


Article

Production Scheduling of Personalized Fashion Goods in a Mass Customization Environment

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Abstract: The COVID-19 pandemic has put fashion manufacturers' needs for optimization in the spotlight. This study argues that mass customization is becoming increasingly instrumental for offering consumers individualized solutions and that suppliers of fashion have to look for more sophisticated solutions in order to face the increasing demand for more sustainable products. With the deduction of a mathematical model derived from production sequencing it became evident that sustainability can be associated with a level production schedule and that cost-based production optimization is useful in achieving holistic sustainability in the fashion industry. The flexibility in the conceived mathematical model specifications allows for a generalizable approach, not limited to a single branch of the fashion industry. This paper additionally delivers a cost-based optimization approach which fashion companies, operating in a mass customization production layout, can easily implement without extensive know-how. The proposed two-stage algorithm is based on the concept of level scheduling. In a first stage, the algorithm determines a feasible production sequence in a time-efficient way while, in the second stage, it further advances the efficiency of the solution. Thus, it offers a framework to optimize a production in a mass customization environment and can contribute to a company taking major steps towards a holistic sustainable orientation as available resources are used more (cost) efficiently.

Keywords: mass customization; optimization; algorithm; production scheduling; fashion production; level scheduling



Citation: Perret, J.K.; Schuck, K.; Hitzegrad, C. Production Scheduling of Personalized Fashion Goods in a Mass Customization Environment. *Sustainability* **2022**, *14*, 538. <https://doi.org/10.3390/su14010538>

Academic Editor: Alessandro Brun

Received: 24 November 2021

Accepted: 21 December 2021

Published: 4 January 2022

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1. Introduction

The voices for transformation of the fashion industry have become louder for years and it was the COVID-19 pandemic that provided the long overdue impetus for change [1,2]. The lockdown phases disrupted entire supply chains and resulted in comparably small product volumes being sold [3]. Especially the fashion industry came under pressure as they are guided by customer demand and usually plan far in advance [4,5]. Due to these restraints, many companies decided not to pay for pre-produced goods and to stop orders—and with it, the resources of income of many supply chain partners drained. This put a number of firms involved in an extremely difficult situation due to the dependency relationship that had been built up for years [6]. Hence, the pandemic can be understood as a catalyst in bringing the fashion industry and its manufacturing practices back into the managerial spotlight.

In garment production, there are different production formats ranging from pure mass production of identical pieces to completely customized products, made to consumers' orders and measurements. The various gradations harbor both opportunities and threats for manufacturers [7,8], resulting in the need of carefully outweighing which customer integration and personalization options should and could be offered from a strategic and operational perspective. Within these production formats, the layouts can also be different:

mass production is carried out on a flow-shop schedule using assembly lines, whereas fully customized products are manufactured on a job-shop schedule with mostly individual workstations [9]. Therefore, the chosen layout of mass customized production is strongly related to the respective level of customization and could vary between individual stations and assembly line layouts [10–12].

Literature discussing fashion manufacturing is mainly focused on the social and environmental responsibility of the supply chain [13–16] and considered the workers involved [17,18] and the materials used [19,20]. Authors also thematized the supply chain in context of production layouts and mainly concentrated on mass customization (MC): in recent years, various brands adopted MC offerings to their portfolios and allowed customers to participate in the design process [21,22]. Scientific elaborations on MC fashion significantly focused on customers and investigated the extent to which customer involvement increases simultaneously with fashion brands' MC offers [23–25]. Findings on the brand and supply chain perspectives are limited. Choi and Guo [26] addressed the customer return stage and found that reaction time and flexibility are essential success factors within MC concepts. Authors also focused on the inclusion of technologies, i.e., 3D printing or RFID techniques [27]. Yeung et al. [8] highlight prerequisites for innovative MC in the fashion segment. Liu et al. [21] add an elaboration of opportunities and threats arising from MC. Shen and Chen [28] provide a case study that covers waste reduction in the fashion industry in different stages, although valuable in itself, their study reflects a more qualitative approach, excluding the optimization perspective.

Nevertheless, more detailed findings on individual fashion supply chain parts and possible optimization approaches for the production process of fashion articles in a MC environment are still to be delivered. The pandemic has once again emphasized that the production of many fashion items—primarily fast fashion—is socially and ecologically problematic and, thus, brought the issue of sustainability in fashion more into focus. This view not only affected fashion consumers' behaviors, but came along with important impulses for the production process [29,30]. Sustainable fashion production refers to environmentally friendly and socially responsible processes, but also strongly requires a minimal waste approach. To achieve this target, it is both imperative that the individual process steps are designed as efficiently as possible and that the entire supply chain is optimized [31]. This can only be realized step by step and requires much effort. To reach this increase in efficiency and also to contribute to the limited scientific literature base of the fashion production process, this paper deals with a production optimization approach for MC fashion manufacturers. Although Fani et al. [32] and Fani et al. [33] are among the few to consider MC in the fashion industry from an operational research point of view, they only consider a particular part of it and do not aim to model or solve problems aimed at the full scope of the final assembly. Additionally, even though they aim at providing management support, both studies propose a simulation rather than an optimization tool. This is where this study fills the existing gap in the literature because it provides a novel approach to production planning in the fashion industry, as well as applies existing production sequence optimization approaches.

Although multiple production layouts in a MC environment are possible (flow shop [34], job shop [35], or assembly line [36]), this paper assumes an assembly line layout. An assembly line optimization not only allows for a broad literature basis to draw upon [37–39] but also offers a more flexible approach. Considering the complexity of production sequencing problems, the use of a heuristic solution approach as motivated by Boysen et al. [40] or more recently by Zhang et al. [41], is considered an appropriate tool to provide management support.

Note that further supply chain components, such as material extraction, delivery, or customer contact were not considered as the paper targeted a purely operational view of the manufacturing process. Consequently, the problem modeling and the deduced solution approach aim to be rather general and give decision makers the option to adjust them to their particular case.

Structurally, it will proceed as follows: First, a background on fashion production will be provided. Following this, production scheduling in the fashion industry will be discussed in more detail which leads to the optimization approach. Lastly, a short discussion summarizes the main findings, leaving implications and suggestions for further research.

2. Production in the Fashion Industry

The basis for the development of an optimization approach for MC fashion production builds the consideration of the different production types and their respective characteristics. In fashion production, there are three production types that have become established: mass production, custom tailoring, and MC. A list of the most important aspects and differences between these concepts can be seen in Figure 1. In the further course of this paper, however, only the MC production type will be discussed in detail.

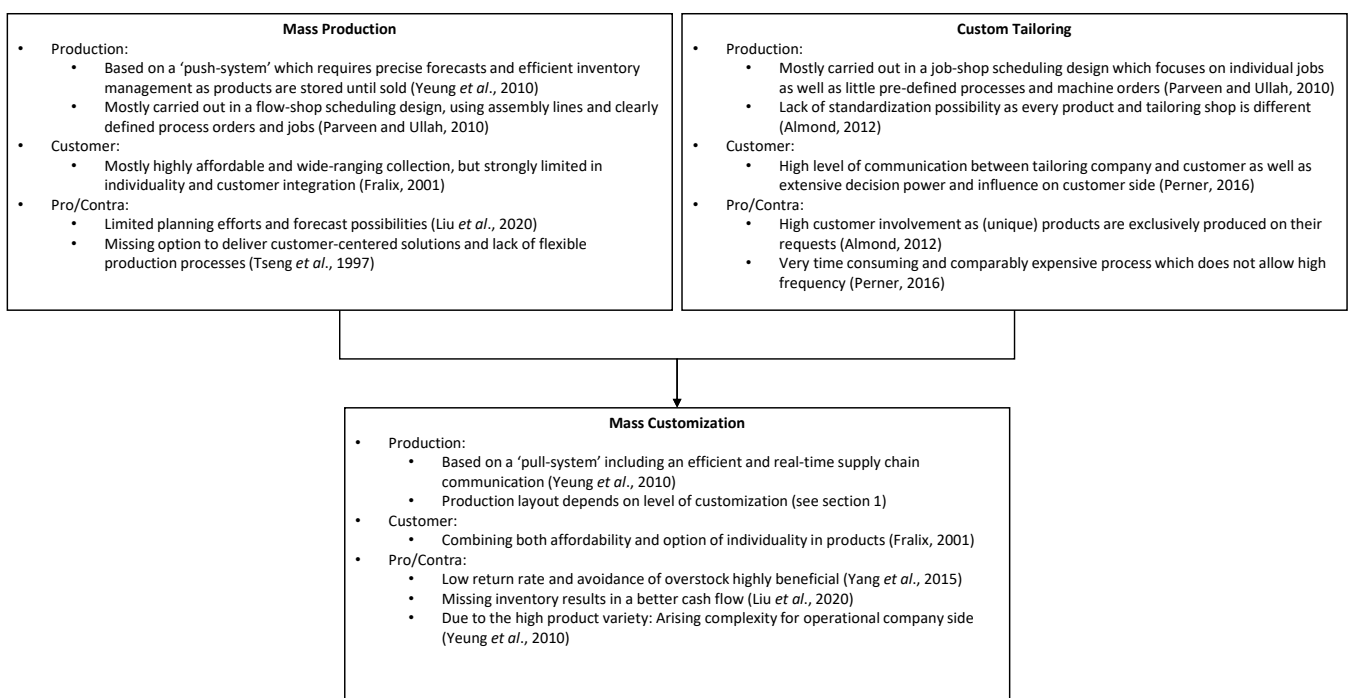


Figure 1. Overview of the three production types in the fashion industry.

As the fashion industry is characterized by trends and changing consumer desires, MC represents a suitable and promising concept [21]. MC is based on a pull-principle, meaning that the number of mistakes in sales forecasting drop, whereby the markdown and finished product inventory is considerably lower. These aspects are especially relevant for the fashion industry [8]. Furthermore, MC may offer the incorporation of both economies of scale and scope. Therefore, it combines the low-cost benefit with the product targeting simultaneously as mass production and custom tailoring are only reflecting one of each [42].

Although aiming for a successful MC production, flexibility and responsiveness are crucial factors [43]. Further, supplier relationships are essential drivers as trust, cooperation, and integration are increasingly important when operating MC. Inventory management faces the challenge of balancing demand and supply. Simultaneously, MC tries to accomplish a short lead time, wide variety, and low costs. A synchronized inventory management supports the coordination of inbound and outbound logistics. Postponement describes the system of storing semi-finished products which have been produced, i.e., using modules. Thereafter, the customization takes place when customers' needs are known. This principle enables firms to improve responsiveness and flexibility as they could outsource material

and production related operations. However, postponement would only be possible if the production site is located nearby which is currently rarely given in the fashion industry [8].

Moreover, the implementation of modularity is essential for a successful MC production, i.e., components can be separated and recombined in times of rapid changes [21]. Additionally, modularity leads to cost reduction and enhanced product variety based on customer requirements [42,44]. Generally, both product and process modularity exist: By applying product modularity, products can easily be configured through the incorporation of independent modules, whereas process modularity is based on the principles of process standardization, postponement, and re-sequencing. Furthermore, modularity holds opportunities for manufacturers and customers because it supports the configuration process through service and usability. Further, it increases flexibility for manufacturers as they might offer more variety in the end product whilst decreasing the component variety. Regarding modularity implementation, computer and automotive companies can be mentioned as leaders [8].

For MC concepts, technology is crucial as it allows communication between supply chain partners while pushing the information flow from customer to producer. If this process runs efficiently, lead times can be reduced. Additionally, flexibility and responsiveness towards the customer can be enhanced which is essential in this industry [8]. Guo et al. [45] consider critical aspects of MC supply chains in detail and particularly mention the use of new technologies and the standardization of modules as means to tackle the inherent complexity of MC supply chains. Due to the high labor intensity in fashion productions, their level of technology adaption is currently quite low [8] which—with regard to efficient MC—requires adaption: The range of efficient technologies reaches from 3D scanning systems, virtual reality, and digital pattern design to RFID-technologies [21]. A more detailed description of possible technologies is offered by Liu et al. [21].

In addition to these aspects, Alptekinoglu and Örsdemir [46] and indirectly also Shen and Chen [28] advocate the approach that MC supports sustainability efforts of fashion companies, resulting in a win-win situation for brands and consumers. It is especially the ‘Lean Management’ concept, firstly implemented by the automotive manufacturer Toyota in 1970 [47,48], that accompanies promising approaches for enhancing MC performance and contributing to sustainable orientation [21]: It is categorized as the management system with the least occurring waste sources [49] and, as the avoidance of waste during the production process is not only long-term goal in operations research but also leads to better resource management in the production, it can be highly beneficial in aligning the company to sustainable values. Although the optimization perspective of the Toyota Production System is currently only covered in few contributions [32,33], the quality focus is continuously moving to the front.

3. Production Scheduling in the Fashion Industry

Although flow shop [34] or job shop [35] based scheduling provide valuable insights for production scheduling in the fashion industry, Section 5 deduced that especially level scheduling—as derived from the Toyota approach—is ideally suited to cope with sequencing production running on assembly lines in a MC environment [50]. Since its inception, the ‘Toyota Production System’ has strived to level the production of multi-variant production lines. Although assuming that each variant consumes approximately the same parts and raw materials—by keeping the distribution of the different variants across the production sequence as even as possible—the part usage becomes a level as well. A level production sequence will automatically reduce work overloads and uneven part requirements, allowing for the use of averages regarding takt times and order quantities. It is the last aspect that is a prerequisite for an efficient just-in-time production and will result in better supplier relations.

In a typical MC environment, the number of possible variants will be much higher than a classical level scheduling algorithm can cope with, especially if it has to perform in real time. VANS’ customizing platform currently allows approximately 67.3 quadrillion

different variants (excluding the shoe size) [51]. However, only few are actually realized. To overcome this problem in the automotive industry, the car sequencing approach has been developed [52]. Instead of treating each variant as a unique entity, it is split into features. In the case of VANS, there are twelve unique features. Each feature—such as the front flap of a shoe—has a given set of attributes, representing the state a feature can take. The current VANS customizer allows between 2 and 122 possible attributes for each feature [51]. Each job, representing a single variant, is thus treated as a bundle of features, with each feature realizing a unique attribute. Although implementing this modular design and working with features and attributes, one can get rid of the assumption that each variant requires approximately the same number of parts and it enables a more detailed leveling of real attribute-based leveling of part requirements. Even though this feature-based perspective has only been transferred into the area of classical level scheduling in the last decade [36], due to its higher degree of realism, it is adopted by the present elaboration.

After illustrating the underlying structure of the optimization problem at hand, waste sources possibly occurring in MC productions can be discussed. Since working with a single objective (function) allows working with standard optimization tools, all waste sources are determined in a financially measurable way, i.e., in monetary units. A modular approach gives decision makers the potential to assign weights to the waste sources, reflecting their assessment of each source's importance. In a modular optimization approach, multiple oftentimes conflicting objectives need to be considered simultaneously. In this regard, the idea of a 'Pareto-optimal boundary' can be introduced: For each solution on the boundary, no objective can be enhanced without reducing the state of another objective. Thus, by switching to a multi-objective optimization approach, the decision maker can select the single solution that mostly concurs his situation assessment and can choose from all solutions on the Pareto-optimal boundary.

Regarding the waste sources, the first source covers the work overloads. Literature discusses three main treatments of work overloads: Shutting down the assembly line until the work is completed, the use of floaters that can step in at critical stations, or the ejection of the unfinished products to be finished on the side and their reintroduction into the production sequence at a later stage. The first approach cannot be considered realistic in the context of the fashion industry with low-margin products. The third approach would not only complicate the optimization problem as such, but it would also be very impractical in its realization as it would prevent the production flow from an uninterrupted run. Thus, this study treats work overloads via the use of floaters. Floaters are actual (or theoretical) employees trained in performing a certain number of tasks. In a production line, they are employed whenever a work overload occurs. By calculating floaters' active times on the line and their wages, work overloads can be measured in monetary terms. Even though floaters would not realistically receive salary solely for their active time, the focus of this elaboration lies on putting a monetary value on work overloads which is why this simplistic treatment of floaters suffices.

Table A1 in the Appendix A summarizes the quantities used in the mathematical model motivated below. Additionally, for each quantity, the unit in which it is measured is given. (T—time unit, M—monetary unit, P—number of parts).

Production costs caused by theoretical floater deployment due to work overloads at the stations

$$\bar{s} = \{s \mid w_{s,t} > 0\} \quad (1)$$

$$\text{OVERLOAD}(X_{t,j}) = \sum_{p=1}^P c_p \cdot \sum_{t=1}^T \sum_{j=1}^J \sum_{s=\bar{s}}^S F_{j,p,s} \cdot X_{t,j} \quad (2)$$

Considering the objective of reducing required inventory space, one has to differentiate between inventory space for final products and inventory space at the assembly line to store parts [40,53,54]. The second aspect is particularly critical since it might have strategic implication regarding the overall size of the production facility.

Inventory costs incurred by materials and preliminary products provided at the line

$$\text{CONTINV}(X_{t,j}) = \sum_{p=1}^P \left(c_p \cdot \sum_{s=1}^S \sum_{t=1}^{T+S-1} l_{p,t,s} \right) \quad (3)$$

Inventory costs caused by finished products

$$i_j = \left\{ \bar{i} \mid \sum_{k=1}^{\bar{i}-1} m_k \leq j \leq \sum_{k=1}^{\bar{i}} m_k \right\} \quad (4)$$

$$\text{FININV}(X_{t,j}) = \sum_{j=1}^J \sum_{p=1}^P c_p \cdot \sum_{s=1}^S F_{j,p,s} \cdot \max \left(0, t_{ij}^U - \sum_{t=1}^T (X_{t,j} \cdot t) - S \right) \quad (5)$$

Although the reduction in lead times represents a rather strategic issue (as discussed in the context of assembly line balancing), the reduction in tardiness of orders complements the reduction in lead times from an operative point of view. Thus, it is included as a fourth component.

Tardiness costs caused by late requests

$$\text{TARDI}(X_{t,j}) = \sum_{j=1}^J \sum_{p=1}^P c_p \cdot \sum_{s=1}^S F_{j,p,s} \cdot \max \left(0, \sum_{t=1}^T (X_{t,j} \cdot t) + S - t_{ij}^U \right) \quad (6)$$

Lastly, supplier relations (in a slightly reduced fashion compared to the first and second part of the objective function) benefit from a smoother more level use of different parts. This problem is automatically solved if all variants require approximately the same parts. Nevertheless, if this is not the case, it requires special consideration in consequence [37].

Costs related to an unbalanced part usage

$$\text{SMOOTH}(X_{t,j}) = \sum_{p=1}^P c_p \cdot T \cdot \max_{g=1, \dots, T/Z} \left(\sum_{j=1}^J \sum_{s=1}^S \frac{F_{j,p,s}}{T} \cdot g - \sum_{s=1}^S \left[\frac{\sum_{t=(z-1)Z+1}^{zZ} l_{p,t,s}}{G_p} \right] \cdot G_p \right) \quad (7)$$

All waste sources described are expressed through their monetary costs. Thus, their summary yields the overall costs generated by a given sequence $X_{t,j}$ and, as such, the relevant total objective function. In addition to the objective function, a set of thirteen constraints is required to achieve an optimal production sequence. Constraints (9), (11) and (20) ensure that all jobs will be scheduled correctly while constraint (10) excludes previous or succeeding shifts. If a rolling production schedule is to be considered, constraint (10) needs adjustment according to both the report of the previous shift and the one at the beginning of the succeeding shift. Additionally, constraint (21) which assures that the shift starts with an empty assembly line would have to be adjusted.

Constraints (12), (13), (14) and (19) are standard constraints, required to calculate work overload and thus, have to be described for the first part of the objective function. In analogy to Scholl [55], restriction (12) ensures that a unit cannot be processed before the preceding unit's completion. Constraint (13) makes sure that work is restricted to the respective station area and assumes workers being limited to their station. At this point, it would also be necessary to calculate required floater capacities. Additional to constraint (12), constraint (14) addresses non-negativity requirements and limits workers to the lower bound of their assigned station. Lastly, (18) assumes that the assembly line starts and finishes in its initial state, i.e., with workers being situated at the beginning of their stations.

A station's space constraints are reflected in (17) whereby it is assumed that all containers used are equally sized and that the station U_s —as the number of maximum containers—is the limiting factor. Considering G_p , a container may however include a different quantity

per part. If different container styles are to be implemented, (17) may be mirrored for each type of container.

The constraints (15), (16) and (18) impose capacity constraints on the part inventory. In contrast to publications like Boysen et al. [40], this approach allows the ordering of more than one container at a time. Although (16) considers the initial situation, constraint (15) is required for the correct calculation of inventory levels on the line, whereas constraint (18) is needed for integrality and non-negativity of the number of parts. The following section shows solution $X_{t,j}$ and the constraints (8) to (21):

$$\min C(X_{t,j}) = \text{OVERLOAD}(X_{t,j}) + \text{CONTINV}(X_{t,j}) + \text{FININV}(X_{t,j}) + \text{TARDI}(X_{t,j}) + \text{SMOOTH}(X_{t,j}) \quad (8)$$

so that

$$\sum_{j=1}^J X_{t,j} = 1 \quad \forall t = 1, \dots, T \quad (9)$$

$$\sum_{j=1}^J X_{t,j} = 0 \quad \forall t = 1 - S, \dots, 0; t = T + 1, \dots, T + S - 1 \quad (10)$$

$$\sum_{t=1}^T X_{t,j} = 1 \quad \forall j = 1, \dots, J \quad (11)$$

$$g_{s,t+1} \geq g_{s,t} + \rho_{s,t} - w_{s,t} - C \quad \forall s = 1, \dots, S; t = 1, \dots, T + S - 2 \quad (12)$$

$$g_{s,t} + \rho_{s,t} - w_{s,t} \leq L_s \quad \forall s = 1, \dots, S; t = 1, \dots, T + S - 1 \quad (13)$$

$$g_{s,t} \geq 0; w_{s,t} \geq 0 \quad \forall s = 1, \dots, S; t = 1, \dots, T + S - 1 \quad (14)$$

$$I_{p,t+1,s} = I_{p,t,s} - \sum_{j=1}^J (X_{t+2-s,j} \cdot F_{j,p,s}) + y_{p,t+1,s} \cdot G_p \quad \forall t = 0, \dots, T + S - 2; p = 1, \dots, P; \\ s = 1, \dots, \min\{S, t + 1\} \quad (15)$$

$$I_{p,0,s} = 0 \quad \forall p = 1, \dots, P; s = 1, \dots, S \quad (16)$$

$$\sum_{p=1}^P y_{p,t,s} \leq U_s \quad \forall s = 1, \dots, S; t = 1, \dots, T + S - 1 \quad (17)$$

$$y_{p,t,s} \in \mathbb{N}^0, I_{p,t,s} \geq 0 \quad \forall s = 1, \dots, S; t = 1, \dots, T + S - 2; p = 1, \dots, P \quad (18)$$

$$g_{s,1} = g_{s,T+S} = 0 \quad \forall s = 1, \dots, S \quad (19)$$

$$X_{t,j} \in \{0; 1\} \quad \forall j = 1, \dots, J; t = 1, \dots, T + S - 1 \quad (20)$$

$$X_{t,j} = 0 \quad \forall j = 1, \dots, J; t = 1 - S, \dots, 0 \quad (21)$$

The solution $X_{t,j}$ describes the optimal or near-optimal production sequence in accordance to the problem stated. It marks for each time period (t) the job (j) to be produced. At this point, it can be stressed that the approach presented solely focuses on the part of the supply chain representing the final assembly, excluding the ordering of parts from suppliers (particularly considered by Fathi et al. [56]), the related problem of minimum order quantities, or the delivery times. It also excludes questions regarding the recombination of orders, their packaging, and the distribution strategy.

4. A Two-Stage Variable Neighborhood Tabu Search Algorithm

4.1. Solution Algorithm

To solve the problem stated in Section 3, a two-stage algorithm is proposed based on the tabu search meta-heuristic and a job-wise shift operator as motivated by Prandtstetter and Raidl [57]. Even though the problem in its entirety is NP-hard—since the work overload

part is already NP-hard by itself [36,55]—partial problems can be solved in polynomial time. Therefore, a two-stage algorithm is proposed:

The first algorithm stage generates a feasible solution which is already partially optimal: It is optimal with regard to the tardiness costs $TARDI(X_{t,j})$ and the finished inventory costs $FININV(X_{t,j})$, but not with regard to the other three waste sources. Therefore, the ‘initial solution’ is improved upon in the second stage. Since tabu search meta heuristics are well suited to work with NP-hard problems and problems focusing on sequencing [58], this approach is followed herein. Note that Hernandez-Gress et al. [59] apply a similar local neighborhood tabu search algorithm in the context of job-shop scheduling with a reference to MC. Furthermore, the algorithm in its design is easy to implement and can be applied not only to the problem as stated in the previous section, but also to several modified versions thereof. In addition to a classical tabu search approach, a job-wise shift in a local neighborhood as motivated by Prandtstetter and Raidl [57] gives additional leeway to managers to decide between the speed of finding a feasible solution to work with and its cost-minimizing quality.

Additionally, the algorithm itself is intuitive enough to be implemented in office spreadsheet software like the Visual Basic for Applications programming language. A recent and detailed summary of more sophisticated approaches can be found in Razali et al. [60] or Guo and Ryan [61]. Especially Rabbani et al. [62]’s approach can be pointed out since they are the first to link customer behavior—and thereby a very important component in the context of fashion management—to the optimization of assembly lines. The following section presents a more detailed procedure of the proposed two-stage solution:

Stage I—Initial Solution

1. Sort all orders by non-decreasing due dates;
2. Select the order with the lowest due date not yet inserted in the sequence and insert it at the earliest position that does not disrupt the due dates of the orders already in the sequence;
3. In the case of multiple orders with identical due dates, generate all possible partial sequences and select the one with the lowest work overload costs;
4. Repeat until all orders are sorted into a sequence.

Stage II—Improvement Heuristic

1. Set a neighborhood size v , the maximum number of iterations Z , the maximum number of steps without improvement W , and the length of the tabu list L ;
2. Set the best solution equal to the result from Stage I, the current iteration z to 1 and the counter for steps without improvement w to 0;
3. Assign each job with the costs it generates via its position in the sequence;
4. Select the job with the highest costs that is not on the tabu list;
5. Optimizing
 - a. Move the selected job upwards in the sequence until it either disrupts its due date, reaches the end of the sequence or is more than v steps away from its original position;
 - b. Move the selected job downwards in the sequence until it either reaches the beginning of the sequence or is more than v steps away from its original position;
 - c. Check if moving the job in steps a. or b. resulted in a solution with lower costs than the best solution.
 - i. Yes:
 1. Set the best solution equal to the new solution;
 2. Erase the tabu list and enter the selected job onto the tabu list. Set $w = 0$;
 3. If $z = Z$ go to 6;
 4. Else increase z by 1 and go to 4.
 - ii. No:

1. Enter the selected job into the tabu list. If the tabu list is full, delete the oldest entry;
 2. Increase w by 1;
 3. If $z = Z$ or $w = W$ then go to 6;
 4. Otherwise, increase z by 1 and go to 3.
6. Report the best solution as the result.

4.2. Proof of Functionality

The construction of a sequence, that uses all orders following their due dates as motivated in Stage I of the algorithm automatically assures that no sequence, where the costs resulting from missing due dates are lower, can exist. This is due to the fact that—while moving any order or job ahead—it results in either the same costs or higher costs of the sequence as the jobs that have to move to a later position might start violating their due dates or existing violation might increase. Since orders are kept together as a unit in Stage I, any sequence resulting from this stage also reduces costs for storing finished products as each order can be shipped as soon as the final job on it is finished (this argument holds if due dates act as an upper bound to the delivery and not as a lower bound). Stage I 3. furthermore assures a more positive outcome regarding work overloads.

Within the improvement phase, the optimality (finished inventory costs) of the sequence resulting from Stage I might be compromised—but only if overall costs can be decreased. Step II 5.a. assures that optimality of the sequence regarding the due dates is maintained. Although relaxing this step might allow a solution that is less cost-intensive, unnecessary late deliveries might lead to negative customer relations outside the scope of this model. After each iteration the costs either decrease or a new job from the sequence is selected.

Since a finite counter for steps without improvement (W) and an overall number of iterations (Z) are set, the algorithm will terminate eventually. Based on the parameters L , W , Z , and v and the restriction via Stage II 5.a., it is not assured that the final solution will be the optimal solution to the problem. In particular, without a fitting adjustment of L even setting Z , W , and v to infinity might not guarantee optimality in the final solution but will keep the algorithm from terminating.

5. Discussion and Conclusions

5.1. General Discussion

This paper explored an unconventional approach while focusing on optimization by means of a production scheduling tool, usually used in the automotive industry. The focus of this study lied on MC-producing fashion companies with special attention to the need for action resulting from the pandemic and the motivation to promote sustainability in fashion production. It was therefore partly based on the ‘Lean Approach’ which particularly focuses on waste source reduction. Here, the goal was to evaluate the waste sources in monetary terms and to keep the costs as low as possible. Low cost equates to low waste and high released potential. Although the entire supply chain is often examined in this way, this study focused only on a small part of it, the final assembly line, to provide concrete decision support for managers.

For the optimization approach discussed, it was first determined which sources of waste—with regard to high cost factors within the final assembly line of a MC fashion production—should be considered, accompanied by their mathematical representation. This step already provided value as they can be applied to any collection type manufactured in a MC environment. The elaboration identified five main sources, thus components of the cost function $\min C(X_{t,j})$: OVERLOAD (costs caused by floaters), CONTINV (inventory costs at line), FININV (inventory costs through finished products laying around), TARDI (costs due to late requests) and SMOOTH (uneven material requirements). Since customer demand is very difficult to forecast in MC concepts [63], the non-uniformity source ‘SMOOTH’ is particularly difficult to avoid in a MC fashion production.

Building on the mathematical model, a ‘two-stage variable neighborhood tabu search algorithm’ was proposed as optimization solution. This algorithm is advantageous because it is designed to support final assembly line optimizing—even without extensive programming background. Given the fact that fashion companies—compared to automotive manufacturers—have most likely devoted less focus on process optimization and the associated specialists, this aspect is highly relevant. Furthermore, the solution deals with the described difficulty of the great number of combination possibilities. Based on the car sequencing approach, the individual product components are viewed as ‘features’ to which attributes are assigned. By viewing each job as a bundle of features (each feature realizing a unique attribute), it is possible to work more efficiently and product-oriented because not every variant requires the same workflows and parts—the assumption made in traditional level scheduling. The proposed algorithm consists of two different stages: Stage I (initial solution) should be applied first if no optimization approach dealing with the described cost parameters has been initiated so far. Although applying this stage is only a first step aimed at the generation of a first feasible solution to the sequencing problem, the costs of two of the five sources of waste (FININV and TARDI) can already be reduced. If Stage I has been applied successfully, one can move to Stage II, the ‘improvement heuristic’. This involves a further optimization of all cost function components until the optimization potential reaches saturation. In addition to its advantages, the two-stage solution only reports one single solution as long as the parameters of the model stay the same. Managers will thus be limited in their decision spectrum. To alleviate this problem, Stage I can be replaced by a random assignment of jobs to the sequence. Although this approach no longer assures partial optimality of the initial solution, a set of initial solutions can be generated and optimized simultaneously in Stage II. By providing the decision maker with a set of alternatives—which may be as close to optimality as the single solution when using Stage I and II in conjunction—this will increase the frame of reference.

In addition to the algorithm, it was suggested that a job-wise shift to a local neighborhood would be helpful in optimizing the assembly line. The discussion of this paper showed that especially in a MC production, only very limited planning certainty is possible so that velocity in the production process must be achieved by flexibility rather than detailed forecasts. Therefore, geographical proximity between production sites and suppliers is an important aspect when it comes to producing MC fashion cost-effectively.

In addition to the purely financial perspective, cost-based optimization using the algorithm and job-wise shift has a much more significant effect on MC fashion manufacturing because it provides a contribution to holistic (economic, social, environmental) sustainability. Sustainability has never been the primary concern of publications dealing with assembly line balancing and sequencing. However, the reduction in required resources and waste sources, which goes along with the Lean Approach described and the idea of shortening lead times while reducing costs, are naturally linked to ‘sustainable development’: Ensuring a smooth production flow, the main goal of level scheduling [64], not only saves costs but also provides a healthier and less stressful work environment by reducing work overload. Additionally, reducing inventory and station space allows a decrease in tied capital which can be invested elsewhere. Moreover, workplace relocation to a local neighborhood reduces long transportation distances, strengthens collaboration with supply partners, and helps shorten lead times. As discussed before, especially the MC production type offers good preconditions for these aspects. Generally spoken, implementing a scheduling tool allows a MC fashion manufacturer to become more sustainable in all three dimensions as capital is used more efficiently (economic), working conditions are improved (social) and less waste occurs (ecologic).

5.2. Managerial Implications

Based on the findings, there are numerous aspects that can be derived for managers: First, the optimization approach requires a corporate culture that is open towards change [65]. Part of this is also transparent communication on the management side since

changes in the production could affect employees experiencing uncertainty which may lead to resistance and unproductive work [21]. Therefore, incorporating the employees in the optimization project is an absolute prerequisite. Moreover, many processes are often stuck and the interfaces do not work together efficiently. An optimization project such as the one described can only be successful with efficient information exchange, requiring a transparent communication from the management side [63,66]. It is important that the responsibilities for the project are precisely defined. As such, the paper provides managers with a mathematical framework to model their production line. Due to the modular flexibility of the model, they can decide which parts to emphasize and which ones to omit, therefore adapt the model to their particular production situation.

Authors argued that MC concepts require high flexibility of the supply chain due to lacking forecast possibilities. Based on this gap and the paper's elaboration, it can be further deduced that flexibility is especially required on the supplier side. It became evident that the costs arising in the final assembly line from, e.g., an unbalanced use of parts, can only be reduced by close cooperation with local partners who can react flexibly due to shorter delivery routes [67]. A respectful cooperation in a manager/supplier relationship is therefore an integral part of the optimization solution discussed, not only for social sustainability reasons [68].

In summary, the proposed heuristic algorithm delivers a new optimization tool for MC fashion production and offers managers all the opportunities described in the last sections. Nowadays, many managers are keen on finding new solutions to drive optimization that they rarely realize the potentials in their existing processes. Therefore, this paper delivered a relevant contribution as the approach is purely based on the processes already in place and is designed for realizing uncomplicated optimization. As the approach is designed to optimize only a small part of the production chain, it can provide the impetus for further improvements.

5.3. Limitations and Outlook

In addition to the promising findings, there are still limitations arising: From a technical perspective, the two-stage algorithm and with it particularly Stage II, favors a local optimization in the neighborhood of the partial optimums regarding tardiness and the finished product inventory but global optima, where tardiness or the finished product inventory objective are not the critical waste sources, might not be reached. A genetic or evolutionary algorithm might not only alleviate this problem but would allow a separate treatment of all five waste sources and eliminate the need of a joined objective function. This could contribute to more flexibility and would equip decision makers with a set of alternative solutions to the problem. However, the implementation of a suitable genetic algorithm—particularly a multi-objective version—requires significantly more effort and specifically educated personnel. Nevertheless, we encourage researchers and practitioners to consider such an algorithm in future studies and explore its potential as it is likely that further optimizations would arise.

The overall aim was to provide generalizable findings on the optimization of the final assembly line of a MC fashion production. This also results in a limitation since specialization on a product category such as footwear would probably provide more comprehensive findings on optimization potentials while examining the specific cost factors, waste sources and supplier relations. Another limitation arises from the lack of company specification. Employees are important in change processes wherefore an empirical study on employees' attitudes towards the changes within the discussed assembly line optimization approach would be required to determine the necessity of training or supporting measures. As the elaboration was based on theoretical and conceptual knowledge—without the inclusion of a 'real company'—and aimed on providing a mathematical approach, a comprehensive process analysis through physical observation and personal communication with the respective interfaces would be required for a holistic approach.

To date, authors do not agree on the extent to which operational and strategic corporate decisions must be examined together [69,70]. This paper solely focused on the operational optimization potential, the existing processes and resources were accepted as fixed. However, considering issues such as minimum/maximum purchase quantities, delivery routes and packaging, this means that not the entire supply chain and therefore not all factors influencing the final assembly line were incorporated into the elaboration. For a holistic view, a future study needs to examine further parts of the supply chain. Moreover, taking the strategic perspective into consideration would possibly reveal further potential with the inclusion of new methodologies or investments.

Finally, the present study only presented a mathematical model and a suitable heuristic solution algorithm; it did not present an evaluation of the proposed algorithm. As such, a future follow-up study might apply the proposed algorithm to real world data and determine its potential in each of the two steps.

Author Contributions: Conceptualization, J.K.P., K.S. and C.H.; methodology (mathematical model), J.K.P.; methodology (theoretical), K.S. and C.H.; software (algorithm), J.K.P.; writing—original draft preparation, J.K.P., K.S. and C.H.; writing—review and editing, J.K.P., K.S. and C.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. List of Symbols.

Symbol	Description	Domain
$X_{t,j}$	1 if job j is launched at position t of the sequence; 0 otherwise	-
n	Number of orders; $i = 1, \dots, n$	-
m_i	Number of jobs belonging to order i	-
J	Total number of jobs with $\sum_{i=1}^n m_i = J$; $j = 1, \dots, J$	-
S	Number of stations; $s = 1, \dots, S$	-
O	Number of options; $o = 1, \dots, O$	-
A_o	Number of possible attributes for option o , $a = 1, \dots, A_o$	-
P	Number of parts; $p = 1, \dots, P$	-
T	Total number of jobs to be produced; $t = 1, \dots, T$	-
K	Number of tasks; $k = 1, \dots, K$	-
Z	Number of supply intervals; $z = 1, \dots, Z$	-
U_s	Maximum of storage containers in station s	-
C	Cycle time	T
L_s	Length of station s	T
c^{inv}	Storage costs for finished products per cycle time	M/T
G_p	Container size of part p	-
c_p^{sc}	Storage costs for one container of part p	M/(PT)
t_i^U	Latest starting time for order i to avoid tardiness costs	T
c_i^{ld}	Tardiness costs for order i per cycle time	M/T
c^w	Wage per time unit for auxiliary workers	M/T
$opt_{j,o,a}$	1 if job j possesses attribute a of option o ; 0 otherwise	-
$incl_{p,o,a}$	Units of part p required to install attribute a of option o	-
$bal_{k,s}$	1 if task k is assigned to station s ; 0 otherwise	-
$t_{k,o,a}^{inst}$	Time required to install attribute a of option o for task k	T
$ro_{k,o}$	1 if option o is relevant to task k ; 0 otherwise	-
M	Arbitrary sufficiently large number	-

Table A1. Cont.

Symbol	Description	Domain
$g_{s,t}$	Starting position of worker in station s at the beginning of time t	-
$w_{s,t}$	Auxiliary work required in station s in time t	T
$l_{p,t,s}$	Number of parts p stored in station s at time t	P
$y_{p,t,s}$	Number of containers of part p assigned to station s in period t	-
$\rho_{s,t}$	Operation time of unit t in station s	T
$\tau_{j,s}$	Processing time of job j in station s	T
δ_i	1 if order i is late; 0 otherwise	-
$F_{j,p,s}$	Number of parts p required at station s to produce job j	-

The following four quantities (A1) through (A4) are the result of a combination of the preceding ones:

$$\tau_{j,s} = \sum_{k=1}^K \sum_{o=1}^O \sum_{a=1}^{A_o} opt_{j,o,a} \cdot bal_{k,s} \cdot t_{k,o,a}^{inst} \cdot ro_{k,o} \quad (A1)$$

$$\rho_{s,t} = \sum_{j=1}^J \tau_{j,s} \cdot X_{t-s+1,j} \quad \forall s = 1, \dots, S; t = 1, \dots, T + S + 1 \quad (A2)$$

$$\delta_i = \left(1 - \prod_{j=(i-1) \cdot m_i + 1}^{i \cdot m_i} \left(1 - \frac{\max(0, \sum_{t=1}^T (X_{t,j} \cdot t) + S - t_i^U)}{\sum_{t=1}^T (X_{t,j} \cdot t) + S - t_i^U} \right) \right) \quad (A3)$$

$$F_{j,p,s} = \sum_{o=1}^O \sum_{a=1}^{A_o} \sum_{k=1}^K incl_{j,o,a} \cdot bal_{k,s} \cdot opt_{j,o,a} \cdot ro_{k,o} \quad (A4)$$

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