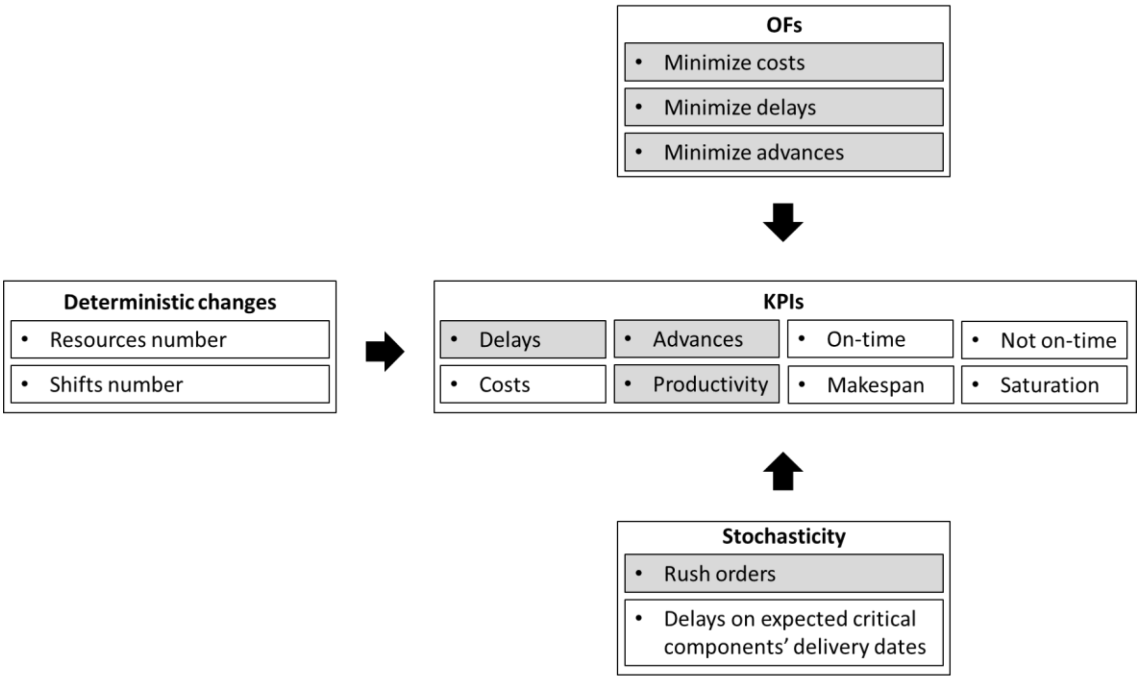

Figure 54 – Metal accessories pilots' implementation framework

5.2.1 Metal accessories sector introduction

The first pilot refers to a metal accessories supplier working in the fashion SC.

Even if metal accessories producers belong to the mechanical industry, they represent an important part of the fashion SC and their processes and CSFs are similar to the ones working for the fashion industry.

In order to understand the peculiarities of these companies, a remark of fashion product features and their technological cycle is reported. In particular, metal accessories are usually composed by two or more elements, assembled together in the final step of the production process. Each component can follow a different workflow due to several factors, mainly linked to functional, aesthetic and economical aspects. After the production of the semi-finished items, through moulding or shaving removal, the production cycle continues with some mechanical operations (e.g. vibration, vibratory finishing, drilling, cutting). Then, these items have to be covered by one or more precious metals, such as gold, palladium and ruthenium, through an electroplating process. Last, the items have to be assembled, pass the quality control, be packaged and delivered to the focal company or façonists in order to be applied on the final product.

A graphical representation of this process is shown in Figure 55.

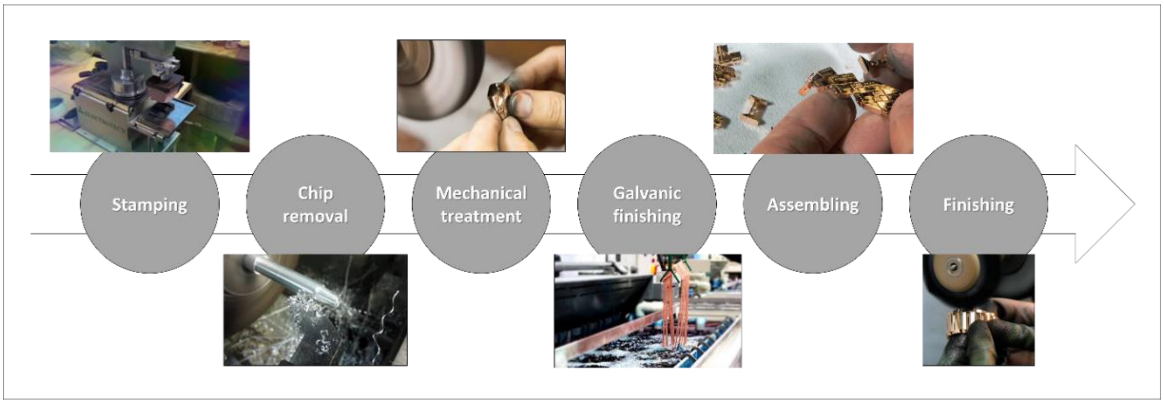

Figure 55 - Metal accessories production process

More in detail, the 6 steps showed in Figure 55 can be described as follows:

1. Stamping

Considering CAD or manually designed sketches, the draft of metal part can be realized using stamping machines or directly starting from the metal (see next production phase).

Stamping (also known as pressing) is the process of placing flat sheet metal in either blank or coil form into a stamping press where a tool and die surface forms the metal into a net shape. Stamping includes a variety of sheet-metal forming manufacturing processes, such as punching using a machine press or stamping press, blanking, embossing, bending, flanging, and coining.

This could be a single stage operation where every stroke of the press produces the desired form on the sheet metal part or could occur through a series of stages.

Depending on part complexity, the number of stations in the die can be determined.

2. Chip removal

In the chip removal process the layers of metal from the parent metal (workpiece) are separated in the form of chips to obtain the required dimension and shape. The workpiece is typically cut from a larger piece of stock, which is available in a variety of standard shapes, such as flat sheets, solid bars, hollow tubes, and shaped beams. Machining can also be performed on an existing part, such as a casting or forging, and can be used to create a variety of features including holes, slots, pockets, flat surfaces, and even complex surface contours.

In this process, a compressive force is applied to shear off the material in the small pieces known as chips.

Non-conventional machining processes may use chemical or thermal means of removing material. Conventional machining processes are often placed in three categories - single point cutting, multi-point cutting, and abrasive machining. Each process in these categories is uniquely defined by the type of cutting tool used and the general motion of that tool and the workpiece. Single point cutting refers to use a cutting tool with a single sharp edge that is used to remove material from the workpiece. The most common single point cutting process is turning, in which the workpiece rotates and the cutting tool feeds into the workpiece, cutting away material. Turning is performed on turning machine and produces cylindrical parts that may have external or internal features. Turning operations such as turning, boring, facing, grooving, cut-off (parting), and thread cutting allow for a wide variety of features to be machined, including slots, tapers, threads, flat surfaces, and complex contours. Other single point cutting processes exist that do not require the workpiece to rotate, such as planing and shaping.

Multi-point cutting refers to using a cutting tool with many sharp teeth that moves against the workpiece to remove material. The two most common multi-point cutting processes are milling and drilling. In both processes, the cutting tool is cylindrical with sharp teeth around its perimeter and rotates at high speeds. In milling, the workpiece is fed into the rotating tool along different paths and depths to create a variety of features. Performed on a milling machine, milling operations such as end milling, chamfer milling, and face milling are used to create slots, chamfers, pockets, flat surfaces, and complex contours. Milling machines can also perform drilling and other hole-making operations as well.

In drilling, the rotating tool is fed vertically into the stationary workpiece to create a hole. A drill press is specifically designed for drilling, but milling machines and turning machines can also perform this process. Drilling operations such as counterboring, countersinking, reaming, and tapping can be used to create recessed holes, high precision holes, and threaded holes. Other multi-point cutting processes exist that do not require the tool to rotate, such as broaching and sawing.

Abrasive machining refers to using a tool formed of tiny abrasive particles to remove material from a workpiece. Abrasive machining is considered a mechanical process like milling or turning because each particle cuts into the workpiece removing a small chip of material. While typically used to improve the surface finish of a part, abrasive machining can still be used to shape a workpiece and form features. The most common abrasive machining process is grinding, in which the cutting tool is abrasive grains bonded into a wheel that rotates against the workpiece. Grinding may be performed on a surface grinding machine which feeds the workpiece into the cutting tool, or a cylindrical grinding machine which rotates the workpiece as the cutting tool feeds into it. Other abrasive machining processes use particles in other ways, such as attached to a soft material or suspended in a liquid. Such processes include honing, lapping, ultrasonic machining, and abrasive jet machining.

3. Mechanical treatment

Final polishing of part surfaces is carried out mechanically through the use of abrasive wheels and tapes with polishing pastes or through the use of round type vibratory machines.

Vibratory finishing is a type of mass finishing manufacturing process used to deburr, radius, descale, burnish, clean, and brighten a large number of relatively small workpiece. In this batch-type operation, specially shaped pellets of media and the workpiece are placed into the tub of a vibratory tumbler.

The tub of the vibratory tumbler and all of its contents are then vibrated. The vibratory action causes the media to rub against the workpiece which yield the desired result. Depending on the application this can be either a dry or wet process. Vibratory finishing systems tend to produce a smooth finish because the media essentially laps the parts. Since the load is moving as a unit, very fragile parts are quite safe in the vibrator. There is no tearing action or unequal forces that tend to bend and distort parts. Unlike rotary tumbling this process can finish internal features, such as holes. It is also quicker and quieter. The process is performed in an open tub, so the operator can easily observe if the required finish has been obtained. Tumble finishing, also known as tumbling or rumbling, is a technique for smoothing and polishing a rough surface on relatively small parts. In the field of metalworking, a similar process called barrelling, or barrel finishing, works upon the same principles.

4. Galvanizing

Electroplated items are made with a layer of gold or other precious metal on the surface over another type of metal underneath.

As first step of galvanizing, the surface preparation is needed. In fact, the surface of the metal to be plated must be very clean, so oils or dirt must be removed, and the piece must be polished. Surface preparation can include stripping, polishing, sandblasting, tumbling, etc. The use of solvents, abrasive materials, alkaline cleaners, acid etch, water, or a combination can be used. Typical methods to clean include acid or non-acid ultrasonic bath and a high rpm rouge wheel polishing. This is necessary for two reasons:

- To improve adherence (dust and dirt interfere with the plated metals adhering to the jewellery piece).
- To keep the plating tanks free of contaminants.

After the surface is prepared, and a visual inspection is done, electrocleaning, ultrasonic cleaning, or steaming, usually takes place. This second, deeper, cleaning step must follow to ensure metal is free of oils and dirt, which helps produce superior plating results. Steam cleaning blasts off any remaining oils that managed to hang on during the polishing phase. Take special note of intricate jewellery that has many nooks and crannies. The piece is then rinsed thoroughly with water to remove any cleaning agents.

A strike layer, or flash layer, adheres a thin layer of high-quality nickel plating to the base metal.

In order to improve the bonding between the plating and the underlying surface, occasionally a buffer layer must be applied between them. With costume jewellery the base metal would contaminate the tanks with the gold in them, so a different metal is plated prior to the gold plating.

Additionally, this step is used when the base metal, like copper, is known to atomically migrate outside of the gold layer to create spots of tarnish after plating. This strike step creates a barrier between the reactive base metal and the plated metal. This extends the life of the bright gold plating.

The piece is then rinsed again thoroughly with water to remove any cleaning agents.

If a base coat below precious metal is used, it is usually nickel. There can be many layers of plating done on one particular piece. For example, a gold-plated silver article is usually a silver substrate with layers of copper, nickel, and gold deposited on top of it.

With time, temperature and voltage carefully controlled, the piece is submerged into the plating solution to attract ions of gold or the final metal that will show on the surface. Different metals require different voltages and temperatures.

The items to be plated are hung from a cathode bar, which is a pole with a negative electrical charge going through it. The pieces of jewellery connected to the cathode bar are also negatively charged. When the jewellery items are submerged in the tank an electrical charge is applied and the negatively charged jewellery attracts the positively charged ions present in the solution. The positively charged metal ions are submersed in the solution bath. When the cathode bar is lowered into the bath the metal jewellery gets plated. After that step, rinsing and drying needs to be done.

5. Assembling and finishing

The galvanized items that compose one kit are assembled together according to the bill of material specification. In many cases, during this part of the process, that is manually done by expert operators, the quality control is performed. Once the lot of metal accessories is completed, the shipment is set up for delivering it to the brand owner.

One of the main criticalities of this sector is represented by the continuous occurrence of rush orders, that has to be priority processed compared to the previously scheduled ones. In addition, changes in the priority of the already scheduled products coming from the brand owners are often requested, in order to follow the demand variability and readapt production plans to the delays along the SC. Finally, two other stochastic events may occur producing changes in the production plan: the request from the brand owners of small lots of sample production, that reduce the suppliers declared production capacity and the delay in the arrival of the molded parts.

5.2.2 Optimization model in a metal accessories company

The structure of the production plan exported from the company ERP that represents the input of the optimization model is summarized in Table 8.

Table 8 - Production plan exported from the ERP

Code	Description
db_id	Order ID
db_key	Item code
db_order	Order code
db_order_line	Order line position
db_machine	CNC machine type (i.e. turn or mill)
db_qt_prod	Number of items to be produced
db_delivery_date	Item due date

The production order considered in the pilot includes 11 articles with different lot sizing, (i.e. from 35 up to 10,000 items for item code) and customer delivery dates between 15^{th} and 23^{th} of February 2017. Data related to the production plan exported from the ERP have been integrated with that ones that characterize the items' working cycle, collecting data from historical information. These parameters are the processing time per item on each companies' CNC machine, the LT per item for the subsequent production steps and the processing costs per item for each machine.

Processing times can vary for different item codes (i.e. longer processing time moving from simpler to more complex SKU) but even for the same one if made by different resource (i.e. working the same article through a newer machine require a shorter processing time than an old one). Processing times for the scheduled items are between 10 and 135 seconds, while costs are equally evaluated for the CNC machines.

Finally, processing time and cost per machine can be recorded as null, because not every machine can be used for producing a specific item code.

All the described parameters represent the input for the optimization model run using the OpenSolver tool on Microsoft Excel®, configured starting from the parameters, constraints and objective function previously defined (see paragraph 4.1.2 Proposed scheduling model for the fashion industry) and according to the procedure described for the proposed optimization model (see paragraph 4.1.3 Implementation of the proposed scheduling model in the fashion industry).

The objective function included in the proposed linear integer optimization model has been defined as OF: Min {cw * C + dw * D + aw * A}, combining costs, delays, and advances, whilst excluding the processing time, saturation balancing and mix balancing.

According to this, the combinations of weights chosen for each one of the three parameters (i.e. values for cw, dw and aw, respectively referred to costs, delays and advances) have been decided by the analysed company, guaranteeing coherence with its specific CSFs.

In particular, in the described pilot have been analysed the two scenarios (i) and (ii) that differ each other in terms of combinations of weights in the OF. More in detail:

(i) OF_1:

Min{cw * C + dw * D + aw * A}

where cw = 1, dw= 1, aw = 1;

(ii) OF_2:

Min{cw * C + dw * D + aw * A}

where cw = 1, dw= 1, aw = 0.

The reason these two scenarios have been chosen is related to the management request to develop a tool able to show which are the different impacts on the scheduling performance if advances are included (i.e OF_1) or not (i.e OF_2), enabling users to analyse the output evidences value of delays and advances in absolute terms or related to a specific working machines or subset of items.

The amount of delays and advances are calculated as sum of all the quantity per item respectively not produced or produced in advance if compared to the requested delivery date, considering both final and intermediate process steps. This comparison has been made per single day during the analysed time slot.

On the other hand, costs value has been calculated multiplying assigned quantity per item with the unitary working cost per machine mapped as input data on the Microsoft Excel® (i.e. exported from the company's ERP) and as agents' parameter on the simulator. According to the management request, in the model implementation costs are considered equal for every item processed by every machine. Moreover, no difference as been made according to the actually used work schedules (i.e. 24 hours per day, 7 days per week), that push the company to not considering overtime and related extra-costs.

The format of the optimal solution is listed in Table 9.

Table 9 - Scheduled optimization plan output

Code	**Description**
db_key	Item code
n-t1	Items assigned on the day n to the turn 1
n-t2	Items assigned on the day n to the turn 2
n-t3	Items assigned on the day n to the turn 3
n-m1	Items assigned on the day n to the mill 1
n-m2	Items assigned on the day n to the mill 2

In the pilot, the optimal scheduled production plan shows that, according to both the OFs and the optimization model constraints (i.e. CNC machines' capacity and demand fulfilment), some items will be produced in advance and some others with a delay respect to the delivery dates specified in the production plan. Considering the scheduling time window (i.e. from the first assignable day to the one last SKU is scheduled), the optimization model results cover 15 days in the first scenario and 24 days in the other.

As result of the optimization model implementation, the first scenario, that takes into account all the three parameters (costs, delays and advances), results in an OF_1 value equals 88,019, composed by (cw * C) = 14,482, (dw * D) = 72,056 and (aw * A) = 1,481. The second one, that differs from the previous scenario for not considering advances as one of the OF's parameters, results in an OF_2 value equals to 19,296, composed by (cw * C) = 14,482 and (dw * D) = 4,814; advances equals to (aw * A) = 110,805.

As expected, the value of delays is lower for OF_2 in comparison with OF_1. In fact, the constraints in terms of CNC machines' capacity and demand fulfilment force to not always respect the requested delivery date in both scenarios but, while in the first one delays and advances are equally weighted, in the other one just delays are taken into account, pushing the optimized scheduling of the items towards anticipate their production respect to the delivery date. In the same way, the advances related to the second scenario largely overcome the ones of the first one because their amount is not included into the OF.

The results came from the optimization model implementation have been validated and none issues regarding the computational time have been found. Regarding the usability of the tool, it has been validated by the production manager of the analysed metal accessories supplier.

5.2.3 Simulation model in a metal accessories company

Once the optimization model has been validated, also the proposed simulation model has been tested comparing the output with the one of the optimization model under a deterministic scenario, that means running both the model with the same parameters under static conditions.

On the other hand, the deterministic optimized scheduled plan has been compared with the one simulated taken into account stochastic elements for evaluating their impact on KPIs (deterministic vs. stochastic). The stochastic elements that have been considered are rush orders, created according to a uniform distribution that represents the unexpected orders received by the company in the last year.

Once the optimization plan has been recorded, the assigned items have been imported into the AnyLogic® simulator using a SQL script as input for the simulation. In fact, the agents (i.e. the list of items included in the company's production plan) are generated according to the parameters within the Microsoft Excel® file containing the optimization model results, as previously defined (see paragraph 4.2.3 Implementation of the proposed simulation model in the fashion industry).

Moreover, the output of the optimization model in terms of end processing date, processed quantity and assigned machine per single item has defined the rules for developing the simulation model (i.e. the way the agents are generated and the path that they have to follow along the process flow).

Deeply analysing the simulated model, it is composed by two resources type (i.e. turns and mills) with several machines for each one (in particular, three turns and two mills, like the company's layout already mapped on the optimization model on the Microsoft Excel®) working 24 hours per day. According to the model overview, each machine processes only the items that have been assigned to itself by the optimization model, considering as processing time the one that is reported on the Microsoft Excel® file and recording it as an agent's parameter. According to the production plan parameters, the total number of agents generated are 14,482.

As mentioned before, all the process activities that follow turning and milling ones are modelled as a unique processing block, called "Post-processing", that covers a specific processing time for each item, extracted from the Microsoft Excel® file as agent's parameter. In the same way, turning and milling processing times are the one defined in the Microsoft Excel® file.

The simulation model described until now represents the same deterministic scenario of that one modelled on Microsoft Excel® and has been successfully used to validate the optimization model in terms of resulting KPIs, such as delays and advances days for each item.

In the pilot, stochastic events have been included considering a deviation from the deterministic plan due to the presence of rush orders. These orders are generated with a uniform statistical distribution U(40,50) considering an arrival rate generated according to a normal distribution with average and variance equals to 1. The percentage of rush orders generated by the simulator during the run is almost the 10% of the total production quantity, according to the historical data collected in the analysed fashion company. The modeled rush orders have been generated as a set of items included into the original production plan, inheriting production cycle, processing and post-processing times. Moreover, rush orders have priority over the scheduled items, that move on the simulated production process following a FIFO queue.

Two simulation campaigns have been conducted: the first one generates the input items from the "Source" block of the AnyLogic® simulator according to the optimized plan that minimize the OF_1, while the second one follows the scheduled production referred to the OF_2. The simulation time slot covers four months, in order to complete the scheduled orders considering the presence of priority rush orders.

In order to compare the different simulation campaigns with the scheduled deterministic optimized production plan, the KPIs reported in Table 10 have been defined.

Table 10 - Simulation model's KPIs

KPI Type	**KPI**	**Formula**
Otm_W_Sum; Atg_W_Sum	gap delivery date1	deathdate - customerRequestedDate
Otm_W_Sum; Atg_W_Sum	gap delivery date2	customerAssignedDate - customerRequestedDate
Otm_W_Sum; Atg_W_Sum	gap delivery date3	deathdate - customerAssignedDate
Otm_S_Sum; Atg_S_Sum	gap processing delivery date1	stopDate - requestedDate
Otm_S_Sum; Atg_S_Sum	gap processing delivery date2	assignedDate - requestedDate
Otm_S_Sum; Atg_S_Sum	gap processing delivery date3	stopDate - assignedDate

Looking at the KPIs in Table 10, "gap delivery date 1", "gap delivery date 2" and "gap delivery date 3" refer to the KPI types "Otm_W_Sum" and "Atg_W_Sum" listed in Table 7 (see "KPI Type" column in Table 10), representing the number of on-time (i.e. "gap delivery date *n*" equals to 0) and not ot-time (i.e. "gap delivery date *n*" not equals to 0) items respectively, that have been calculated to compare requested, optimized and simulated production plans at the "Sink" block. On the other hand, "gap processing delivery date 1", "gap processing delivery date 2" and "gap processing delivery date 3" refer to the KPI types "Otm_S_Sum" and "Atg_S_Sum" listed in Table 7, differing from the previous ones in terms of reference system: "gap delivery date *n*" calculate values at the end of the whole process (i.e "Sink" block) while "gap processing delivery date *n*" at the exit of the finite-capacity resource (i.e "Processing" block).

More in detail, the "gap delivery date 1" shows the gap between the simulated end processing date for the final product and the one requested by the customer. In other words, it shows the lateness, as calculated by the simulation model. The "gap delivery date 2" is the lateness but referred to the optimization model's output (i.e. Microsoft Excel® file). Finally, the "gap delivery date 3" compares the simulator and the optimization models' outputs, again in terms of delays or advances per item related to the final product production. This KPI represents the deviation between the optimized lateness and the one evaluated by the simulation.

KPIs "gap processing delivery date 1", "gap processing delivery date 2" and "gap processing delivery date 3" are defined as the previous ones but refers to the semi-finished products (i.e. outputs of turning and milling machines) instead of final ones (i.e. outputs of "Sink" block).

As first result of the present work, the simulation model has been successfully validated comparing the resulting outputs to the ones calculated through the optimization model on the Microsoft Excel®. In particular, for each run of the simulation campaign the gap, in terms of days, between real and requested delivery date per each item calculated through the two models (i.e. the ones run on OpenSolver and AnyLogic®) has been compared, considering both final and intermediate steps. This comparison results in a punctual alignment between the two models' outputs and it has been evaluated considering both the OFs (i.e. OF_1 and OF_2).

The second result of this work is related to the comparison between the scheduling plan simulated considering unexpected orders to be priority processed and the optimal solution that considers just pre-scheduled orders as input.

This gap analysis has been conducted considering both the OFs, and the compared KPIs are shown for OF_1 and OF_2 respectively in Table 11 and Table 12.

KPIs related to the output of the models, in terms of number of worked items, refer both to the scheduled and rush orders in the analysis on the simulation model, while the others related to delays and advances are related just the scheduled orders. The reason why we have chosen to consider only these orders is that the aim is to assess the impact of rush orders on the previous scheduling, modeled on the Microsoft Excel®. Moreover, due to the fact that rush orders are priority by definition, they report null delays and advances.

The column "KPI Type" in Table 11 and Table 12 links the analysed KPIs (i.e. "KPI" column) to the KPI types listed in Table 7. More in detail, the KPI types analysed in the present pilot refer to the productivity per resource (i.e. "Prd_S_Sum") and the delays and advances calculated as total (i.e. "Del_W_Sum", "Del_S_Sum", "Adv_W_Sum" and "Adv_S_Sum"), average (i.e. "Del_W_Avg", "Del_S_Avg", "Adv_W_Avg" and "Adv_S_Avg"), minimum (i.e. "Del_W_Min", "Del_S_Min", "Adv_W_Min" and "Adv_S_Min") and maximum (i.e. "Del_W_Max", “Del_S_Max”, “Adv_W_Max” and “Adv_S_Max”) values, both at the end of the process (i.e. “Sink” block) and at the exit of the finite-capacity resource (i.e. “Processing” block).

Table 11 - Comparison between models’ KPIs (OF_1)

KPI Type	**KPI**	**Optimized plan**	**Stochastic simulation**	**Δ%**
Prd_S_Sum	Output quantity per turn 1 [(a)]	10,020	12,185	21.61
Prd_S_Sum	Output quantity per turn 2 [(a)]	44	485	1002.27
Prd_S_Sum	Output quantity per mill 1 [(a)]	1,060	2,639	148.96
Prd_S_Sum	Output quantity per mill 2 [(a)]	3,358	5,383	60.30
Del_S_Sum	Delays per turn 1 [(a)]	0	387,285	-
Del_W_Sum	Delays Post-processing [(a)]	72,056	491,236	581.74
Adv_S_Sum	Advances per turn 1 [(a)]	16,237	16,237	0
Adv_S_Sum	Advances per turn 2 [(a)]	88	88	0
Adv_S_Sum	Advances per mill 1 [(a)]	2,119	2,119	0
Adv_S_Sum	Advances per mill 2 [(a)]	6,715	6,715	0
Adv_W_Sum	Advances Post-processing [(a)]	1,481	37,099	2405
Del_S_Max	Max delay per turn 1 [(b)]	0	367	-
Del_S_Avg	Average delay per turn 1 [(b)]	0	178.88	-
Del_W_Max	Max delay Post-processing [(b)]	21	141	571.43
Del_W_Avg	Average delay Post-processing [(b)]	6.46	76.74	1087.93
Adv_S_Max	Max advance per turn 1 [(b)]	3	3	0
Adv_S_Avg	Average advance per turn 1 [(b)]	1.62	2	23.46
Adv_S_Max	Max advance per turn 2 [(b)]	2	2	0
Adv_S_Avg	Average advance per turn 2 [(b)]	2	2	0
Adv_S_Max	Max advance per mill 1 [(b)]	2	2	0
Adv_S_Avg	Average advance per mill 1 [(b)]	2	2	0
Adv_S_Max	Max advance per mill 2 [(b)]	2	2	0
Adv_S_Avg	Average advance per mill 2 [(b)]	2	2	0
Adv_W_Max	Max advance Post-processing [(b)]	7	7	0
Adv_W_Avg	Average advance Post-processing [(b)]	3.16	4.59	45.25

* Units of measurement: (a) number of items; (b) days.
** Output quantity per turn 3 [(a)], Delays per turn 2 [(a)], Delays per turn 3 [(a)], Delays per mill 1 [(a)], Delays per mill 2 [(a)], Advances per turn 3 [(a)], Average and Max delay per turn 2 [(b)], Average and Max delay per turn 3 [(b)], Average and Max delay per mill 1 [(b)], Average and Max delay per mill 2 [(b)], Average and Max advance per turn 3 [(b)] value zero both for optimized plan and stochastic simulation.

Table 12 - Comparison between models' KPIs (OF_2)

KPI Type	KPI	Optimized plan	Stochastic simulation	Δ%
Prd_S_Sum	Output quantity per turn 1 [(a)]	10,000	11,726	17.26
Prd_S_Sum	Output quantity per turn 2 [(a)]	44	444	909.09
Prd_S_Sum	Output quantity per turn 3 [(a)]	20	433	2065
Prd_S_Sum	Output quantity per mill 1 [(a)]	3,067	5,129	67.23
Prd_S_Sum	Output quantity per mill 2 [(a)]	1,351	3,042	125.17
Del_S_Sum	Delays per turn 2 [(a)]	132	132	0
Del_S_Sum	Delays per turn 3 [(a)]	340	340	0
Del_S_Sum	Delays per mill 1 [(a)]	3,77	3,77	0
Del_S_Sum	Delays per mill 2 [(a)]	572	572	0
Del_W_Sum	Delays Post-processing [(a)]	4,814	699,982	14,440.55
Adv_S_Sum	Advances per turn 1 [(a)]	81,100	81,100	0
Adv_S_Sum	Advances per mill 1 [(a)]	19,330	19,330	0
Adv_S_Sum	Advances per mill 2 [(a)]	10,375	10,375	0
Adv_W_Sum	Advances Post-processing [(a)]	110,805	81,875	-26.11
Del_S_Max	Max delay per turn 2 [(b)]	3	3	0
Del_S_Avg	Average delay per turn 2 [(b)]	3	3	0
Del_S_Max	Max delay per turn 3 [(b)]	17	17	0
Del_S_Avg	Average delay per turn 3 [(b)]	17	17	0
Del_S_Max	Max delay per mill 1 [(b)]	9	9	0
Del_S_Avg	Average delay per mill 1 [(b)]	8.38	8.38	0
Del_S_Max	Max delay per mill 2 [(b)]	13	13	0
Del_S_Avg	Average delay per mill 2 [(b)]	13	13	0
Del_W_Max	Max delay Post-processing [(b)]	17	125	635.29
Del_W_Avg	Average delay Post-processing [(b)]	8.63	109	1,163.04
Adv_S_Max	Max advance per turn 1 [(b)]	10	10	0
Adv_S_Avg	Average advance per turn 1 [(b)]	8.11	8.11	0
Adv_S_Max	Max advance per mill 1 [(b)]	9	9	0
Adv_S_Avg	Average advance per mill 1 [(b)]	7.39	7.39	0
Adv_S_Max	Max advance per mill 2 [(b)]	9	9	0
Adv_S_Avg	Average advance per mill 2 [(b)]	7.94	7.94	0
Adv_W_Max	Max advance Post-processing [(b)]	10	13	30
Adv_W_Avg	Average advance Post-processing [(b)]	7.96	10.18	27.89

* Units of measurement: (a) number of items; (b) days.
** Delays per turn 1 [(a)], Advances per turn 2 [(a)], Advances per turn 3 [(a)], Average and Max delay per turn 1 [(b)], Average and Max delay per turn 2 [(b)], Average and Max delay per turn 3 [(b)] value zero both for optimized plan and stochastic simulation.

As shown in Table 11, the number of processed items grown from 14,482 to 20,692 if rush orders are considered (+42.88%). Delays for items worked by the turn 1, that are null for the scheduled plan, grown up to 387, and the same KPI related to the Post-processing increases in a more than proportional way in comparison to the total number of items (rush orders included). This is due to the fact that, in the simulation run, most of the rush orders have been processed by the first machine.

At the same time, as shown in Table 12, the number of items to be processed, considering rush orders, increased by 43.45% (i.e. from 14,482 to 20,774). Referring to the OF_2, a relevant gap in terms of delays on the delivery date considering rush orders can be registered for the post-processing phase, aligned to the fact that the production flow of all the processed items converges on the same working station, being more stressed by the extra-work. On the other hand, KPIs related to the single CNCs do not worsen their value. This is justified but the fact that OF_2 does not consider the advance as a damage. Consequently, the optimized plan is anticipated in comparison to the customer requested date, and a production of unexpected items can be done without having to change the planned scheduling. From an industrial point of view, it is important to remark that OF_2 could not be feasible at all as production scheduling strategy. In fact, fashion orders, in terms of quantity and delivery date, are usually confirmed quite close to last date available for processing them on-time, making advances in production risky.

It is important to highlight that the negative effect of rush orders is amplified in most industries, included the fashion one, because of the fact that orders can be delivered to the client (i.e. the brand owner) only when the lot is completed. Analysing the OF_2, it is possible to see that the effect that rush orders have in terms of delay quite overcomes the increasing value of products in input in the simulated model (see Table 12), and even worse is the scenario considering the OF_1, when the delay value arrives up to 141 days (see Table 11). In fact, for an incremented quantity of items to be produced around the 45%, the maximum value of delay registered in the post-processing is up to 635.29% (i.e. 125 days) for OF_2 and up to 571.43% for OF_1.

These results have been shared with the management of the company where the pilot has been conducted, in order to validate two aspects. The first one is related to the validation of the results according to their experience, considering both the outputs of the optimization model and the impacts of stochasticity on the PP&C performances. The second one is linked to the usability of the KPIs dashboard derived to the simulation pilot.

Both of them have been done with positive results.

5.3 Leather goods

The second pilot has been conducted in the leather goods market segment.

In detail, the model has been applied into a real pilot considering two brand owners (B_1 and B_2) and a subset of their supply base, composed by three suppliers (S_1, S_2 and S_3), two of them having an exclusive labour-relationship respectively with B_1 and B_2, while the third one works for both the brand owners. In particular, the schema is the one showed in Figure 56 as a particular case of the proposed framework of Figure 47 when it is described (see paragraph 4.3.1.1 Simulation-optimization model description), having the brand owner B_1 working with suppliers S_1 and S_2 and the brand owner B_2 with suppliers S_2 and S_3.

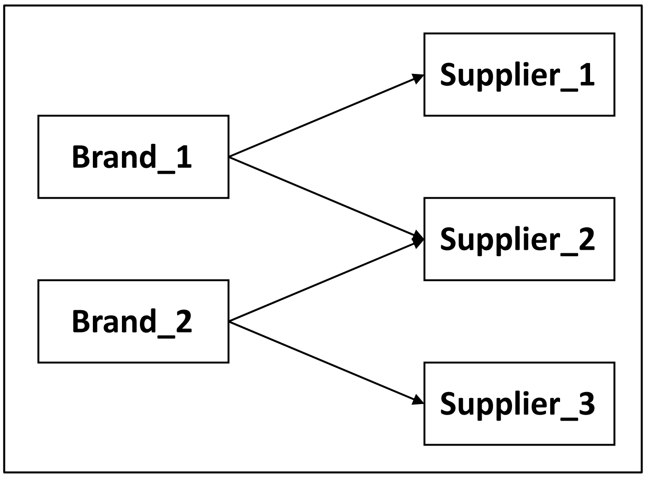

Figure 56 - SC network in the leather goods pilot

The implementation of the optimization model has been done both on brand owners and the common supplier, while the simulation has been run only considering the output coming from the implementation on supplier production plan.

According to this, one of the main purposes of this pilot has been testing the adaptability of the proposed models to different companies working in the leather goods SC (i.e. brand owner and supplier) through changing inputs configuration.

Looking at the proposed optimization model, its implementation for the supplier has been quite similar to the one on the metal accessories market segment, but further constraints have to be added. In particular, the availability of raw materials, first of all leather, is an important variable to be consider in managing production plans, and the related constraint has been configured as model input.

Moreover, scenario analyses have been made for a multiple scope. On the one hand, to understand how output in terms of assigned quantities and delivery dates can vary moving from a brand owner to a supplier perspective. On the other hand, through simulation is possible to study the impact of stochastic events on the optimized plan, including them in the analysis. In detail, two gap analyses have been conducted: the first one compares the deterministic scenario from the brand owners' and the supplier's perspectives to the one that includes only rush orders; the second gap analysis takes into account different types of stochastic events.

While the first gap analysis is quite similar to the one done for the metal accessories supplier, the second one better fits with the challenges of the leather goods producers. In fact, as previously detailed, the availability of raw materials is one of the main constraints that has to be taken into account in the production of leather goods. This is the reason why, moving from the pilot for the metal accessories supplier to the leather goods one, it is needed to include another stochastic event during the simulation runs, that is 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.

In order to summing up, the framework in Figure 53 has been filled, highlighting the configuration of the input and output parameters that have been used for the conduction of the scenario analyses in the leather goods pilot, as exemplified in Figure 57.

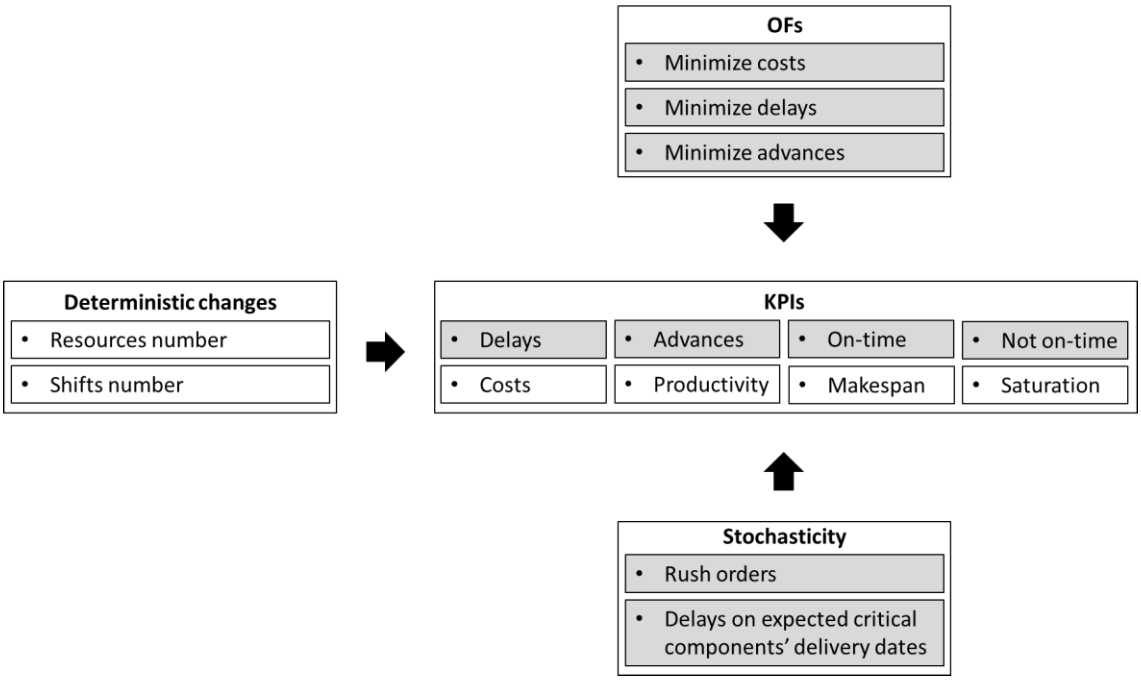

Figure 57 – Leather goods pilots' implementation framework

5.3.1 Leather goods sector introduction

The second pilot refers to a leather goods producer working in the fashion SC.

The manufacturing process for leather goods can be summarized in 4 steps (see Figure 58):

1. Cutting
2. Preparing components
3. Assembling
4. Finishing

These steps are usually made partially inside the company and partially outsourced. In details, the cutting phase, especially for the fine leather, is centralized, in order both to optimize the production process than to better control the traceability of the raw material.

Once the leather is cut, it is distributed to external suppliers for the phases of Preparing components, Assembling and Finishing.

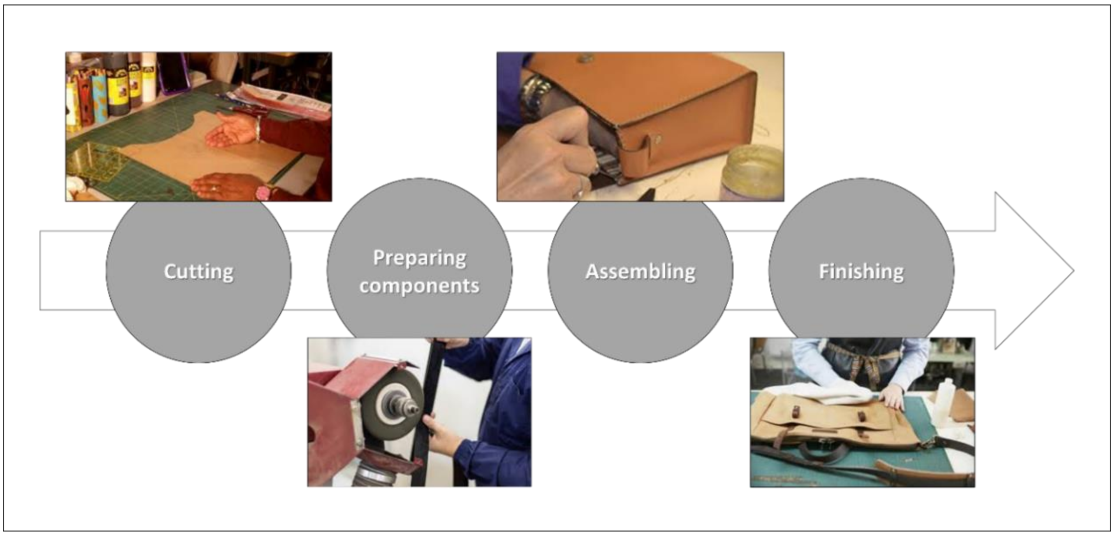

Figure 58 - Production process in the leather goods industry

More in detail, the 4 steps showed in Figure 58 can be described as follows:

1. Cutting

Using metal strip knives or automatic machines, the worker cuts out pieces of various shapes that will take the form of lining fabrics and leather parts of final product. This operation requires a high level of skill in order to reduce as more as possible waste. Considering leather, it may also have various defects on the surface such as barbed wire scratches which needs to be avoided, so that they are not used for the leather parts.

2. Preparing components

During the preparing components step, semi-finished products are realized, starting from the cut materials at the first step. Here, for example, dyeing and drying processes are included, but also component pieces are sewn together by highly skilled machinists so as to produce the completed components, such as back and front parts, bottoms, gussets or lining fabrics.

3. Assembling

The assembly phase includes both the stitching and the properly assembly steps.

Once the pieces are sewn together, all them are assembled together, in order to realize the final product.

This is the more complex step of the production process, and its complexity can be higher or lower according to the specificity of the final product, such as the material (in terms, for example, of its softness, that is directly proportional to how it is easy to be worked) or the number of hierarchical levels of the bill of materials (the more are the numbers of inside and outside pockets or zip fasteners, the more are the time and skills needed).

4. Finishing

The final purpose of this step is realizing the products that can be sold to the consumer. According to this, all the quality checking on the final products are made, and the compliant ones are inserted in the required packaging to be delivered.

Criticalities in this production process are represented by the assembling phase, where the process can start only when all the raw material are arrived and once they have successfully passed the quality control. Delays in the arrival of critical components, that can be both the leather, or the metal accessories, or even a button if it is needed in order to finalize the product, can cause significant variation in the production plan, moving the beginning of the assembly phase to one day to another.

Moreover, replenishment orders are another significant stochastically event that usually occurs in this field, that has to be taken into account in the re-scheduling of the production plan.

5.3.2 Optimization model in a leather goods company

The optimization model has been re-adapted starting from the one described for the implementation on the metal accessories supplier, moving from the supplier perspective to the brand owner's one. More in detail, instead of focusing on the optimal assignment of each SKU to one of the 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 produce it.

According to this, the main difference between the present pilot and the one showed before is the resource type, with machines in one case and suppliers in the present one.

Another difference is the way the production capacity has been included in the model. On the one hand, brand owners consider as the available production capacity the number of SKUs each supplier declares he is able to guarantee per period, instead of minutes per item as previously (see paragraph 5.2.2 Optimization model in a metal accessories company).

On the other hand, considering the two brand owners included in the present pilot, the available capacity is communicated in terms of number of "equivalent bags" per week and not referred to the specific SKU. This value has to be defined in order to avoid that suppliers declare a general and, consequently, not reliable number of SKUs that he can produce per day, having no correlation to the complexity related to the production of the item itself. In fact, considering a supplier that declare he is able to averagely produce 100 bags, this value has to be different if bags to be produced are all easy-to-produce or not: in the first case, the supplier under-estimated his available capacity per day while, in the opposite case, he over-estimated that value.

According to this, in the present pilot 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".

In particular, the demand plan as input for running the optimization model at the brand owners' level has been the one showed in Table 13.

Table 13 - Demand plan for brand owners in the leather goods pilot

Item code	Item complexity	Required Qty _ B1	Required Qty _ B2
Alpha_1	Medium	521	0
Alpha_2	Medium	44	0
Alpha_3	Medium	0	20
Beta_1	Medium	44	0
Beta_2	Medium	435	0
Gamma_1	Easy	1233	0
Gamma_2	Easy	280	0
Gamma_3	Easy	868	630
Gamma_4	Easy	0	170
Delta_1	Difficult	96	23
Delta_3	Difficult	0	27

Looking at the Table 13, the item code listed on the first column refers to the SKU to be produced by only one or both the brand owners B_1 and B_2, with the first part of the code referred to the model and the number to the colour to be produced.

On the other hand, the second column in Table 13 (i.e. “item complexity”) refers to the product categories previously described.

Finally, the columns “Required Qty _ B1” and “Required Qty _ B2” refers to the quantity per SKU to be produced by each one of the involved brand owners respectively, equals to 3521 for B_1 and 870 for B_2 considering their entire demand plan with customer delivery dates between 17th of May and 7th of June 2017.

Using these data as input, the proposed optimization model has been configured starting from the parameters, constraints and objective function previously defined (see paragraph 4.1.2 Proposed scheduling model for the fashion industry) and according to the procedure described for the proposed optimization model (see paragraph 4.1.3 Implementation of the proposed scheduling model in the fashion industry).

More in detail, the OF considered for the pilot is the following:

OF: Min{cw *C + dw * D + aw * A + ptw * PT + rpbw * RPB + rbw * RB + mbw * MB},

where cw = 1, dw= 1, aw = 1, ptw = 0, rpbw = 0, rbw = 0 and mbw = 0.

The weight used in the OF have been chosen according to the management of the company where the pilot has been carried out. In details, advantages and delays have been considered with an equal score. Advances, delays and costs have been considered with an equal importance, whilst processing time, saturation balancing and mix balancing have son been taken into account.

For both the brand owners’ and the supplier’s implementations, another difference between the metal accessories’ market segment and this one is that, for the leather goods, one of the main challenge is to preventively manage the critical components availability, mainly referable to the leather, in order to allocate the production only when they are stocked in the company raw materials and components warehouse. According to this, the constraint related to the availability of critical components (see paragraph 4.1.2.3 Constraints) has been included in the present pilot.

The results of running the proposed optimization model at the brand owners’ level are showed in Table 14.

Table 14 - Assigned quantity per SKU for brand owners in the leather goods pilot

	S_1		S_2		S_3	
Item code	**Assigned Qty _ B1**	**Assigned Qty _ B2**	**Assigned Qty _ B1**	**Assigned Qty _ B2**	**Assigned Qty _ B1**	**Assigned Qty _ B2**
Alpha_1	0	0	521	0	0	0
Alpha_2	44	0	0	0	0	0
Alpha_3	0	0	0	20	0	0
Beta_1	0	0	44	0	0	0
Beta_2	435	0	0	0	0	0
Gamma_1	1233	0	0	0	0	0
Gamma_2	280	0	0	0	0	0
Gamma_3	0	0	868	400	0	230
Gamma_4	0	0	0	0	0	170
Delta_1	58	0	38	23	0	0
Delta_3	0	0	0	0	0	27
% Demand Plan	**58%**	**0%**	**42%**	**51%**	**0%**	**49%**

According to the enabled suppliers, S_1 and S_3 has to produce only for brand owners B_1 and B_2 respectively, while S_2 for both of them. Moreover, aligned to the setting of the optimization model, the quantities included in the demand plan for each one of the brand owners has been almost equally splitted on the enabled suppliers. In particular, considering B_1, a 58% of production has been allocated to S_1 and the other 42% to S_2; on the other hand, the 51% of the production for B_2 has been realized by S_2 and the other 49% to S_3.

Once the optimization model outputs come out from each one of the two analysed brand owners 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 overall production plan to be considered as input for modeling S_2 is composed by 1,914 items, assigned to both the brand owners B_1 and B_2 over a period of one month (see Table 14).

Moving from the brand owner to the supplier perspective, the optimization model is quite similar to the one described for the implementation on the metal accessories supplier, but the resources differ again: instead of the CNC machines that characterized the metal accessories suppliers, in the present pilot the model has been applied considering the assembling phase as the critical one, with 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). According to this, the production phase scheduled with a finite capacity is the assembly one.

As previously anticipated, the items have been divided into three different groups, due to their complexity for being processed. The “easy bags” require a production time of 45 minutes, while the “medium bags” 90 minutes and the “difficult bags” 120 minutes.

The OF can be personalized varying the weights cw, dw, aw, ptw moving from one to another SC actor, in order to fit their different peculiarities. Usually suppliers are more interested in maximizing the workstation saturation, in comparison with the minimization of the delay, whilst the brands are more interested in reducing the delay. In this pilot the aim is to assess if some misalignments can be shown even in case of equal-weighted OFs. According to this, the OF for supplier S_2 has been set as the same one of B_1 and B_2.

The expected misalignment results from the configuration of the optimized production plans of B_1 and B_2 considering the fact that S_1 declares the same capacity and production cost to each one of the brand owners. Consequently, the overall available capacity of the common supplier (i.e. considering both the brand owners) doubles the real one.

This possibility usually occurs in the fashion industry with not-exclusive suppliers, that do not share the actual capacity with their clients (e.g. the brand owners).

To conclude, the results of the proposed optimization model implementation and its usability for both brand owners and suppliers working in the leather goods market segment have been validated by the production manager of the analysed company.

5.3.3 Simulation model in a leather goods company

The results of running of the optimization model on S_2 are the object of the application of the simulation model to the supplier itself, according to the parameters previously described (see paragraph 4.2.2 Proposed simulation model for the fashion industry).

Several runs of the proposed simulation model have been done in order to conduct different scenario analysis, even if the parameters to model the deterministic scenario as starting point have been the same one for all the runs.

In particular, 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). In line with the pilot on the metal accessories supplier (see paragraph 5.2.3 Simulation model in a metal accessories company), while the described workstations have been modelled considering a processing time per item, all the downstream activities that follow it have been grouped in a unique Post-processing block that works at an infinite capacity, expressed by a post-processing LT.

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

The first scenario replicates the same deterministic one modeled within the optimization tool in order to evaluate the effect of the over-estimation of the available capacity that usually refers to not-exclusive suppliers that promise to each one of their customers (i.e. brand owners) an available capacity higher than the real one. In fact, this is a quite common evidence that affects the fashion SC, where not-exclusive suppliers, that represent most of the supply base of each brand owner, aim to collect the higher number of orders to maximise the saturation of their production lines.

Rush orders are then considered in the second and third scenarios with a different occurrence, in order to evaluate how relevant is the impact of stochastic events compared to the one of suppliers' over-saturation. In particular, the value of rush orders compared to the regular production orders has been chosen as equal to the +10% in the second scenario and doubled in the third one (i.e. 20%).

According to the KPIs dashboard defined considering the implementation of the proposed framework (see paragraph 4.3.2 Implementation of the proposed iterative simulation-optimization model in the fashion industry), these analyses compare the delivery date requested by the market planning with, on the one hand, 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's level (i.e. "ProcessingDate_gap_A" in Figure 52) and, on the other hand, with the simulation model applied at the supplier's level (i.e. "ProcessingDate_gap_B" in Figure 52).

Considering the schema in Figure 52, the delivery date requested by the market planning is called "demandPlan_Date", the delivery date at the brand owner's level is the "requestedDate" and, finally, the one at the supplier's level is the "stopDate". According to this:

- ProcessingDate_gap_A= demandPlan_Date - requestedDate;
- ProcessingDate_gap_B= demandPlan_Date - stopDate.

This comparison firstly aims to highlight if there are differences between the optimized plan generated respectively at the brand owners' and the supplier's level, both in case of including or not the occurrence of rush orders.

Moreover, through simulation it is possible to evaluate how these values change moving from a scenario to another one, giving a concrete support for the decision-making process.

The result of the comparison between the ends of processing dates is shown in Table 15.

Table 15 - Summary of the gap analysis results in the leather goods pilot

		gap_A	gap_B			Δ%		
KPI Type	**KPI**	**End Processing Date**	**End Processing Date_1**	**End Processing Date_2**	**End Processing Date_3**	**Δ%_1**	**Δ%_2**	**Δ%_3**
Otm_W_Sum	Null absolute deviation (a)	198 (10.34% X)	96 (5.02% X)	93 (4.86% X)	93 (4.86% X)	-52	-53	-53
Atg_W_Sum	Absolute deviation (b)	7,510	14,212	15,168	15,599	+89	+102	+108
Del_W_Max	Maximum delays (c)	14 (1.99% X)	22 (0.16% X)	27 (0.21% X)	32 (0.21% X)	+57	+93	+129
Adv_W_Max	Maximum advances (d)	6 (1.20% X)	3 (4.86% X)	3 (4.86% X)	3 (4.86% X)	-50	-50	-50
Del_W_Avg	Average delays (c)	3.35 (36.99% Y)	7.13 (44.83% Y)	7.63 (45.61% Y)	7.85 (46.55% Y)	+113	+128	+134
Adv_W_Avg	Average advances (d)	0.57 (28.37% Y)	0.3 (14.89% Y)	0.3 (14.89% Y)	0.3 (14.89% Y)	-48	-48	-48

* Units of measurement: (a) number of items assigned on-time; (b) days per delayed and advanced items; (c) days per delayed items; (d) days per advanced items; (e)
** "_1": no rush orders; "_2": rush orders = 10%; "_3": rush orders = 20%.
*** "X": number of total items; "Y": number of items above average.

The column "KPI Type" in Table 15 links the analysed KPIs (i.e. "KPI" column) to the KPI types listed in Table 7. In particular, the KPI types analysed in the leather goods pilot refer all to the time dimension and have been calculated at the end of the process (i.e. "Sink" block). First of all, the on-time items (i.e. "Otm_W_Sum") and the not on-time days (i.e. "Atg_W_Sum") to obtain an overview of the service level to the customers. On the other hand, the days per delayed and advanced items have been calculated as average (i.e. "Del_W_Avg" and "Adv_W_Avg") and maximum (i.e. "Del_W_Max" and "Adv_W_Max") values.

More in detail, the column "Δ%" represents the comparison between gap_A and gap_B, resulting in the evidence that 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%).

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 number 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.

A second gap analysis has been conducted in order to include delays in critical components' delivery date as stochastic event, generated with a normal statistical distribution. In fact, leather goods companies have usually to face with that kind of delays, that have to be considered in terms of their influences on the performances related to the production plan, especially looking at the delays on the due dates.

Moreover, this kind of stochastic event can occur by itself or combined to other types, such as the rush orders previously included in the first gap analysis.

According to this, another run of simulation has been set and a gap analysis has been conducted for comparing the 8 scenarios described in Table 16.

Table 16 - Scenario analysis in the leather goods industry

		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; ** Earliest Due Date; *** Rush Orders; **** Delays in Critical Components

The scenario “0” refers to the application of the optimization model 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 has 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 and, respectively, no stochastic events, only rush orders, only delays in critical components’ delivery and both of them. The EDD is a priority rule that sequences the jobs in a queue according to their (operation or job) due dates: according to this, jobs with the earliest due date first have to be processed first.

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 17, Table 18 and Table 19 sum up the KPIs dashboard for a significant subset of the analysed scenarios and associate, through the column “KPI Type”, the analysed KPIs (i.e. “KPI” column) to the KPI types listed in Table 7.

The first set of results have been evaluated using a production plan taken from the historical data of the suppliers, where the three assembly workstations were saturated respectively for the 100%, 100% and 97%. The production plan is the same one considered for the first gap analysis and include 1,914 items and the scenario previously described represents the starting point for modeling the analysed one.

As stochastic values, rush orders have 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 analysing 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 17 - KPIs dashboard for scenarios 1 and 5

KPI type	**KPI**	**MOF/RO**	**EDD/RO**
Adv_W_Max	Max advance [(a)]	0	-26
Adv_W_Avg	Average advance [(a)]	0	-1.87
Del_W_Max	Max delay [(b)]	28	8
Del_W_Avg	Average delay [(b)]	3.45	1.76
Atg_W_Sum	Sum of average advances and delay [(c)]	3.45	-0.11
Atg_W_Sum	Absolute sum of average advances and delay [(c)]	3.45	3.63

*Units of measurement: (a) days per advanced items; (b) days per delayed items; (c) days per items.

Table 18 - KPIs dashboard for scenarios 2 and 6

KPI type	**KPI**	**MOF/DCC**	**EDD/DCC**
Adv_W_Max	Max advance [(a)]	0	-26
Adv_W_Avg	Average advance [(a)]	0	-1.29
Del_W_Max	Max delay [(b)]	8	12
Del_W_Avg	Average delay [(b)]	2.89	2.67
Atg_W_Sum	Sum of average advances and delay [(c)]	2.89	2.51
Atg_W_Sum	Absolute sum of average advances and delay [(c)]	2.89	5.09

*Units of measurement: (a) days per advanced items; (b) days per delayed items; (c) days per items.

Table 19 - KPIs dashboard for scenarios 3 and 7

KPI type	**KPI**	**MOF/RO/DCC**	**EDD/RO/DCC**
Adv_W_Max	Max advance [(a)]	0	-25
Adv_W_Avg	Average advance [(a)]	0	-4.47
Del_W_Max	Max delay [(b)]	30	13
Del_W_Avg	Average delay [(b)]	8.51	4.41
Atg_W_Sum	Sum of average advances and delay [(c)]	8.51	0.06
Atg_W_Sum	Absolute sum of average advances and delay [(c)]	8.51	8.88

*Units of measurement: (a) days per advanced items; (b) days per delayed items; (c) days per items.

Analysing the results, it is possible to observe that, considering 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 scenario, this effect is more relevant with the introduction of the rush orders than with the delay of the critical component. Whilst in scenarios “1” and “5” the absolute sums of average 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, analysing scenarios “2” and “6”, is it possible to observe that the average delays are almost equivalent, while the absolute sum of average advances and delays in scenario “2” are the 56% of the scenario “6”.

The comparison between scenarios “3” and “7” shows the effects of both rush orders and critical components’ delay. With the data used in the simulation campaign, the results show 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 almost equivalent to the one in the scenario “7”.

From an industrial point of view, these results demonstrate that, considering the data used in the simulation scenario, the KPIs obtained with the MOF production scheduling applied 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 stochastic 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 and the number of items per order), collecting the results with both MOF than EDD scheduling rules.

Table 20 and Table 21 show the results of these simulation runs, listing per each scenario the occurrence of rush orders (i.e. column “% RO”), their frequency per week (i.e. column “RO FR”), their average value (i.e. column “RO AVG”), the maximum delay in terms of days (i.e. column “MAX DELAY”) and the average value (i.e. column “ABS AVG DELAY”).

Table 20 - KPIs dashboard with MOF, RO and DCC

MOF	%RO	RO FR (A)	RO AVG (B)	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

*** UNITS OF MEASUREMENT: (A) RUSH ORDERS PER WEEK; (B) NUMBER OF ITEMS PER RUSH ORDER.**

Table 21 - KPIs dashboard with EDD, RO and DCC

EDD	%RO	RO FR (A)	RO AVG (B)	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

*** UNITS OF MEASUREMENT: (A) RUSH ORDERS PER WEEK; (B) NUMBER OF ITEMS PER RUSH ORDER.**

The number of items per rush order have been decreased in scenarios “1”, “3” and “5”, while the rush order frequency has been increased in scenarios “2” and “4”.

In the same way of the previous pilot, the results have been shared with the management of the company where the pilot has been conducted, in order to validate them, both in relation to the stochastic results and to the usability of the KPIs dashboard used during the implementation of the proposed simulation model. Also in this case, both of them have been done with positive results.

5.4 Footwear

The third pilot has been conducted on a footwear company.

This sector, in comparison with the previous ones, has significant differences because of the more complexity of the product and of the SC.

Moreover, considering the production process described in Figure 61, the related phases are commonly outsourced, especially cutting and stitching but, sometimes, also the final assembly. In fact, subcontracting in footwear is a common practice, due to the high specialization required for the production of each component of shoes. This is one of the reasons why the footwear SC is really fragmented, with a lot of SMEs working along it, each one of them highly specialized on one of the steps described above.

These evidences can be translated in a high complexity to be managed in terms of information and production flows exchanged between different companies.

In this way, as highlighted in the work of Bord and Dulio (2007), investments on ICT solutions in terms of software integration between different SC partners but also higher performance of the ones used at the single-company level represent a key to gain competitive advantages within the industry, with the main purpose of being able to monitor real-time each production process step in order to guarantee the flexibility needed to quickly respond to the unpredictable changes in demand.

In addition to technological improvement, in fact, changes oriented to collaboration between SC actors have to be included, in order to reach a trade-off between guaranteeing flexibility and quickness without a negative effect on final products' quality.

Due to the fact that most of the companies along the footwear SC, and in the fashion SC in general, are SMEs, using an open-source software, as the optimization one integrated into the proposed framework, positively impacts their effectiveness and efficiency in working on the market, as demonstrated by Chituc et al. (2008) in their work.

Footwear manufacturing encompasses major processes such as cutting, stitching and assembly. The pilot regards the assembly line process. Because of the fixed cycle time, 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.

According to this, as in the leather goods pilot, it is needed to take into account another stochastic events during the simulation runs, that is 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, if compare with other pilots, modeling companies working in the footwear SC requires to include balancing and sequencing problems in the optimization and simulation models respectively.

This way, the MSP approach, taking into account that some items need major labour time in comparison with other ones, determines the right alternation of different type of products on the line, in order to guarantee the minimization of free time in every station of the assembly line. Then, the distributed simulation is used as empirical technique to validate the result.

In order to summing up, the framework in Figure 53 has been filled, highlighting the configuration of the input and output parameters that have been used for the conduction of the scenario analyses in the footwear pilot, as exemplified in Figure 59.

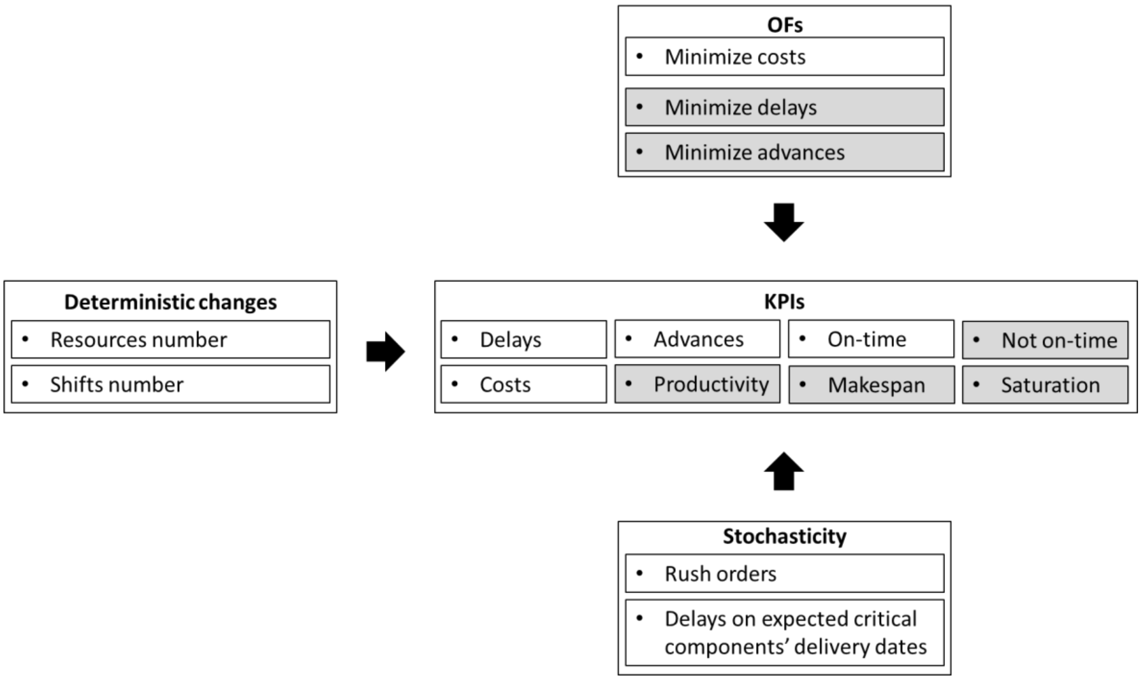

Figure 59 – Footwear pilots' implementation framework

5.4.1 Footwear sector introduction

One of the main criticalities in this market segment is represented to the high number of components needed to realize a pair of shoes.

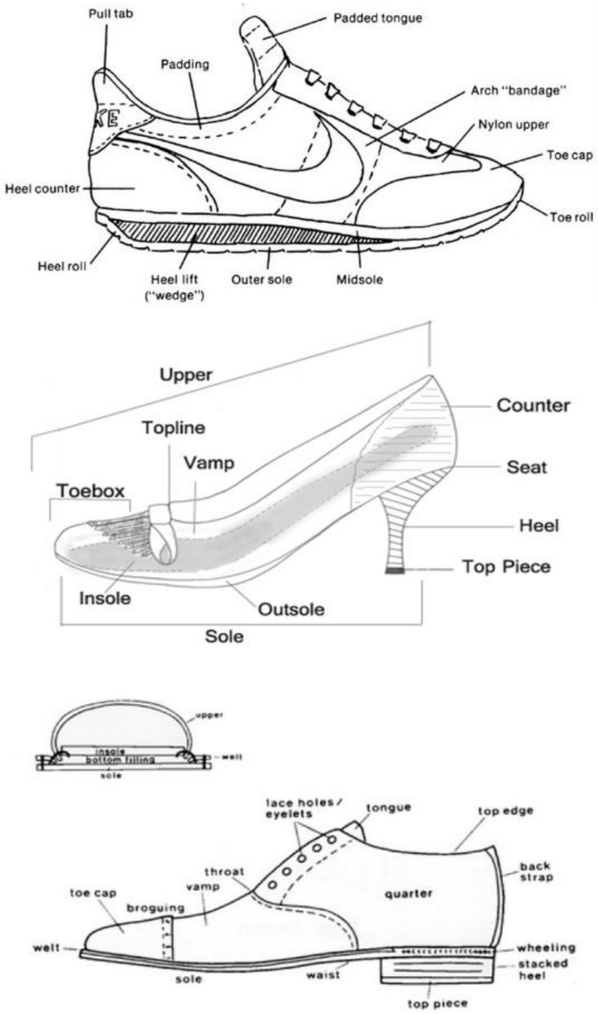

Figure 60 - Shoe_anatomy

Considering examples in Figure 60, the main components can be summarized as follows[8]:

- Breast: The forward facing part of the heel, under the arch of the sole.
- Counter: A stiff piece of material at the heel of a shoe positioned between the lining and upper that helps maintain the shape of the shoe. The counter helps strengthen the rear of the sole.
- Feather: The part of the shoe where the upper's edge meets the sole.

[8] Anatomy of Shoe, www.shoeguide.org

- Heel: The heel is the part of the sole that raises the rear of the shoe in relation to the front. The heal seat is the top of the heal that touches the upper, this is typically shaped to match the form of the upper. The part of the heel that comes in contact with the ground is known as the top piece.
- Linings: Most shoes include a lining on the inside of the shoe, around the vamp and quarter. These linings improve comfort and can help increase the lifespan of the shoe.
- Puff: a reinforcing inside the upper which gives the toe its shape and support. Similar in function to a toe cap.
- Quarter: The rear and sides of the upper that covers the heel that are behind the vamp. The heel section of the quarter is often strengthened with a stiffener, which helps support the rear of the foot. Some shoe designs use a continuous piece of leather for the vamp and quarter.
- Seat: Where the heel of the fit sits in the shoe. It normally matches the shape of the heal for comfort and support.
- Shank: A piece of metal inserted between the sole and the insole lying against the arch of the foot.
- Sole: The entire part of the shoe that sits below the wearers foot. As opposed to the upper. The upper and sole make up the whole of the shoe.
    - It is usually constructed of several layers:

        - *Insole*: The insole is the part of the sole that sits directly beneath the wearers foot. Its purpose is to provide a comfortable layer above the joining of the upper to the sole.
        - *Mid-sole*: A mid-sole can be found on some shoes and is a layer between the in-sole and the out-sole.
        - *Outsole*: The outsole is the layer of sole that is exposed to the ground. Due to the amount of wear and stress this part of the shoe receives it is usually made of a very durable material. It is also important that it provides enough friction with the floor to prevent the wearer from slipping.
- Throat: The front of the vamp next to the toe cap. For shoes were the vamp and quarter panels are one piece the throat is at the eye-stay.
- Toe cap: Shoes may have a toe cap in the front upper of the shoe. Toe caps can take various forms, but the distinct types are: complete replacements for the front upper of the shoe; stitched over toecaps that add an extra layer to the upper; solid toe caps for protection, such as steel toe caps. Stitch over toe caps may be decorative in nature. Toe caps help add strength to the upper front of the shoe, an area that receives a lot of stress and wear from use.
- Top Piece: The part of the heel that comes in contact with the ground. Made of a durable material that helps maintain friction with the ground.
- Topline: The top edge of the upper
- Upper: The entire part of the shoe that covers the foot.
- Vamp: The section of upper that covers the front of the foot as far as the back as the join ot the quarter.
- Waist: The arch and in-step of the foot.
- Welt: A strip of material that joins the upper to the sole.

In line with the high number of components, also the required raw materials are numerous, such as:

- Adhesives and bonding
- Shoe and leather colouring
- Footwear additions
- Randing and welting
- Soling materials
- Soles and heals
- Cork
- Leather board
- Screws, rivets and stems
- Cords and threads
- Shanks
- Finishing ink and waxes
- Traditional bristles

In the footwear SC, the complex supply base that provide raw materials and/or shoe components to producers and/or sub-contracted companies includes:

- Last makers
- Tawery/Tannery (leather)
- Synthetic material suppliers
- Components suppliers (e.g. soles, heels, insoles)

Looking at the production process, the labour-intensive production steps followed to realise shoes can be summed up as suggested by Carpanzano and Ballarino (2008).

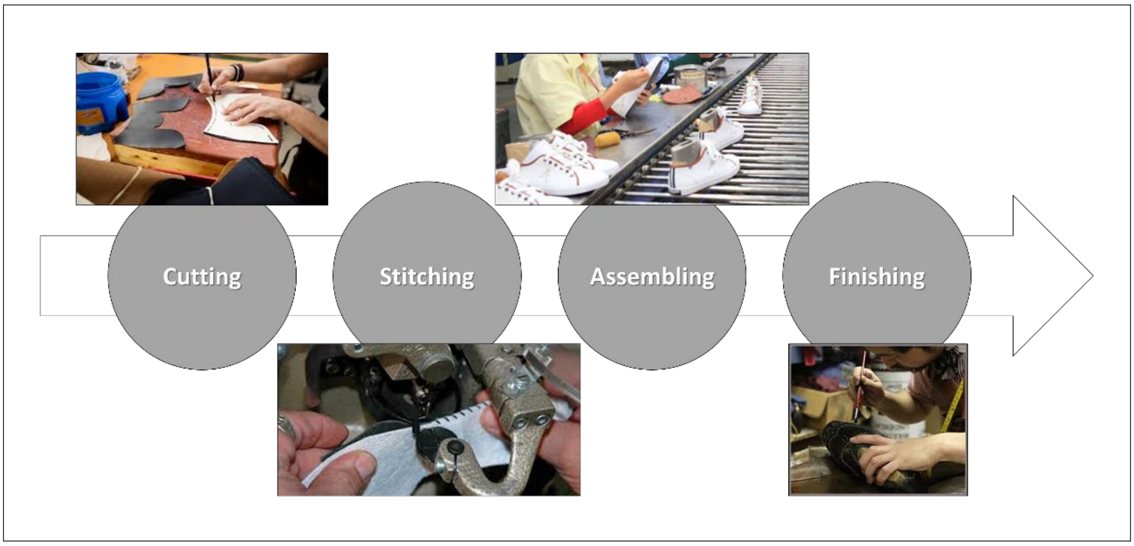

Figure 61 - Production process in the footwear industry

More in detail, the 4 steps showed in Figure 61 can be described as follows:

1. Cutting

The top part of the shoe (i.e. the upper) is made. The cutting operative is given skins of leather, mostly cow leather but not restricted to this type of leather. Using metal strip knives, the worker cuts out pieces of various shapes that will take the form of uppers. This operation requires a high level of skill as the expensive leather has to be wasted at the minimum level possible. Leather may also have various defects on the surface such as barbed wire scratches which needs to be avoided, so that they are not used for the uppers.

2. Stitching

Component pieces are sewn together by highly skilled machinists to produce completed uppers. The work is divided in stages. In early stages, the pieces are sewn together on the flat machine. In the later stages, when the upper is no longer flat and has become three-dimensional, the machine called post machine is used. The sewing surface of the machine is elevated on a post to enable the operative to sew the three dimensional upper. Various edge treatments are also done onto the leather for giving an attractive look to the finished upper. At this stage only, the eyelets are also inserted in order to accommodate the laces in the finished shoes.

3. Assembling

Last, upper, heel and sole are the 4 main components for the assembling phase.

The completed uppers are molded into a shape of foot with the help of a last. Last is a plastic shape that simulates the foot shape. It is later removed from the finished shoe to be used further in making other shoes. Firstly, an insole to the bottom of the last is attached. It is only a temporary attachment. Sometimes, mostly when welted shoes are manufactured, the insole has a rib attached to its under edge. The upper is stretched and molded over the last and attached to the insole rib. After the procedure completes, a lasted shoe is obtained. Now, the welt- a strip of leather or plastic- is sewn onto the shoe through the rib.

The upper and the surplus material is trimmed off the seam. The sole is then attached to the welt and stitched together. The heel is then attached, completing the assembly of the shoe.

That was the process for heeled shoes. When a flat shoe is in the making, there are considerably fewer operations. The insoles in this case is flat and when the uppers are lasted, they are glued down to the surface of the inner side of the insole.

The part of the upper, that is glued down, is then roughed with a brush to take off the smooth finish of the leather. This is done because rough surface absorbs glue to give a stronger bond.

The soles are usually cut, finished and prepared as a separate component so that when they are glued to the lasted upper, the result is a complete and finished shoe. Soles can also be pre-molded as a separate component out of various synthetic materials and again glued to the lasted upper to complete the shoe.

4. Finishing

The finishing of a shoe depends on the material used for making it. If made of leather, the sole edge and heel are trimmed and buffed to give a smooth finish. To give them an attractive finish and to ensure that the edge is waterproof, they are stained, polished and waxed. The bottom of the sole is often lightly buffed, stained and polished and different types of patterns are marked on the surface to give it a craft finished look.

If included in the bill of materials, accessories are attached.

Criticalities related to the production of shoes are mostly related to the assembly phase. Different from the production of bags, that is organized according to a job shop schema, the assembly phase of the shoes is organized using conveyors, where in each station one or more operators do a single or more operation. Balancing the production plan in order to guarantee the same saturation level of each station and optimizing the sequencing of the orders in order to avoid jam represent the two important challenges in optimizing the production. Changing in order priority or such order, this way, can represent critical aspect in the optimization of the production.

In addition to the balancing and sequencing topics, another criticality of the production of leather shoes is, in the same way as bags, the availability of raw material.

5.4.2 Optimization model in a footwear company

Suppliers working in the footwear market segment have to develop their production plan according to their strategical objectives, guaranteeing the compliance to the requested delivery date, that is the main KPIs that brand owners use for evaluating their supply base performances.

The main objectives these companies take into account are related to maximize their performances, like more or less every supplier working in the fashion SC, but also the production mix balancing and sequencing, that represent a peculiarity of this market segment that has to be managed.

Starting from the literature review previously described, the proposed framework, as reported in 4.1.2 Proposed scheduling model for the fashion industry, has been used in order to resolve MALB problem of type F (i.e. MALBP-F), using the parameters (P27) – (P29) in the linear model optimization and including the objective function to minimize the horizontal balancing.

The objective function included in the proposed linear integer optimization model has been defined, according to 4.1.2.4 Objectives, as Min{cw *C + dw * D + aw * A + ptw * PT + rpbw * RPB + rbw * RB + mbw * MB} where: cw =0, dw =1, aw =1, ptw =0, rpbw =0, rbw =0 and mbw =1.

This way, only the delays, the advances and the mix balancing have been taken into account.

The elementary objectives included in the OF (i.e. the ones having positive weight) have been chosen because better fit the CSFs of companies working in the footwear industry, and the results of the optimization model implementation have been validated comparing themselves to both the historical data and the production manager's experience.

The pilot has been carried out in a footwear company producing leather shoes for a big Italian Luxury brand, and the working phase analysed has been the conveyor.

In the optimization model, the cycle time and the number of stations have not been considered as variables because their values have been already defined at the tactical level.

The reason why the mix balancing has been defined as a weighted part of the objective function and not as a constraint is that it cannot be assumed that the demand is an exact multiple of the optimal balancing.

Using the MALB problem approach, shoes have been classified into three types: “easy”, “medium” and “difficult”.

In this company the number of products assembled is 8, with a total number of tasks equals to 42, composed by 91 elementary jobs. Every station can do one or more tasks.

Taking the data from the balancing schema decided by the company at a tactical level, in Table 22 the association between tasks and station is reported.

The names of the tasks have not been reported because the company has not permitted to publish them, together with the names of both the stations and the items codes.

Table 22 - Association between tasks and station in the footwear pilot

Tasks	Stations
Task 1, Task 2, Task 3	1
Task 4, Task 5, Task 6, Task 7	2
Task 8, Task 9	3
Task 10, Task 11, Task 12	4
Task 13	5
Task 14, Task 15	6
Task 16, Task 17	7
Task 18, Task 19, Task 20, Task 21, Task 22	8
Task 23, Task 24	9
Task 25, Task 26, Task 27	10
Task 28	11
Task 29	12
Task 30, Task 31, Task 32	13
Task 33, Task 34, Task 35, Task 36, Task 37	14
Task 38	15
Task 39	16
Task 40	17
Task 41, Task 42	18

Starting from the production cycle of the 8 different products, every code of the single item has been associated to one of the three categories ("easy", "medium" and "difficult"), as shown in Table 23.

Table 23 - Association between item code and difficulty in the footwear pilot

Item Code	Difficulty*
xxxxx1	Easy
xxxxx2	Difficult
xxxxx3	Medium
xxxxx4	Easy
xxxxx5	Medium
xxxxx6	Difficult
xxxxx7	Medium
xxxxx8	Difficult

Once defined the association in Table 23, the binary diagram of the tasks done for every type of product in every station has been defined and reported in Table 24.

Table 24 - Binary diagram of the tasks in the footwear pilot

TASKS	STATION	EASY*	MEDIUM*	DIFFICULT*
TASK 1	1	X	X	X
TASK 2	1	X	X	X
TASK 3	1	X	X	X
TASK 4	2	X		
TASK 5	2	X		
TASK 6	2			X

TASK 7	2			X
TASK 8	3		X	X
TASK 9	3	X		
TASK 10	4	X	X	X
TASK 11	4	X		
TASK 12	4	X		
TASK 13	5		X	X
TASK 14	6	X	X	X
TASK 15	6	X	X	X
TASK 16	7			X
TASK 17	7			X
TASK 18	8		X	
TASK 19	8		X	X
TASK 20	8	X	X	X
TASK 21	8			X
TASK 22	8		X	X
TASK 23	9		X	X
TASK 24	9	X	X	X
TASK 25	10			X
TASK 26	10		X	X
TASK 27	10	X	X	X
TASK 28	11	X	X	X
TASK 29	12	X	X	X
TASK 30	13	X	X	X
TASK 31	13	X	X	X
TASK 32	13			X
TASK 33	14		X	X
TASK 34	14			
TASK 35	14		X	X
TASK 36	14			X
TASK 37	14	X	X	X
TASK 38	15			
TASK 39	16		X	X
TASK 40	17			X
TASK 41	18		X	
TASK 42	18			

*** X: TASK PERFORMED**

Whilst in the leather pilot the processing time of the product mix has been assumed by the experience of the company's production manager, in this case a production time data collection has been done together with the company, in order to find the processing time of every task and, consequently, the cycle time of each product.

The technique utilized to collect the data has been the one named Bedaux[9] (Weatherburn, 2014). Every processing time has been recorded 10 times and then the standard time has been evaluated.

[9] The Bedaux method, developed by Charles Bedaux, is a labor technique developed at the beginning of the 1900. Data collection is a part of the methodology.

In the end, the standard time has been defined as the registered time plus an extra-time considering:

- Increases for physiologic factors
- Increases for wearying
- Increases for unexpected events

Looking at the Table 25, an example of the used Bedaux table has been showed. In particular, in the header have to be inserted the information related to the conveyor line and the specific station where the timings are recorded, while the grid below lists the tasks performed and, for each one of them, the parameters to be included, starting from the task timing "T", the worker's speed "S" and the unit of measure "UM" (e.g. number of pairs for the footwear industry) for each timing session.

Once these values have been recorded, the average value per task (i.e. "Average Time") has been calculated and, then, normalized (i.e. "Normalized Time") according to the equivalent unit of measure chosen. For example, if the timings per task have been recorded considering a single shoe while the equivalent unit of measure is represented by a pair of shoes, the "Average Time" has to be doubled to obtain the "Normalized Time".

Finally, in order to calculate the "Standard Time", the "Normalized Time" has been increased by fixed values to include "Physiologic factors", "Wearying" and "Unexpected events".

Table 25 - Example of Bedaux table

Conveyor name ____________ **Employee** ____________

Station ____________ **Worker** ____________

		Time													Increases for			
N.	**Task**	1 T S	2 T S	3 T S	4 T S	5 T S	6 T S	7 T S	8 T S	9 T S	10 T S	**UM**	**Average Time**	**Normalized Time**	**Physiologic factors**	**Wearying**	**Unexpected events**	**Standard Time**
1																		
2																		
3																		
4																		
5																		
6																		
7																		

As a result, the processing time per station and the cycle time for each SKU type (i.e. “easy”, “medium” and “difficult”) have been listed in Table 26.

Table 26 - Processing time and Cycle time in the footwear pilot

Station	Processing time (s)		
	Easy	Medium	Difficult
1	38.29	46.32	34.50
2	31.04		94.50
3	26.70	35.20	47.06
4	14.00	34.22	50.37
5		53.22	79.30
6			
7			91.26
8		24.59	30.04
9	56.91	40.45	61.09
10	10.72	46.14	63.33
11	38.29	31.02	44.02
12	56.08	37.62	50.53
13	32.70	33.70	89.98
14		31.03	72.94
15			
16			
17		13.01	56.51
18		27.68	
Cycle time	**304.73**	**413.51**	**808.92**

Once the cycle time of every category of the products has been defined, the optimize plan has been evaluated according to the following input data:

- Item code
- SKU type
- Requested quantity
- Requested date

Consider a production launch of 4,890 shoes, the optimized balanced plan is reported in Table 27.

Table 27 - Demand plan for the footwear pilot

Item Code	**SKU type**	**Requested Qty**	**Requested Date**	**07/06/2018**	**07/09/2018**	**07/10/2018**	**07/11/2018**	**07/12/2018**	**07/13/2018**	**07/16/2018**	**07/17/2018**
xxxxx1	1	2,580	07/16/2018	250	200	192	666	340	394	115	423
xxxxx2	3	118	07/16/2018	1	0	42	4	2	0	45	24
xxxxx3	2	228	07/17/2018	66	17	17	0	77	0	0	51
xxxxx4	1	896	07/16/2018	29	44	24	0	34	306	379	80
xxxxx5	2	160	07/17/2018	15	44	16	0	25	0	0	60
xxxxx6	3	182	07/17/2018	84	11	84	0	0	0	3	0
xxxxx7	2	98	07/17/2018	48	11	12	15	12	0	0	0
xxxxx8	3	628	07/15/2018	42	244	116	0	204	21	1	0
Total		**4,890**		**535**	**571**	**503**	**685**	**694**	**721**	**543**	**638**

The assembly line balancing has been declared by the company's management and, according to this, not included in the optimization model. In fact, the requested quantities for the items xxxxx1-8 included in the production plan received from the brand owner have been previously balanced according to the number of the stations and the binary diagram of the tasks.

Moreover, the constraint of the raw material availability has been previously taken into account. In fact, all the raw materials were available before the first day of production. This way, the constraint has not been included into the OF.

As a result, the balanced production plan reported in Table 27 has been optimized through the proposed model including only the daily mix of products in terms of “easy”, “medium” and “difficult” items and taking into account the delivery date of each order.

On the other hand, the resolution of the sequencing problem has been demanded to the simulation model implementation (see 4.1.1 Literature review on scheduling model for the fashion industry), in order to evaluate the feasibility of the production plan changing the sequencing rules.

5.4.3 Simulation model in a footwear company

As for the previous pilot, the results of running of the optimization model are the object of the application of the simulation model to the supplier itself, according to the parameters previously described (see paragraph 4.2.2 Proposed simulation model for the fashion industry).

In the footwear pilot, the main purpose of simulation is to support companies for both the ALB problem and the MSP (see paragraph 4.1.1 Literature review on scheduling model for the fashion industry).

In fact, balancing and sequencing are the two most important short-term planning issues in mixed-model assembly line balancing systems. The balancing objective is to determine an allocation of assembly tasks for a mix of products among the assembly stations with limited work space in order to balance the station workloads. On the other hand, the scheduling objective is to determine the detailed sequencing and timing of all assembly tasks for each individual product, in order to maximize the line's productivity, which may be defined in terms of daily productivity and resource saturation.

According to the evidences come from the literature review, these problems can be solved through simulation, that has been used in order to solve MALB problem of type F (see MALBP-F in the paragraph 4.1.1 Literature review on scheduling model for the fashion industry), establishing whether or not a feasible line balancing exists for a given combination of number of stations and cycle time. In fact, the footwear company included in the present pilot had already configured its assembly line both in terms of layout (i.e. type, sequence and number of stations) and tasks that can be done on each station, according to the machineries they have.

Moreover, simulation can be used by itself in order to conduct scenario analyses, comparing the actual balancing allocation with other ones, with different number of stations or tasks association to different stations. Last, simulation can be used in order to determine the optimal number of workers to be allocated in every station, according to the balancing and to the production plan.

As previously described (see paragraph 5.4.2 Optimization model in a footwear company), in the proposed framework the cycle time has not been considered as a variable to be optimized but as a parameter of the model, associating a fixed value of processing time per item per single task included on its production cycle (see Table 24).

The feasibility of different sequencing configurations has then been analysed through simulation, comparing performances related to different sequencing empirical rules in order to identify which ones allow to complete the optimized production plan, maximizing the productivity of the assembly line.

In order to run the proposed simulation model, it has been set in a really different way if compared to the pilots on metal accessories and leather goods companies. In fact, the model moves from a job shop to an assembly line configuration, requiring a different set of input data such as the length of the assembly line and the constant speed it moves at. The company's assembly line moves 87 boxes, each of them with a maximum capacity of 4 pairs of shoes to be assembled, and 18 stations and relative machineries are located in the perimeter.

Moving solidly to the assembly line, the items have to pass in front of all the 18 stations but, according to the items' classification between "easy", "medium" and "difficult" shoes (see paragraph 5.4.2 Optimization model in a footwear company), each of them can be or not processed on a single station and the workers will do only the tasks of the station that are included in the item's production cycle (see Table 24). If no tasks have to be done for processing an item on a specific station, the related worker has to skip the item and look for the next one in the assembly line that has to be processed in that station. According to this, in the modeled system workers can move from the station they have been associated to the assembly line, in order to take the first item that needs to be processed on the station and put again the item itself on the box where it was once it has been processed.

For example, considering the SKUs "△", "○" and "□" in Figure 62, the first one has to be processed by all the three stations (i.e. S_1, S_2 and S_3), while "○" by the first two (i.e. S_1 and S_2) and "□" by S_1 and S_3. Looking at the point "d" and "e" in Figure 62, the described scenario is the following: if the worker W_3 ends to process the SKU "△" before "○" exits from the station S_2 (see point "d" in Figure 62), the worker W_3 can process the SKU "□" that has not to be worked by the station S_2.

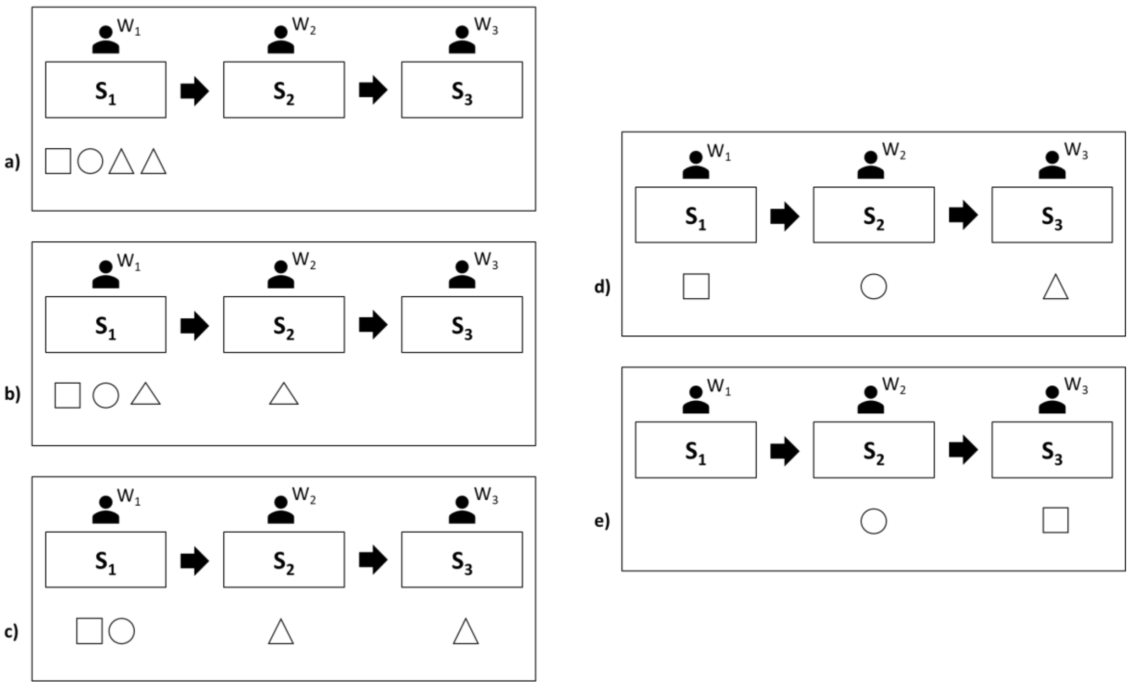

Figure 62 - Example of SKUs allocation per station

In Figure 63, the simulation model developed for the analysed footwear company is shown.

More in detail, the assembly line analysed in this pilot has been modeled as a conveyor (see grey line in Figure 63).

Around it, red-squared boxes have been modeled, according to the number and location of the stations, each one of them surrounded by the relative machineries as blue-squared boxes.

The area where shoes to be assembled are stocked is the green-squared one, really close to the first station of the assembly line.

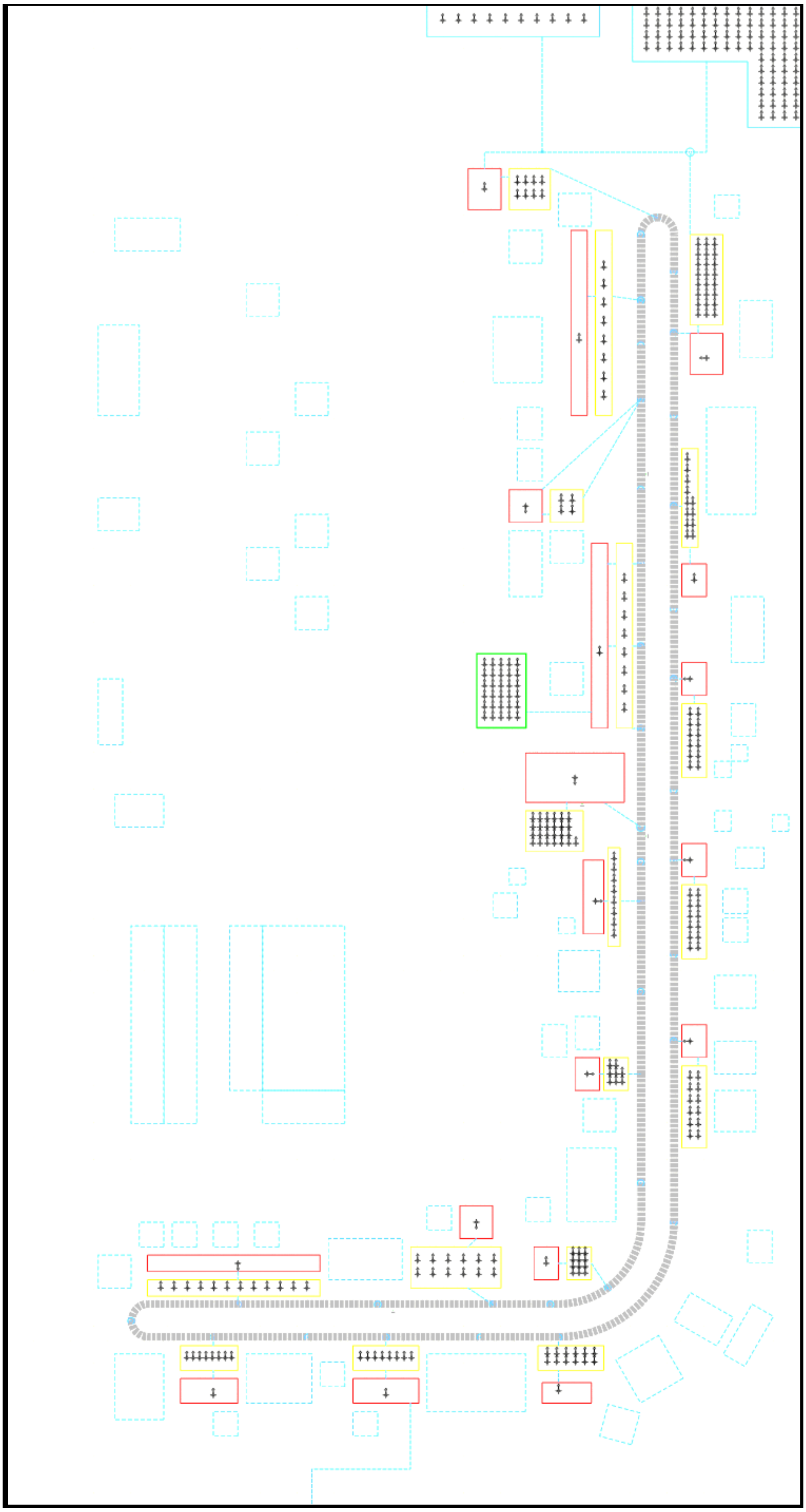

Figure 63 - Simulation model in the footwear pilot

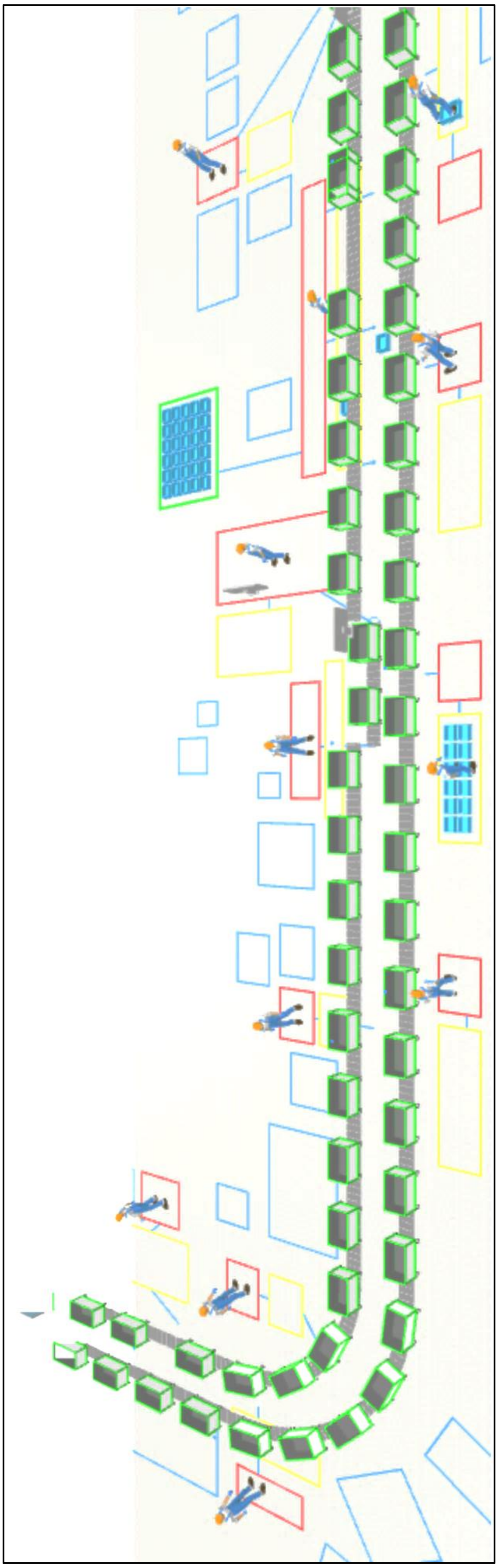

Figure 64 - 3D view of the simulation model in the footwear pilot

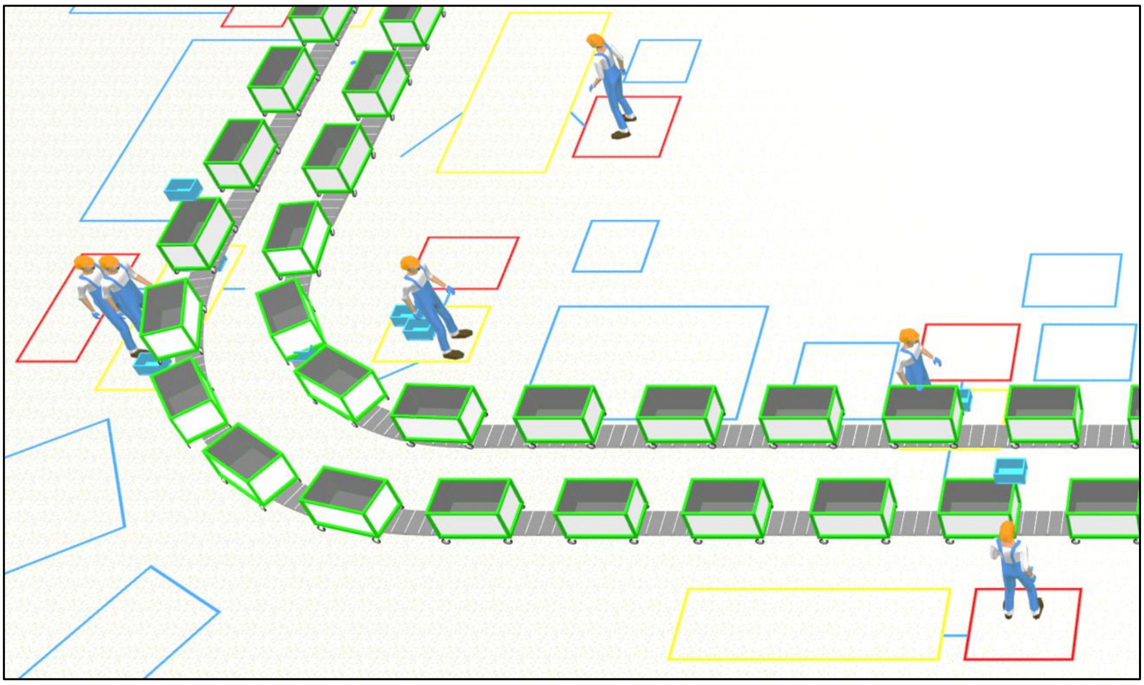

Figure 65 - Detail of the modeled working stations in the assembly line of the footwear sector

The inputs for running the proposed simulation model are summarized in the following tables (see Table 28 and Table 29). A single day of production has been simulated, and the used data are the one of the last days of the optimization plan (see Table 27).

Table 28 - Simulation model inputs in the footwear pilot: daily scheduled plan

Item Code	Difficulty	Requested Qty	Batch	Assigned Date	Sequence
xxxxx1	1	423	4	07/17/2018	1
xxxxx2	3	24	2	07/17/2018	2
xxxxx3	2	51	3	07/17/2018	3
xxxxx4	1	80	3	07/17/2018	4
xxxxx5	1	60	4	07/17/2018	5

Table 29 - Simulation model inputs in the footwear pilot: processing time per station

Item Code	Difficulty	Batch	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8	Station 9
xxxxx1	1	4	38,29	31,04	26,70	14,00	0,00	0,00	0,00	0,00	56,91
xxxxx2	3	2	34,60	94,78	47,20	50,52	79,53	0,00	91,53	39,15	61,27
xxxxx3	2	3	46,32	0,00	35,20	34,22	53,22	0,00	0,00	24,59	49,45
xxxxx4	1	3	38,29	31,04	26,70	14,00	0,00	0,00	0,00	0,00	56,91
xxxxx5	1	4	38,29	31,04	26,70	14,00	0,00	0,00	0,00	0,00	56,91
xxxxx6	3	2	34,60	94,78	47,20	50,52	79,53	0,00	91,53	39,15	61,27
xxxxx7	2	3	46,32	0,00	35,20	34,22	53,22	0,00	0,00	24,59	49,45
xxxxx8	3	2	34,60	94,78	47,20	50,52	79,53	0,00	91,53	39,15	61,27

Item Code	Difficulty	Batch	Station 10	Station 11	Station 12	Station 13	Station 14	Station 15	Station 16	Station 17	Station 18
xxxxx1	1	4	1,00	38,29	31,04	26,70	14,00	0,00	0,00	0,00	0,00
xxxxx2	3	2	3,00	34,60	94,78	47,20	50,52	79,53	0,00	91,53	39,15
xxxxx3	2	3	2,00	46,32	0,00	35,20	34,22	53,22	0,00	0,00	24,59
xxxxx4	1	3	1,00	38,29	31,04	26,70	14,00	0,00	0,00	0,00	0,00
xxxxx5	1	4	1,00	38,29	31,04	26,70	14,00	0,00	0,00	0,00	0,00
xxxxx6	3	2	3,00	34,60	94,78	47,20	50,52	79,53	0,00	91,53	39,15
xxxxx7	2	3	2,00	46,32	0,00	35,20	34,22	53,22	0,00	0,00	24,59
xxxxx8	3	2	3,00	34,60	94,78	47,20	50,52	79,53	0,00	91,53	39,15

Looking at the simulation model and the inputs needed (see Figure 63 and Table 28 and Table 29 respectively), in the purple-squared box the agents “shoes” are generated, according to the quantity per SKU detailed in the column “batch” in Table 29. Each batch of pairs of shoes, once generates, is associated to another agent, the “box”, that solidly moves with the assembly line, transferring the shoes from the first to the next station, and the next again until the final one. According to this and to the facts previously described, the association shoes-box is fixed, and workers take and put back shoes from and on the same box respectively.

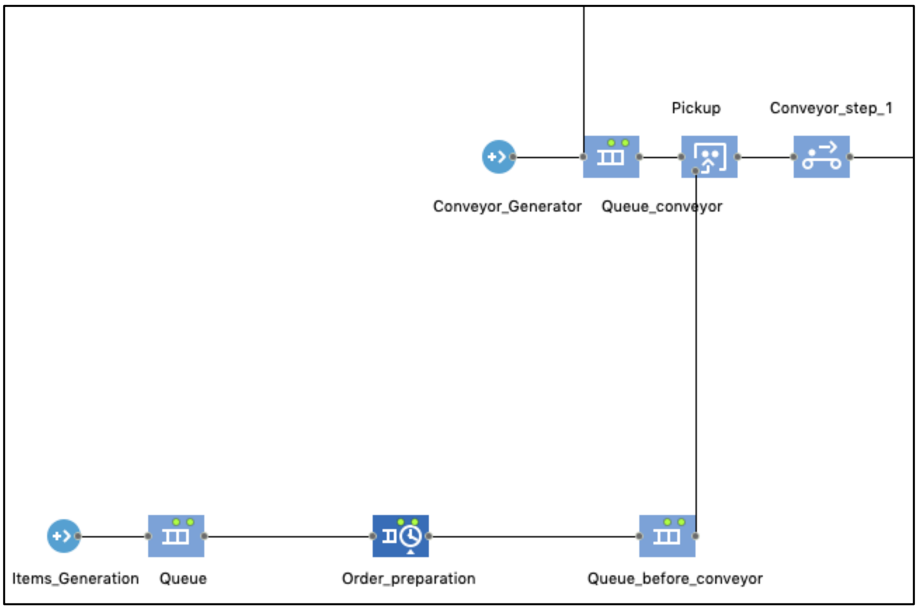

Figure 66 - Source blocks in the simulation model for generating agents “shoes” and “box”

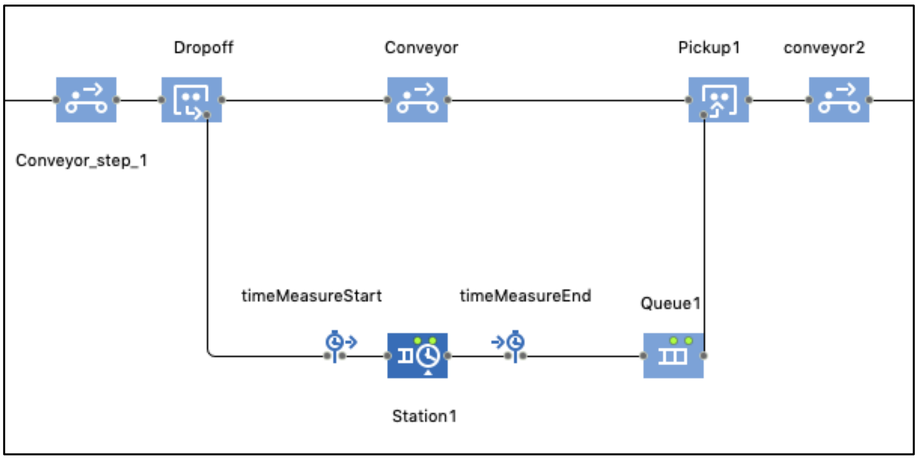

Figure 67 - Detail of a station in the simulation model where the item is processed

The first runs of the simulation model have been done in order to validate the processing time measured and assigned to each SKU type (i.e. "easy", "medium" and "difficult") considering a single worker per station. In particular, runs of simulation have been done using as input only the "easy" shoes, only the "medium" shoes and only the "difficult" ones respectively. According to the expected results, 700 pairs of "easy" shoes, 360 pairs of "medium" shoes and 280 pairs of "difficult" shoes can be processed per day.

Due to the fact that the scheduled production usually refers to few SKUs per day, the feasibility has been checked through second runs of the simulation model considering different sequencing empirical rules, represented by the different combination of "easy", "medium" and "difficult" shoes according to the products mix defined by the daily scheduled production plan.

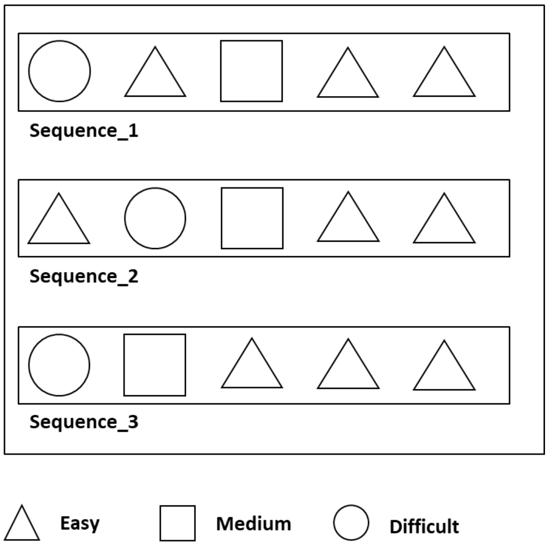

Figure 68 - Assembly line sequencing empirical rules tested through simulation

Because of the fact that the simulation model starts with an empty conveyor, a warm-up period of 2 hours has been taken into account in order to achieve the steady-state situation.

In order to check the feasibility of the simulation model, the KPI that has been evaluated is the average daily assembly line productivity, especially the average percentage of the assembled products and the daily scheduled production detailed in Table 28. Moreover, the saturation of all the active stations (i.e. “Station 6” and “Station 16” are the excluded ones) for the SKUs to be produced has been taken into account, in order to compare the feasible solutions.

Table 30 - KPIs dashboard per sequencing empirical rules: overall values

KPI Type	KPI	Sequence_1	Sequence_2	Sequence_3
Prd_W_Avg	Average daily productivity	100%	100%	100%
Sat_W_Avg	Average daily saturation	29,48%	30,08%	29,62%
Mks_W_Sum	Makespan [hh:mm:ss]	11:43:54	11:29:44	11:40:32

The column “KPI Type” in Table 30 links the analysed KPIs (i.e. “KPI” column) to the KPI types listed in Table 7. In particular, the KPI types analysed in the footwear pilot refer all to the efficiency dimension and have been calculated at the end of the process (i.e. “Sink” block). First of all, the average value per day has been calculated for both the productivity (i.e. “Prd_W_Avg”) and the saturation (i.e. “Sat_W_Avg”) to obtain an overview of the flexibility and reactivity that the system can guarantee to perform extra-orders requested by the customers. In addition, the time between first item entering and last item exiting from the model (i.e. “Mks_W_Sum”) has been calculated in order to identify the sequence that enables to process the whole production plan in the shortest time.

More in detail, looking at the Table 30, all the sequencing rules confirm the feasibility of the daily scheduling plan (i.e. “Average daily productivity” equals to 100%), enabling the company to process all the scheduled SKUs. Considering the other KPIs, the average daily saturation has been calculated including only the active stations and refers to the makespan (i.e. the difference between the last exit date from a processing block and the first enter date on a processing block). For these two KPIs, the values differ considering the implementation of one or another sequencing rule, highlighting how the “Sequence_2” results in a higher average daily saturation and a shorter makespan.

Table 31 - KPIs dashboard per sequencing empirical rules: overall values (including reworking)

KPI Type	KPI	Sequence_1	Sequence_2	Sequence_3
Prd_W_Avg	Average daily productivity	99,34%	98,40%	99,24%
Sat_W_Avg	Average daily saturation	29,15%	29,55%	29,21%
Mks_W_Sum	Makespan [hh:mm:ss]	11:43:54	11:29:44	11:40:32

Moving from Table 30 to Table 31, the implementation of none of the sequencing rules listed in Figure 68 allows the company to process all the daily scheduled SKUs, and this is related to the fact that a percentage of reworking (i.e. 2%) has been introduced according to the management requirements.

On the other hand, the implementation of the simulation model including this type of stochasticity shows how the “Sequence_3” is the worst sequencing rule in terms of KPIs. In fact, its implementation results neither in the higher values for average daily productivity and the average daily saturation or the shorter makespan. On the other hand, the best sequencing rule between the “Sequence_1” and “Sequence_2” depends of the company’s CSF: implementing “Sequence_2” results in the higher average saturation and shorter makespan, while “Sequence_1” guarantee the higher average daily productivity.

Table 32 shows the detailed saturation per station, highlighting what is the bottleneck station for the analysed assembly line and production plan. The related KPI type, considering the one listed in Table 7, is “Sat_S_Avg”, that measures the average saturation per resource.

Table 32 - KPIs dashboard per best sequencing empirical rules: average saturation per station

	Sequence_1 (Sat_S_Avg)	**Sequence_2 (Sat_S_Avg)**	**Sequence_3 (Sat_S_Avg)**
Station_1	57,88%	58,9%	57,97%
Station_2	46,18%	46,9%	46,25%
Station_3	42,02%	42,7%	42,09%
Station_4	25,40%	25,7%	25,46%
Station_5	10,95%	10,9%	11,00%
Station_6	0,00%	0,0%	0,00%
Station_7	5,20%	5,1%	5,23%
Station_8	5,19%	5,1%	5,22%
Station_9	84,24%	85,7%	84,37%
Station_10	1,73%	1,7%	1,73%
Station_11	57,88%	58,9%	57,97%
Station_12	46,18%	46,9%	46,25%
Station_13	42,02%	42,7%	42,09%
Station_14	25,40%	25,7%	25,46%
Station_15	10,95%	10,9%	11,00%
Station_16	0,00%	0,0%	0,00%
Station_17	5,20%	5,1%	5,23%
Station_18	5,19%	5,1%	5,22%

Once the feasibility has been checked and the KPIs for the balanced assembly line have been evaluated, the optimization of the number of workers per station has been the object of another scenario analysis conducted through simulation, assessing how the KPIs changes varying the number of workers associated to one or more stations.

According to this, starting from the results in Table 32, one more worker has been associated to the station with the higher saturation independently from the implemented sequencing rule (i.e. “Station 9”).

Moreover, the sequencing rule chosen to conduct this scenario analysis has been the one that results in better performances in (i.e. “Sequence_2”).

The compared scenarios have been listed in Table 33.

Table 33 - Scenarios for simulation model in the footwear case study

	Description
Scenario_1	No reworking; 1 resource for each station (see “Sequence_2” in Table 30)
Scenario_2	Reworking; 1 resource for each station (see “Sequence_2” in Table 31)
Scenario_3	No reworking; 2 resources per “Station 9”
Scenario_4	Reworking; 2 resources per “Station 9”

For each one of the scenarios described in Table 33, the KPIs values used to the comparison have been listed in Table 34.

Table 34 - KPIs dashboard per sequencing empirical rules: overall values

KPI Type	KPI	Scenario_1	Scenario_2	Scenario_3	Scenario_4
Prd_W_Avg	Average daily productivity	100%	98,40%	100%	99,67%
Sat_W_Avg	Average daily saturation	30,08%	29,55%	30,20%	29,91%
Mks_W_Sum	Makespan [hh:mm:ss]	11:29:44	11:29:44	10:24:56	10:24:56

Looking at the results in Table 34, comparing the scenarios with no stochasticity (i.e. “Scenario_1” and “Scenario_3”), their implementation results in a shorter makespan (-9.4%) and a slightly higher average saturation (+0.4%) considering 2 workers on the “Station 9”. Comparing the other two scenarios that include reworking (i.e. “Scenario_2” and “Scenario_4”), moving from 1 to 2 workers on the “Station_9” the makespan has been reduced in the same way of the previous comparison (-9.4%) while the average saturation increases (+1.2%) in the “Scenario_4”. In addition, also the average daily productivity increases (+1.3%).

Table 35 shows the detailed saturation per station (i.e. KPI type equals to “Sat_S_Avg”, as listed in Table 7) for each one of the three scenarios described in Table 34.

Table 35 - Scenario analysis for the best sequencing rule: average saturation per station

	Sequence_2 Scenario_1	Sequence_2 Scenario_2	Sequence_2 Scenario_3	Sequence_2 Scenario_4
Station_1	59,81%	58,9%	66,01%	65,29%
Station_2	47,72%	46,9%	52,67%	52,09%
Station_3	43,40%	42,7%	47,90%	47,40%
Station_4	26,19%	25,7%	28,91%	28,65%
Station_5	11,17%	10,9%	12,33%	12,33%
Station_6	0,00%	0,0%	0,00%	0,00%
Station_7	5,31%	5,1%	5,86%	5,86%
Station_8	5,30%	5,1%	5,85%	5,85%
Station_9	87,07%	85,7%	48,05%	47,52%
Station_10	1,78%	1,7%	1,97%	1,95%
Station_11	59,81%	58,9%	66,01%	65,29%
Station_12	47,72%	46,9%	52,67%	52,09%
Station_13	43,40%	42,7%	47,90%	47,40%
Station_14	26,19%	25,7%	28,91%	28,65%
Station_15	11,17%	10,9%	12,33%	12,33%
Station_16	0,00%	0,0%	0,00%	0,00%
Station_17	5,31%	5,1%	5,86%	5,86%
Station_18	5,30%	5,1%	5,85%	5,85%

6. Conclusions

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. Moreover, the complexity related to the fashion SC structure, composed by a high number of supply levels where usually operate SMEs, and the stochastic events that characterized this industry increases the required efforts to be on-time in a such dynamic context.

According to this, the relevance of optimizing production planning and scheduling performances is increasing in the last years, pushing companies to pay even more attention on find a way to be more compliant with the service levels required by the market involving all the SC actors working on the fashion SC.

Despite this, no optimization tools are widely applied in the industry, even if PP&C for the fashion SC is a debated topic both from an academical and an industrial point of view.

This evidence is mainly related to the fact that most of the companies working along the fashion SC are SMEs, characterized by a low informatization level and, for this, looking for an easy-to-use and affordable tool that supports them in choosing the optimal production plan according their own CSFs that can be, and usually are, different from the ones of the SC actor that gives them the demand plan as input.

Moreover, one of the main weakness that optimization tools have is their static nature, that makes the optimized plan rarely usable due to the high-dynamic context where the analysed companies work. In addition, due to the quick-responses they have to give, these companies need to rapidly compare different scenarios that vary each other in terms of parameters in inputs, occurrence and type of included stochasticity or a combination of them.

According to this, the first and the second RQs aim to develop an optimization and a simulation tool respectively.

First of all, the optimization tool has been developed to define the optimal output in terms of production allocation according to the company's CSFs. It has been modeled using an integer linear-optimization scheduler, based on a commercial spreadsheet and an open-source solver (OpenSolver), in order to be successfully used by these companies, which are mostly SMEs with low investment capability in IT solutions. According to the purpose to develop a model suitable by all the companies working along the fashion SC, it has been developed in a parametric way.

For example, it has been defined a weighted multi-OF, in order to fit the peculiarities of the different actors operating along the fashion SC just enabling them to change the weights of the elements included in the OF in order to reflect the specific company's CSFs.

After the optimization one, the simulation model has been developed as second step of the research, in order to move from a deterministic to a stochastic context and to allow scenario analyses to support production managers in the decision-making process.

In the same way of the optimization model, the structure and logics of the simulation model had been defined in order to apply the model itself on different SC actors. The scenario analyses enabled through simulation allow to compare different outputs that come running the model, considering different inputs (e.g. decreased resource capacity) and/or under different deterministic and/or stochastic conditions (e.g. increased percentage of rush orders). The comparison has been done through a gap analysis referred to a set of KPIs that has been defined, studying how these KPIs' values change moving from a scenario to another one.

Once both the optimization and the simulation models had been developed, they have been jointly used to define an iterative simulation-optimization framework for improving the global SC PP&C performances, in order to include the effects that the feedbacks coming from the implementation of simulation-optimization models at the single-companies level may have on the overall SC performances.

The iterative procedure in the proposed framework 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 may 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 for each one of the analysed scenarios; (v) the application of a second iteration of the whole model changing the input according to the selected output at the end of the first iteration.

Consequently, the main challenge that this work aims to reach is to define an iterative framework enabling a set of decision-making tools to be given to all the SC actors in order to preventively highlight the criticalities related to the feasibility of optimized production plans and the way to manage them comparing the different results, related to each one of the input configuration, that can be more or less influenced to the occurrence of stochastic events.

The model has been applied to real companies working along the fashion SC, where different CSFs have been considered in order to define the OF, whilst rush orders and delays on the critical components' delivery date have been introduced to simulate stochastic events. The on-field implementations on the metal accessories, leather goods and footwear market segments have been used to test the usability of the tool and to validate the models by the production managers evaluation and comparing the resulting outputs to the historical data.

First of all, the optimization model has been validated by the production managers both from a brand owner's and a supplier's perspective, including different OFs in the analysis.

After that, simulation model has been successfully validated comparing the resulting outputs (i.e. end processing dates and processed quantities, considering both final and intermediate steps) to the ones calculated through the optimization model on the Microsoft Excel®.

Moreover, the impact on the KPIs' values related to the occurrence of stochastic events, such as unexpected orders to be processed and delays in the critical components' delivery date, has been analysed using the simulation model, allowing to measure the gap between scheduling outputs considering the optimization of the OF under deterministic and not-deterministic condition, but also analysing the different impacts on KPIs changing the type and the occurrence of stochastic events.

In addition, simulation has been also used to assess the feasibility of optimized production plans. For example, looking at the footwear industry, solve the balancing and sequencing problems represents one of the main challenges for the belonged companies, and through simulation has been possible to compare the outputs related to the implementation of different sequencing rules in terms of changes in the resulting KPIs' values, such as the daily productivity and the average resource saturation.

As further results of this work, the analysed sample can be enlarged, in order to consolidate the obtained results, to confirm the parametrical way the models have been developed and to eventually add new elements to the OFs and/or parameters to be included.

Moreover, the three RQs defined and then answered considering the fashion industry can be readapted to the peculiarities of other sectors, starting from the ones where PP&C represents a relevant challenge.

To conclude, the results of the present work have been concretized in the creation of a start-up, called Balance, whose goal is to industrialize and commercialize the solution conceived, starting from its implementation in the analysed industry and continuing with the others, according to the further developments previously described.

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