Optimization for mixed model assembly lines: a case study in the fashion industry

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Abstract: The fashion industry is characterized by a fragmented production environment. The sector requires organizations to demonstrate a high degree of flexibility so they can respond to customer needs. Consequently, mixed-model lines are relevant, in which multiple models are produced by alternating production between different batches without any set-up.

Optimizing the sequencing of mixed-model assembly lines is crucial to ensuring their flexibility and efficiency. A sequencing problem involves the determination of the best sequence in which products should be introduced into production in order to meet the planned demand and achieve the objectives. Due to the operational level of decision-making for sequencing problems, they have a short-term planning horizon, as they involve considerations for plant floor activities and daily production results. Optimization tools often require high computational power to find the absolute optimum.

The purpose of this research is to present a flexible solution to the sequencing problem. A case study has been conducted based on first-hand observations of a company that manufactures bags as part of a luxury group. In this case, it is the preparation department that requires the most attention, like a mixed-model line. There were two stages to the implementation of the proposed case study model. The first phase involved the implementation of an Excel spreadsheet to define an optimized sequence using the evolutionary algorithm solver to optimize the department's mixed-model line. As part of the second phase, the simulation model was implemented and validated using real-life data. Consequently, the proposed sequencing model was validated, and the current situation was compared with the TO - BE scenario. Based on the results obtained from the implemented optimization tool, the sequence proposed by the tool improves the department's performance compared to the current situation in terms of productivity (+7,9%) and utilization (+5,7%).

Keywords: Optimization, Fashion, Assembly line

I. INTRODUCTION

The Fashion sector, in particular the Luxury segment, has always been one of the most relevant sectors of the market. Over time, it has evolved and taken on different forms until reaching the current conformation in which the most successful players are the large groups that include several brands within them, such as the Kering group and the LVMH group. The concept of "fashion" is a cross-cutting concept and undoubtedly applicable not only to the apparel industry but also to enterprises operating in diverse sectors, including leather goods, footwear, accessories, and jewelry (Bevilacqua *et al.*, 2013). A common element to all is that the sector to which they pertain is distinguished by the presence of both significant volatility and a lack of optimization. (Perret, 2022); therefore, creating a system to effectively improve performance is very important.

The fashion sector is predominantly focused on the agility to promptly respond to shifts in consumers' preferences, thereby heightening the urgency to condense time-to-market. Conversely, fashion patrons now demand an elevated level of service, especially concerning quality. (Fani, Bandinelli and Rinaldi, 2017). Within fashion production plants, it is important to be able to achieve the quality standards and the performance required by the organization in terms of performance since a company today must be able to understand its weaknesses and errors, to make forecasts on possible changes and quickly understand where, how and when to make the necessary changes to optimize its management system. To meet market demand, the enterprise has transitioned its production line from a single-line approach to a mixed production line (Wang *et al.*, 2022).

Despite the relevance of mixed-model assembly lines and their growing adoption in the fashion industry, there is still a significant gap in the literature regarding flexible solutions to the optimal sequencing problem. Existing solutions often require high computational power to identify the absolute optimum, limiting their practicality and applicability in an operational context with a short-term time horizon. This article aims to fill this gap by presenting a flexible approach to solving the sequencing problem. To this end, a case study was conducted in a company producing luxury handbags, focusing on the preparation department, which can be assimilated to a mixed model assembly line. The effectiveness of the proposed solution was verified through two phases of implementation of the proposed study model, both using an Excel spreadsheet optimized with the Evolutionary Algorithm to define an optimal sequence, and through the implementation and validation of a simulation model based on real data.

The paper is structured as follows: in the first section a review of the relevant literature is carried out. In the second section, the aims and objectives of the research and how they were addressed are described. In the third section, the results are presented in terms of implemented model and application to the case study with the results deriving from comparisons between current situation and TO - BE scenarios; finally, conclusions are presented.

II. LITERATURE REVIEW

It is possible to classify production lines also based on how many models are produced in a single line. There are three types related to this classification (Becker and Scholl, 2006): single model line, mixed model line and multi model line. They are represented in Figure 1 where each model is associated with a different geometric shape.

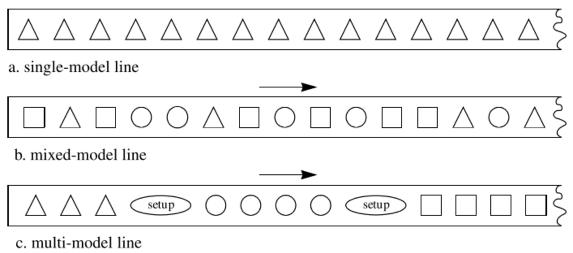

Figure 1. Assembly lines for single and multiple products (Becker and Scholl, 2006)

In the figure provided, three models are represented by different symbols, namely a triangle for model 1, a square for model 2, and a circle for model 3. The first case denoted as "a" represents a single-model line. These lines are specifically designed to efficiently produce large quantities of a singular product model. Moving on, the second scenario illustrated as "b" depicts a mixed-model line. In this case, several consecutive models are produced without any set-up between each model due to the presence of flexible resources. Lastly, the third case marked as "c" is a multi-model line. In such lines, production is based on the economic production batch, after which a mandatory set-up is required in order to change models. It is important to note that the difference between mixed model lines and multi-model lines is the requirement of a set-up to change models due to the lack of flexibility in the multi model line. Some of the main challenges that companies must address include the optimal design of the layout and the balancing of the production line(Meresa, 2018). For the optimization of a line, two main aspects can be considered: Balancing Problem, in which the tasks must be assigned to the stations (task allocation) in order to balance the workloads as much as possible and Sequencing Problem: optimal choice of sequencing of pieces to be assembled with respect to a pre-established company objective. In general, exist Generalized Assembly Line Balancing Problem (GALBP), belong to this category: Mixed-Model Assembly Line Balancing Problem (MALBP), Mixed-Model Sequencing Problem (MSP), U-line Balancing Problem (UALBP) (Razali *et al.*, 2019). Considering a mixed-model line, the Sequencing Problem, or the optimal sequencing, concerns the definition of the best sequence according to which the products are launched in production to satisfy the demand and achieve the planned targets. The distinction between balancing and sequencing problems is dictated by the planning horizon, balancing problems are medium-long term as they have as main objectives the installation of the line, rebalancing, or division of work in the various stations, representing high-level decisions with considerations on the strategic objectives of the company. The problems related to sequencing have a short-term planning horizon as they have as level of decision-making process the operational level with considerations on the production plant and daily production. Considering the mixed-model sequencing problem, some simplifying assumptions are therefore accepted fond in the literature, the main assumptions are that the line is already balanced in the best possible way depending on the type of balancing problem and the layout of the line is defined, as it is not advisable to intervene on it in the short term. Furthermore, it is necessary to define an objective function that must be optimized according to the objectives established by the company based on its needs and priorities.

The total number of sequences for a sequencing problem of a mixed-model assembly line can be calculated as follows:

$$\text{total sequences} = \frac{\left(\sum_{m=1}^{M} d_m\right)!}{\prod_{m=1}^{M} (d_m!)}$$

in which: M is the number of different models; m is the type of model and d_m is the demand of model m. As the size of the problem increases, the number of feasible solutions increases exponentially. Moreover, when considering the multi-objective nature of the problem, finding production sequences with desirable levels of all objectives is an NP-hard problem and for this kind of problem existing solutions often require high computational power to identify the absolute optimum,. (Akgündüz and Tunali, 2010).

The MSP approach, considering that some items require more labour time than others, determines the correct alternation of different types of products on the line in order to ensure the minimisation of free time at each station of the assembly line. Considering a particular example in the literature, the technique used to collect the data was called Bedaux. Each processing time was recorded ten times and then the standard time was evaluated. In the end, the standard time was defined as the recorded time plus an additional time considering: Increases for physiological factors, Increases for fatigue and Increases for contingencies. Once the cycle time of each product category had been defined, the optimisation plan was evaluated based on the following input data input: article code, type of storage unit (SKU), quantity required, date required (Fani, Bindi and Bandinelli, 2020).

Regarding sequencing, the optimisation of the production sequence in fashion assembly line environments, (Perret,

2022) considers this line of research. As fashion trend cycles are becoming shorter and shorter, delivery times are also getting shorter, and collections must be produced faster and more flexibly. While in the luxury segment this means that no longer only two collections are offered per year, but two to three times more, for the trend-oriented fast fashion segment this means that new collections are launched every few weeks. Production stations in the fashion industry, particularly in the labour-intensive segments, could be single people who can be 'rebalanced' much more easily than production equipment in the automotive industry. The first contribution in the literature that considered a joint balancing and sequencing approach, (Merengo, Nava and Pozzetti, 1999) was able to show that the balancing solution improves when knowledge of optimal sequencing results can be used in the production planning phase.

Thus, the main objectives for optimising the production line are related to line productivity, line properties, product quality and resource cost. The indicators to consider are takt time, line efficiency, number of workstations, cycle time, resource idle time, throughput, workstation saturation and line balance level is the key element to improve the performance of the production line (Xu *et al.*, 2017).

In general, optimisation methods can be classified into mathematical programming methods such as (Linear Programming-LP, Non-Linear Programming-NLP, Dynamic Programming-DP) and evolutionary or heuristic methods such as genetic algorithms and simulated annealing. Due to the difficulties in the mathematical modelling of the problem and the computational time required, evolutionary methods such as Genetic Algorithm (GA) are preferred over traditional mathematical programming approaches. GA uses mechanisms inspired by biological evolution, reproduction, mutation, recombination, and selection. Their application has largely reduced the computational time required to solve NP-difficult problems while maintaining the quality of the solutions obtained. For GA, the following are required: a method to measure the quality of a potential solution, a combination of solutions to generate new individuals in the population, and selection criteria to maintain or remove solutions in the search process (Ferro *et al.*, 2021) . For the fashion sector, only a few contributions have been found in the literature that deal with solving the sequencing problem such as Wang *et al.* (2022), propose the optimization simulation of hybrid assembly line of the production scheduling in garment enterprises using evolutionary algorithm, specifically a genetic algorithm combined with a simulation model, but does not consider the production batch size. Bevilacqua *et al.*,(2013) instead, consider lot size in their case study of a clothing company, but only use simulation without considering a precise optimization method. So, expanding the perspective to optimization works on sequencing problems in mixed model lines, regardless of their specific application to the fashion industry, various contributions can be found where the evolutionary algorithm is employed as the sequencing technique for a mixed model assembly line. Hence, in this research, it was chosen to focus on this particular approach.

III. OBJECTIVES OF THE RESEARCH

The aim of the fashion industry is to produce high-quality fashion products that meet the demands and expectations of consumers. Over recent years, the fashion product lifecycle has been noticeably reduced, and the number of fashion seasons has increased. Consequently, the industry has focused on the ability to rapidly respond to changes in customer preferences, intensifying the need to compress time-to-market. The trend towards product personalization has led to a high degree of variability within the industry. A critical challenge that arises in production facilities is the necessity of managing production lines, in terms of balancing and sequencing, to meet business objectives in performance areas such as lead time, production capacity, and timely delivery. In the fashion production plants there are purely manual assembly lines, as the industry requires highly skilled operators. Therefore, aside from the application of fundamental Lean Production concepts that are gaining traction in the sector, balancing and sequencing techniques are critical. The centrality of aligning production with business goals is fundamental to the provision of requisite flexibility to respond to market demands.

In order to maintain the benefits of efficiency that are associated with continuous flow production while also being able to produce a variety of products, mixed-model assembly lines are implemented. This strategy allows for the flexible and efficient production of different product types within a single production line, thereby reducing the need for multiple dedicated production lines. By utilizing mixed-model assembly lines, companies can achieve a balance between flexibility and efficiency, while still being able to satisfy the varied demands of their customers.

This research aims to propose a sequencing model for optimizing the mixed-model line in the preparation department of a leather goods company examined in the case study. This is motivated by the identification of critical issues resulting from the analysis of the plant. The proposed model is designed to identify the optimal sequence for the production process, with a particular focus on reducing lead time and increasing production capacity. To validate the proposed sequencing model, an AS-IS simulation model will be developed and validated using real data from the department. The model will incorporate the optimized sequence and deterministic times to evaluate its performance. A comparison will be made between the current and the TO-BE situations, considering stochastic times, to determine the effectiveness of the proposed model.

Initially, the case study company will be introduced, describing the features of the production plant and specifically the department that will be the focus of the project. Subsequently, the starting dataset, which forms the basis for the implementation of the model, will be presented. The implementation of the model, which is characterized by two steps, namely sequencing problem solved through evolutionary algorithm in Excel and simulation to validate the proposed tool, will be explained. The results will then be presented in terms of a comparison between the current performance of the department and the performance with the optimized sequence obtained from the simulation of the current situation and the TO-BE scenario.

IV. KEY FINDINGS

A. Case study

The present case study concerns a leather goods company owned by a fashion brand belonging to a renowned luxury group. The company specializes in the production of "Made in Italy" bags and is located within the district of Florentine leather goods, as both the plant headquarters and its respective suppliers are based in the area. The production facility operates from Monday to Friday, with hours from 8:00 a.m. to 5:00 p.m. Operators work a single 8-hour shift, with two 15-minute breaks, one in the morning and one in the afternoon, and a one-hour lunch break from 1:00 p.m. to 2:00 p.m. The plant employs 120 workers who produce approximately 950 bags per week. The quality of these bags is of paramount importance, as both the finished product and the raw materials used must meet excellent standards. Indeed, the products are subject to external testing to verify compliance with quality standards. The considered facility is structured into six main areas, namely:

- Warehouse (raw materials and finished products): it is the storage area of all the necessary raw materials (such as leather, linings, metallic accessories) to produce bags, as well as the related equipment, materials, and tools. Once the bags are assembled and packaged in the production line, they return to the warehouse where they are stored awaiting shipment.
- Cutting department: here the leather is cut and prepared for subsequent processing. In this department, the material is cut according to the specific requirements to produce various items.
- Shoulder strap department: it is the area where the shoulder straps of the various bag models are prepared and assembled.
- Kitting department: it separates the preparation area from the production lines and takes in the carts coming out of preparation that are distinguished by lot, giving as output the baskets for each single-model line.
- Preparation department: it is characterized by the fact that all models pass through it (mixed-model line).
- Five single-model lines.

This study focuses on the preparation department, which can be regarded as a mixed model line considering that all five bag models produced in the plant cross it. Splitting, skiving, gluing, assembling, and stitching are the production processes that characterise this department. The sequencing problem is constrained by the production cycle, in terms of the precedence of stations, while no priorities have been defined for the order in which the different production batches are scheduled. The processing times for each station vary for each bag model, except for models B and E, which have the same processing times for each station, at least for the preparation department, as they differ only in color. The mixed-model line is composed of 15 different stations in total. Each station is characterized by two types of resources: the workstation and the operator. As for the workstation, it can consist of a single machine (manual or automatic) or a set of machines that make up a work island where the operator resource moves to perform the various operations. One or more operators can be assigned to each station. It should be noted that not all models pass through all stations and that there is a clear distinction by model family in the last section of the department. Most stations work in series, with some exceptions working in parallel with others, identified by station numbers and decimal points (e.g., station 2.1 runs in parallel with station 2). Station 2 and 2.1 will start processing the batch in sync, while the leather components of the bag go to station 2 and reinforcements to 2.1. Only after the two second stations have completed their processing can the model be conveyed to station 3. This approach is also used for stations 4 and 4.1.

TABLE I. OVERVIEW OF THE PREPARATION DEPARTMENT

#Station	#Operator	Models
1	*1*	*A – B – C – D – E*
2	*1*	*A – B – C – D – E*
2.1	*1*	*A – B – C – D – E*
3	*1*	*A – B – C – D – E*
4	*2*	*A – B – C – D – E*
4.1	*2*	*A – B – C – D – E*
5	*1*	*A – B – C – D – E*
6	*2*	*A – B – C – D – E*
7	*1*	*A – C*
8	*1*	*A – B – C – D – E*
9	*1*	*B – E*
10	*1*	*B – E*
11	*1*	*B – E*
12	*1*	*B – E*
13	*1*	*A – C – D*

The primary challenge detected in the preparation department concerns the lead times of diverse production batches. In practice, lead time is the amount of time required for bags to pass through the preparation department. This is comprised of the sum of the processing times, namely the time allocated for the batch to be processed at each station, along with any waiting times that the batch may have to endure in order to be processed at that station.

B. Dataset

To define the AS-IS state and subsequently implement the TO-BE model for the preparation department, it was necessary to gather a comprehensive dataset that accurately reflected the department's operations. The first step involved mapping the production flows and conducting ten-time measurements at each station for each model to determine processing times. Subsequently, the resulting database was subjected to outlier analysis, where any observations deviating significantly from the normal range were deemed outliers. Such deviations could be attributed to unforeseen events during the measurements, which may have resulted in prolonged processing times beyond the normative conditions. This analysis was performed for each station and model, using the probability plot technique within the Minitab statistical software. It was determined that a P-value greater than 0.05 was achieved, indicating that the collected data conformed to a Gaussian distribution and that the values were normally distributed.

C. Model implementation

The proposed model for the case study was implemented in two phases. In the first phase, an Excel spreadsheet was developed to define a daily sequence of model launches for the mixed-model line of the preparation department. The problem was formulated and solved using an evolutionary algorithm in the solver. Based on the findings of the literature review, evolutionary methods were chosen as they provide a satisfactory solution to the problem that is not guaranteed to be optimal but is still computationally feasible. In the second phase, the simulation model was implemented using the AnyLogic software to represent the preparation department's production line, aiming to validate the Excel model and understand the impacts of stochastic processing times by comparing the proposed solution with the current situation. The Excel model was implemented by considering the deterministic average processing times for each workstation and production batch and the technological precedence of each workstation. The average processing times per batch were reported in the Excel spreadsheet as the number of bags in each batch was left variable in the model implementation. The establishment of the Excel spreadsheet involved formulating assumptions, which were derived from relevant literature. The salient assumptions are as follows:

- The production line is already balanced according to the best possible approach for the specific type of balancing problem at hand (i.e., 18 operators, 15 stations, processing time for each-model/station).
- The layout of the production line is defined, and any short-term interventions are not recommended.
- Each workstation can process only one lot at a time.
- The first-in-first-out (FIFO) rule governs the queues.
- If a lot cannot move to the next station after completing processing at a particular station because that station is still occupied, a waiting time will ensue.
- The processing times are considered deterministic.
- The times for operator movements are ignored.

The quantity of bags within a production lot is left as a variable, as well as the model that will be scheduled during the daily launches. Therefore, the decision variables will be as follow, x_s, which represents the bag model associated with its respective processing time and y, which represents the quantity of bags that the production lot can be composed of.

Regarding the constraints: $1 \leq x \leq 6$, where: 1 represents model A, 2 represents model B, 3 represents model C, 4 represents model D, 5 represents model E, and 6 represents a dummy model with all processing times equal to 0, which was introduced to facilitate the spreadsheet setup. $5 \leq y \leq 10$, where 5 and 10 were chosen as possible limits within which to vary the production lot size. For each workstation defined in the model, the following constraint was imposed: $\sum_{s=1}^{S} PT_s \leq 27000\ seconds$ where PT_s are the processing times of the model launched in scheduling "s", with s ranging from 1 to S (the last scheduling of the day), and 27000 seconds representing the maximum daily working time of the workstation (30 minutes for morning and afternoon breaks and 1 hour for lunch breaks were subtracted from the plant opening hours). In addition, a constraint was imposed on the production mix, considering the need to produce the bags that allow reaching the TO-BE production target of the assembly lines.

TABLE II. DAILY PRODUCTIVITY TARGET

Model	AS-IS	TO - BE
1	*40*	*40*
2	*40*	*40*
3	*40*	*45*
4	*40*	*45*
5	*30*	*35*

The objective function (OF) considers idle time at the workstations as well as waiting time at the lot. This OF is designed to minimize these two factors in order to increase production and reduce the lead time for the various models in the department.

$$OF = min\,(\sum_{p=1}^{P} Idletime_p + \sum_{p=1}^{P}\sum_{s=1}^{S} WT_{ps})$$

where P denotes the last workstation in the department, and S denotes the last daily scheduling. Then starting from the sequence of the current situation, by launching the solver with the "Evolutionary" resolution method and all constraints set, an optimized solution was obtained. The Evolutionary Algorithm is not a custom development, but is directly embedded in Solver Excel, with the aim of using a tool available on the market and not built ad hoc by the authors.

However, it is not guaranteed that the obtained solution is the absolute optimum, as observed in evolutionary methods reported in the literature. Indeed, suboptimal solutions can be found with these methods, which still provide room for improvement compared to the initial solution and are compatible with the required computational capabilities. During the second phase, the simulation model was implemented to validate the Excel model and to determine the impact of stochasticity on processing times by comparing the proposed solution with the current situation. The simulation model was developed using the AnyLogic software with the aim of replicating the operations of the manufacturing department analysed in the case study. The production flow diagram was used as the starting point for the model development, and objects were subsequently created to represent the department in AnyLogic.

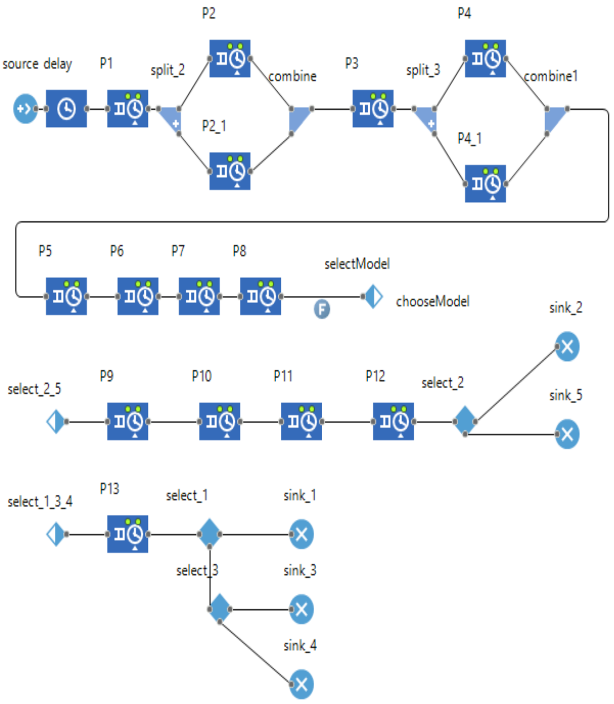

Figure 2. Department structure developed in AnyLogic

In order to determine the warm-up time of the simulation model and subsequently validate its performance, the following key performance indicators (KPIs) were chosen Utilization of the production department and Productivity. The validation of the simulation model was carried out by comparing the actual performance values with those obtained from AnyLogic.

D. Results

As a result of the solver, the following is the optimized sequence: $x_2 - x_2 - x_3 - x_2 - x_3 - x_2 - x_1 - x_2 - x_1 - x_2 - x_1 - x_4 - x_3 - x_2 - x_2 - x_3 - x_4 - x_3 - x_5 - x_1 - x_4 - x_5 - x_4 - x_3 - x_4 - x_5 - x_3 - x_5 - x_1 - x_4 - x_5 - x_1 - x_5 - x_4 - x_3 - x_4 - x_4 - x_1 - x_5 - x_3 - x_1$.

TABLE III. TO - BE SEQUENCE SUMMARY

Model (x)	#Bag in batch (y)	#Bag produced
x_1	5	40
x_2	5	40
x_3	5	45
x_4	5	45
x_5	5	35

TABLE III shows that the optimized sequence achieves TO-BE productivity targets and reduces the production batch size from 10 to 5 bags in comparison to the current situation. With respect to the validation of the simulation model, a comparison was drawn between the performance values obtained from the actual department and those obtained from the model implemented in AnyLogic. The key performance indicators (KPIs) extracted from the real department's performance included the utilization of the department, which was 75.76%, and the daily productivity, which was 189.4 bags. To validate the KPIs derived from the simulation model in AnyLogic, a one-sample t-test was conducted using the MiniTab software. A P-value greater than 0,05 is obtained to confirm the acceptance of the null hypothesis (H_0: $\mu = \mu_0$) so that the historical data and the simulated AS-IS model are comparable and supporting the assertion that the AS-IS simulation model was validated with 95% confidence. The simulation model and its performance can be used as a reference for validating the Excel-based model and the performance of the TO-BE situation. An initial comparison was conducted by replicating the conditions implemented in Excel on the simulator. The results demonstrate that there are no discrepancies between the AnyLogic and Excel-based models. Therefore, it can be concluded that the optimized sequencing model's logic is valid. Subsequently, the TO-BE scenario was implemented in the simulator using the optimized sequence as input and reintroducing the stochasticity of times. The statistical significance of the TO-BE scenario was evaluated by analysing the same KPIs previously used to validate the AS-IS model. To conduct this analysis, a two-sample t-test was performed using the MiniTab software.

TABLE IV. COMPARISON OF KPIS BETWEEN CURRENT AND FUTURE SCENARIOS.

	AS – IS	TO – BE
Department utilization	*75, 9 %*	*81,6 %*
Daily Productivity	*190 bags*	*205 bags*

From TABLE IV, it is evident that the KPIs evaluated in the TO-BE scenario are significantly higher than those calculated in the AS-IS scenario, indicating that performance has improved. Additionally, the mean lead times for each bag model were evaluated by extracting them from the simulation model's logfile. The theoretical lead time, on the other hand, was calculated by summing the processing times of the stations through which the model traverses, assuming that the production batch is continuously being processed without waiting. The mean waiting time was computed as the difference between the average lead time for that model and its corresponding theoretical lead time. A percentage of waiting time was also defined as the proportion of time that the model spent waiting based on the average lead time. These results are presented in order to compare the current situation with the TO-BE scenario.

TABLE V. COMPARISON OF % WAITING BETWEEN THE CURRENT AND FUTURE SCENARIO.

Model	%Waiting AS – IS	%Waiting TO – BE
x_1	*15 %*	*14%*
x_2	*33 %*	*30 %*
x_3	*24 %*	*18 %*
x_4	*32 %*	*28 %*
x_5	*34 %*	*31 %*

From TABLE V It is noticeable that the waiting percentages in the future scenario have decreased by at least one percentage point, ultimately leading to a reduction of six percentage points for model 3.

V. CONCLUSION

This study presents a model for optimizing the production sequence in a mixed-model line applied to a specific case study. According to this, the aim of the work is to find a flexible tool for solving the sequencing problem, specifically in a mixed model line. By implementing an Excel-based model and validating it through simulation, the study aimed to enhance the current situation by devising a novel daily launch sequence for handbag models. The two-step approach, involving Excel-based modelling and simulation, ensured the reliability and accuracy of the proposed model by incorporating both deterministic and stochastic factors. The improvement in departmental performance with the optimized sequence compared to the current situation is demonstrated. The implemented model can be used in the company for planning the sequence entering the preparation department. In case there are changes in the department's structure, such as in terms of station precedences and processing time, it is necessary to update it. It is, however, essential to conduct a secondary simulation step to understand the real trend of KPIs with the obtained sequence launched over a longer time horizon than a day and considering processing time with the related statistical distributions. The utilization of evolutionary algorithms in sequencing problem of mixed model assembly line highlights their suitability for addressing similar optimization challenges in various manufacturing environments.

In conclusion, this study contributes to the literature on production optimization by emphasizing the effectiveness of evolutionary algorithms in addressing the challenges associated with model sequencing within mixed-model production systems, even in the fashion industry. The results confirm that the combination of evolutionary algorithm and simulation can identify sequences that can considerably increase the productivity of a plant.

The main limitation concerns the construction of the simulation model, in which data-driven logic is absent in addition to the lack of functions built ad hoc in the Java language.

It is possible that future research efforts will focus on further refinement of the proposed approach, considering additional factors such as stochastic variability and real-time adjustments to optimize model sequencing. The main future development to be considered involves handling the entire problem on the simulator, having the sequence analysis solved by the optimizer in Anylogic. Another future development may be the application of this study in other areas characterized by mixed-model production systems.

The main advantage is that by making the model data-driven and handling the sequencing on the simulator, it is possible to reduce the time for changes and modifications, as well as making the software more user-friendly.

VI. REFERENCES

[1] Akgündüz, O.S. and Tunali, S. (2010) 'An adaptive genetic algorithm approach for the mixed-model assembly line sequencing problem', *International Journal of Production Research*, 48(17), pp. 5157–5179. Available at: https://doi.org/10.1080/00207540903117857.

[2] Becker, C. and Scholl, A. (2006) 'A survey on problems and methods in generalized assembly line balancing', 168, pp. 694–715. Available at: https://doi.org/10.1016/j.ejor.2004.07.023.

[3] Bevilacqua, M. *et al.* (2013) 'Designing an efficient production system: A case study of a clothing company', *International Journal of Engineering Business Management*, 5(SPL.ISSUE), pp. 1–8. Available at: https://doi.org/10.5772/56842.

[4] Fani, V., Bandinelli, R. and Rinaldi, R. (2017) 'A simulation optimization tool for the metal accessory suppliers in the fashion industry: A case study', *Proceedings - 31st European Conference on Modelling and Simulation, ECMS 2017*, 6(Cd), pp. 240–246. Available at: https://doi.org/10.7148/2017-0240.

[5] Fani, V., Bindi, B. and Bandinelli, R. (2020) 'Balancing assembly line in the footwear industry using simulation: A case study', *Proceedings - European Council for Modelling and Simulation, ECMS*, 34(1), pp. 56–64. Available at: https://doi.org/10.7148/2020-0056.

[6] Ferro, R. *et al.* (2021) 'An optimization tool for production planning: A case study in a textile industry', *Applied Sciences (Switzerland)*, 11(18). Available at: https://doi.org/10.3390/app11188312.

[7] Merengo, C., Nava, F. and Pozzetti, A. (1999) 'Balancing and sequencing manual mixed-model assembly lines', *International Journal of Production Research*, 37(12), pp. 2835–2860. Available at: https://doi.org/10.1080/002075499190545.

[8] Meresa, A. (2018) 'Optimal Layout Design by Line Balancing Using Simulation Modeling (Case Study on MAA Garment and Textile Factory)', *Journal of Optimization in Industrial Engineering*, 11(1), pp. 1–14.

[9] Perret, J.K. (2022) 'A simultaneous balancing and sequencing algorithm to plan assembly lines in the fashion industry', *Research Journal of Textile and Apparel* [Preprint]. Available at: https://doi.org/10.1108/RJTA-04-2022-0045.

[10] Razali, M.M. *et al.* (2019) 'Recent trend in mixed-model assembly line balancing optimization using soft computing approaches'. Available at: https://doi.org/10.1108/EC-05-2018-0205.

[11] Wang, D. *et al.* (2022) 'Optimization Simulation of Hybrid Assembly Line Production Scheduling in Garment Enterprises', *IEEE 6th Information Technology and Mechatronics Engineering Conference, ITOEC 2022*, pp. 1375–1379. Available at: https://doi.org/10.1109/ITOEC53115.2022.9734580.

[12] Xu, Y. *et al.* (2017) 'Comprehensive evaluation of garment assembly line with simulation', *IOP Conference Series: Materials Science and Engineering*, 254(16). Available at: https://doi.org/10.1088/1757-899X/254/16/162013.