A SIMULATION OPTIMIZATION TOOL FOR THE METAL ACCESSORY SUPPLIERS IN THE FASHION INDUSTRY: A CASE STUDY

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ABSTRACT

This paper presents a Simulation Optimization (SO), decision-support tool developed for metal accessories' suppliers in the fashion industry. The tool is composed of a discrete-event simulator and a multi-objective, integer linear-optimization scheduler, based on a commercial spreadsheet and an open-source solver, linked together through an import-export routine. The tool can be used to enable suppliers to compare scheduling algorithms in order to optimize their performances in terms of customers' due dates compliance and cost and processing time reduction. The analyzed scenario takes into account variable and uncertain production plans, represented by the aggregation of orders received from different brands. The model has been applied to a real company, where costs, delay, and advances are considered in order to define the Objective Function (OF), whilst rush orders are introduced to simulate stochastics events.

INTRODUCTION

As widely recognized in the literature, challenges in the fashion–product industry do not only deal with creativity and styles, but also supply chain (SC) management. One of the main criticalities of the fashion SC is the high uncertainty of the demand (Ait-Alla et al. 2014; d'Avolio et al. 2015; Hu et al. 2013). In recent years, the fashion-product lifecycle has become ever shorter, and the number of fashion seasons has increased. As a consequence, the fashion industry is centered on the ability to react quickly to changes in customers' desires, increasing the need to compress time-to-market. On the other hand, fashion customers ask for a higher service level, mainly in terms of quality. All of these aspects have pushed companies to increase their own pressure on the upstream SC actors. This evidence reflects the fact that these results cannot be obtained through operations at the single-company level, but rather throughout the entire SC, because outstanding quality and delays of a final product are directly linked to other components (Caniato et al. 2013). Within this SC, an important role is played by metal accessories suppliers, often SMEs, located close to the fashion brands. The optimization of the performance of various production units, identifying the optimal quantities and places to allocate items production, which affect the problems of multi-plant production planning, are widely discussed in the literature and several surveys can be found (e.g. Fujimoto 2015; Jeon and Kim 2016;). In this paper, a first step of the problem concerns the local optimization of scheduling performance in the domain of Simulation and Optimization Integration. Even if this topic has been debated in the literature and applied to various domains, from manufacturing to healthcare (Jung et al. 2004; Sowle et al. 2014), no contributions have been found related to the fashion industry, making the present work innovative as first implementation of a model combining optimization and simulation tools within this industry.

FASHION SCHEDULING OPTIMIZATION REVIEW

In the scientific literature, several different approaches to the definition of scheduling formulation can be found. Published reviewing papers on scheduling (Maravelias 2012; Méndez et al. 2006; Mula et al. 2010; Phanden et al. 2011; Ribas et al. 2010) study various problems, moving from single to parallel machines, job, or flow shop, and considering different levels of data aggregation (i.e., strategical, tactical, and operative). Focusing on contributions related to the fashion industry in the literature, there are many papers considering finite or infinite capacity, where finite capacity can be considered in terms of hours (Rahmani et al. 2013) or units per resource (Ait-Alla et al. 2014; Guo et al. 2015; Wong et al. 2014; Rahmani et al. 2013). Betrand and Van Onijen (2008) present various multi-objective OFs, both liner and not linear, including costs, time, and plant-performance optimization. At the same time, several contributions can be identified where simulation techniques are used in order to optimize production in the fashion industry, i.e. Al-Zubaidi et al. (2004), Cagliano et al. (2011) and Jung et al. (2004). Nevertheless, no contribution can be found where a combined simulation-optimization model is described and applied that considers the specific characteristic of this industry.

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PROBLEM STATEMENT

One of the consequence of the high pressure applied by brand owners on suppliers of metal accessories is their motivation to adopt optimization of process planning and scheduling. On the other hand, fashion brands, due to the variability of the demand, are at the same time reducing the suppliers' orders visibility, consequently increasing the frequency of re-scheduling their production plan. This dichotomy has caused fashion suppliers to ask for inexpensive and easy-to-use tools capable of determining optimal, or sub-optimal, scheduling techniques to be adopted for the production plan they have to accomplish. An important aspect of this optimization model deals with the fact that metal fashion suppliers have to optimize a local production plan that is a matrix of several fashion-brands production plants, each of them developed according to different criteria, and in which seasonal products and carryover are mixed together and can quickly and significantly change from one day to another. Another important boundary of the problem is the use of sub-suppliers with unknown production capacity. These sub-suppliers are used to perform mechanical work, except for the machine shop, which is internal and considered to possess finite capacity in the model.

Model Description

Starting from the boundaries described above, the simulation-optimization model proposed in the paper has the objective to define the optimal supplier- production plan, according to a set of KPI mixed with various weights, based on the companies Critical Success Factors (CSFs) and on the uncertainty due to internal factors (machine failures, reworks, employees unavailability) and external stochastics events (rush orders). The importance of including rush orders is due to the uncertainty and high variability of the brands' production orders. Unexpected orders can represent a high proportion of the value of the production, up to the 20% of the total capacity. The variables considered by the model are derived from time measurements (tardiness, lateness), costs (machine costs, labor costs, overtime costs), and production (wip, leadtime).
The model describes, in a stochastic way, the behavior of metal suppliers' production cycle and that of one of their sub-suppliers, while the scheduler, according to an Objective Function (OF) defined as a mix of parameters (costs, delays and minimization of processing time) chosen by the company, defines the optimal scheduling solution for a single phase of the production process.
In the specific, the solver model has been developed with the following function:
$OF: Min\{\sum_{i \in II} (cw_i * C_i + dw_i * D_i + aw_i * A_i + ptw_i * PT_i)\}$ where cw_i, dw_i, aw_i, ptw_i, and weights of the various objectives, according to Guo et al. (2008), and C_i, D_i, A_i, and PT_i are respectively $\sum_{i \in II}$ *Costs* (C_i), $\sum_{i \in II}$ *Delays* (D_i), $\sum_{i \in II}$ *Advances* (A_i), and $\sum_{i \in II}$ *Processing Time* (PT_i).
More information on the model and how the objectives are evaluated can be found in Fani et al. (2016).

Model Architecture

The model is composed of a Java discrete-event simulator, AnyLogic® (www.anylogic.com), and an open solver optimization tool, OpenSolver (www.opensolver.org). The version of AnyLogic that has been used is the 7.3, and the version of the Solver is the 2.8.5. The solver has been used integrated on Microsoft Excel®. The architecture of the model, assuming a comparison between three different OFs weights distribution, is represented in Fig. 1.

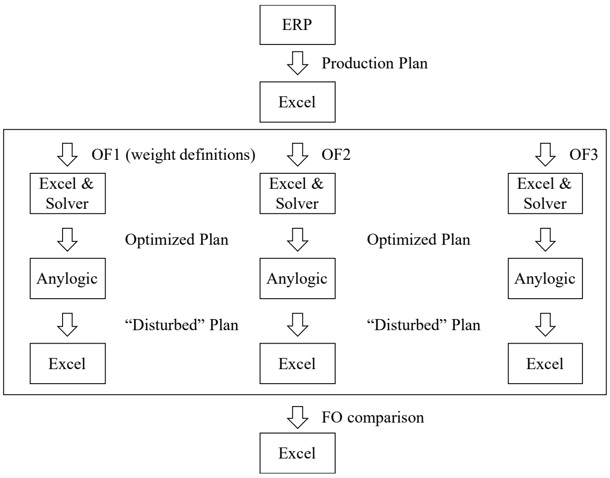

Figure 1: Model Architecture

The procedure to define the optimal scheduling solution, according to a specific production plan of the company, the stochastics events estimated for that company and the defined KPIs, is described in Fig. 2. This procedure has to be done for each of the OFs that has to be compared.

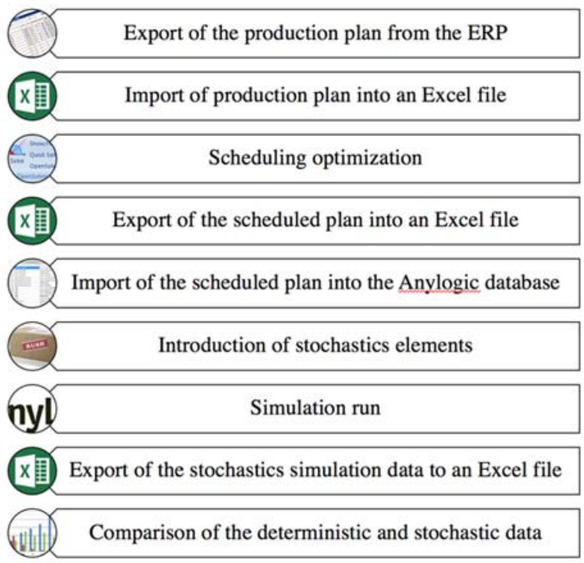

Fig. 2 Scheduling simulation optimization procedure

CASE STUDY

Implementation of the model

The model described in the previous section has been validated using a data set acquired from the real experience of a supplier of fashion metal accessories, where the production starts with the realization of a semifinished item and proceeds through shaving removal, followed by some mechanical operations (e.g., vibration, vibratory finishing, drilling, cutting). Then, items have to be covered by one or more precious metals, such as gold, palladium, and ruthenium, through an electroplating process. In the final step, the items have to pass the quality control, be packaged, and be delivered in order to be applied on the final product.

In the case study, the phase characterized by finite capacity is the machine shop, where the shape-removal is done by Computer Numerical Control (CNC) machines. All the steps after this phase have been considered working at infinite capacity and have been modeled with a generic processor. 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.

The optimization tool has been parametrized with an OF that has been defined combining costs, delays, and advances, whilst processing time has not been considered in this first implementation. According to this, the two combinations of weights (i.e. one for each OF) chosen for each one of the three parameters have been decided by the analysed company, guaranteeing coherence with its specific CSFs.

The aim of this work is twofold: on the one hand, the developed simulation model has been validated comparing the output with that one of the optimization model; 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.

The structure of the production plan exported from the company ERP that represents the input of the optimization model is summarized in Table 1.

Table 1: 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 type (turn, mill)
db_qt_prod	Number of items to be produced
db_delivery_date	Item due date

The production order considered in the case study includes 11 articles with different lot sizing, (i.e from 35 up to 10,000 items for item code) and customer delivery dates between 15th and 23th 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. This prarameters are the processing time per item on each companies' CNC machines, the lead time per item for the subsequent production steps and the processing costs per item for each machines.

Processing times can be different for different item codes (i.e longer moving from simpler to more complex) but even for the same one (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 information represent the input for the optimization model run using the OpenSolver tool on Excel®.

The OFs of the two analyzed scenarios are the following:

a) OF_1: $Min\{\sum_{i \in II} (cw_i * C_i + dw_i * D_i + aw_i * A_i)\}$
where $cw_i = 1$, $dw_i = 1$, $aw_i = 1$;

b) OF_2: $Min\{\sum_{i \in II} (cw_i * C_i + dw_i * D_i + aw_i * A_i)\}$
where $cw_i = 1$, $dw_i = 1$, $aw_i = 0$.

The reason these two scenarios have been chosen is related to the management request to develop a tool able to show what are different impact on the scheduling performance if advances are included (i.e OF_1) or not (i.e OF_2), enabling users to analyze the output evidences value of delays and advances in terms 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 analyzed 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 Excel® (i.e. exported from the company's ERP) and as agents' parameter on the simulator. According to the management request, at the first stage of model implementation costs are considered equal for every item processed by every machine. Moreover, no difference as been made according to the work schedules actually used (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 2.

Table 2: 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 case study, the optimal scheduled production plan shows that, according to both the OFs and the optimization model constraints (i.e. CNC machines' capacity and demand fulfillment), some items will be produced in advance and some others with a delay respect to the delivery dates specified in the production plan (see the "Results" section).
Considering the schedulation time slot, the optimization model results cover 15 days in the first scenario and 24 days in the other.
Once the optimization plan has been recorded, the assigned items have been imported into the AnyLogic® simulator using an sql script and represent the 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 Excel® file containing the optimization model results.
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 analyzing 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, as the company's layout already mapped on the optimization model on the Excel®). 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 Excel® file and recording it as an agent 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 modeled as a unique processing block, called "postpocessing", that covers a specific processing time for each item, extracted from the Excel® file as agent's parameter (in the same way of turning and milling processing times).
The simulation model described until now represents the same deterministic scenario of that one modeled on Excel® and has been successfully used to validate the optimization model in terms of resulting key performance indicators (KPIs), such as delays and advances days for each item.
In the case study, 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 analyzed 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, on the other hand, move on the simulated production process following a FIFO queue.
Two simulation campains 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 processes items following 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 campains with the scheduled deterministic optimizated production plan, the key performances indicators (KPIs) reported in Table 3 have been defined.

Table 3: Simulation model's KPIs

KPI	Formula
gap delivery date1	deathdate – customerRequestedDate
gap delivery date2	customerAssignedDate – customerRequestedDate
gap delivery date3	deathdate – customerAssignedDate
gap processing delivery date1	stopDate – requestedDate
gap processing delivery date2	assignedDate – requestedDate
gap processing delivery date3	stopDate – assignedDate

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. 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 semifinished products (i.e. outputs of turning and milling machines) instead of final ones (i.e. outputs of post-processing block).

Results

As first result of the present work, the simulation model has been successfully validated comparing the resulting outputs to that ones calculated through the optimization model on the Excel®. In particular, for each run simulation campaign the gap, in terms of days, between real and requested delivery date per each item calculated through the two models (i.e. 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).

In particular, 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 $\sum_{i \in II} (cw_i * C_i) = 14{,}482$, $\sum_{i \in II} (dw_i * D_i) = 72{,}056$ and $\sum_{i \in II} (aw_i * A_i) = 1{,}481$. The second one, that differs from the prievious scenario for not considering advances as one of the OF's parameters, results in an OF_2 value equals to 19,296, composed by $\sum_{i \in II} (cw_i * C_i) = 14{,}482$ and $\sum_{i \in II} (dw_i * D_i) = 4{,}814$; advances equals to $\sum_{i \in II} (aw_i * A_i) = 110{,}805$.

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 fulfillment 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 schedulation 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 that ones of the first one because their amount is not included into the OF.

The second results of this work is related to the comparison between the schedulation 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 4 and 5.

KPIs related to the output of the models, in terms of number of worked items, refers 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 schedulation, modeled on the Excel®. Moreover, due to the fact that rush orders are priority by definition, they report null delays and advances.

Table 4: Comparison between models' KPIs (OF_1)

KPI	Optimized plan	Stochastic simulation	Δ %
Output quantity per turn 1 (a)	10,020	12,185	21.61%
Output quantity per turn 2 (a)	44	485	1002.27%
Output quantity per mill 1 (a)	1,060	2,639	148.96%
Output quantity per mill 2 (a)	3,358	5,383	60.30%
Delays per turn 1 (a)	0	387,285	---%
Delays post-processing (a)	72,056	491,236	581.74%
Advances per turn 1 (a)	16,237	16,237	0%
Advances per turn 2 (a)	88	88	0%
Advances per mill 1 (a)	2,119	2,119	0%
Advances per mill 2 (a)	6,715	6,715	0%
Advances post-processing (a)	1,481	37,099	2405.00%
Max delay per turn 1 (b)	0	367	---%
Average delay per turn 1 (b)	0	178.88	---%
Max delay post-processing (b)	21	141	571.43%
Average delay post-processing (b)	6.46	76.74	1087.93%
Max advance per turn 1 (b)	3	3	0%
Average advance per turn 1 (b)	1.62	2	23.46%
Max advance per turn 2 (b)	2	2	0%
Average advance per turn 2 (b)	2	2	0%
Max advance per mill 1 (b)	2	2	0%
Average advance per mill 1 (b)	2	2	0%
Max advance per mill 2 (b)	2	2	0%
Average advance per mill 2 (b)	2	2	0%
Max advance post-processing (b)	7	7	0%
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 maximum delay per turn 2, turn 3, mill 1 and mill 2 (b); Max advance per turn 3 (b); Average advance per turn 3 (b);

Table 5: Comparison between models' KPIs (OF_2)

KPI	Optimized plan	Stochastic simulation	Δ %
Output quantity per turn 1 (a)	10,000	11,726	17.26%
Output quantity per turn 2 (a)	44	444	909.09%
Output quantity per turn 3 (a)	20	433	2065.00%
Output quantity per mill 1 (a)	3,067	5,129	67.23%
Output quantity per mill 2 (a)	1,351	3,042	125.17%
Delays per turn 2 (a)	132	132	0%
Delays per turn 3 (a)	340	340	0%
Delays per mill 1 (a)	3,770	3,770	0%

Delays per mill 2 (a)	572	572	0%
Delays post-processing (a)	4,814	699,982	14,440.55%
Advances per turn 1 (a)	81,100	81,100	0%
Advances per mill 1 (a)	19,330	19,330	0%
Advances per mill 2 (a)	10,375	10,375	0%
Advances post-processing (a)	110,805	81,875	-26.11%
Max delay per turn 2 (b)	3	3	0%
Average delay per turn 2 (b)	3	3	0%
Max delay per turn 3 (b)	17	17	0%
Average delay per turn 3 (b)	17	17	0%
Max delay per mill 1 (b)	9	9	0%
Average delay per mill 1 (b)	8.38	8.38	0%
Max delay per mill 2 (b)	13	13	0%
Average delay per mill 2 (b)	13	13	0%
Max delay post-processing (b)	17	125	635.29%
Average delay post-processing (b)	8.63	109	1,163.04%
Max advance per turn 1 (b)	10	10	0%
Average advance per turn 1 (b)	8.11	8.11	0%
Max advance per mill 1 (b)	9	9	0%
Average advance per mill 1 (b)	7.39	7.39	0%
Max advance per mill 2 (b)	9	9	0%
Average advance per mill 2 (b)	7.94	7.94	0%
Max advance post-processing (b)	10	13	30.00%
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); Max delay per turn 1 (b); Average delay per turn 1 (b); Max advance per turn 2 (b); Average advance per turn 2 (b); Max advance per turn 3 (b) values are zero both for optimized than stochastic simulation.

As shown in Table 4, 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 5, 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. Analyzing 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 5), and even worse is the scenario considering the OF_1, when the delay value arrives up to 141 days (see Table 4). 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 2,405% (i.e. 125 days) for OF_1 and up to 635.29% for OF_2.

CONCLUSION

The paper describes an SO decision-support tool developed for the fashion metal accessories' suppliers. The tool has been developed using an open-source solver (OpenSolver) and a commercial simulator (AnyLogic®), in order to be usable by these companies, and validated using a real production plan. The production plan of the company has been optimized using the solver with different OFs. The discrete-event simulator is used to validate and compare various scheduled production plans produced by the optimization tool, introducing internal and external stochastics elements.

First of all, the 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 that ones calculated through the optimization model on the Excel®.

Moreover, the impact of unexpected orders to be processed on the KPIs have been analysed using the simulation model, allowing to measure the gap between schedulation outputs considering just the minimization of costs and delays (OF_2) or also advances (OF_1) and results have been reported.

Future development of this work deals with firms' ERP integration in order to automatize the process of import of the production plan and the visualization of the scheduling results. Moreover, an in-depth analysis of the post-processing activities, modeled on the simulator as a unique block, will be conducted, and other business objectives, such as reducing processing time and leveling machines utilization, will be included in the OF.

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