ORIGINAL ARTICLE

Optimization of garment sizing and cutting order planning in the context of mass customization

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Abstract

In this paper, we present a mass customization (MC)-oriented garment production planning system using mathematical optimization methods to generate the most efficient size chart and cutting order plan. It is composed of two subsystems, i.e., the fit-oriented garment sizing system and the cost-oriented garment cutting-order-planning (COP) system. In the fit-oriented sizing system, additional sizes are generated based on classical standard sizes, where a genetic algorithm (GA) is used to find the global optimum within an acceptable computation time. The comprehensive fit (CF), an overall garment fit evaluation of the target population, is taken as the objective function of the GA. In the cost-oriented COP system, under the hypothesis that fabric-cutting markers vary greatly (regarding the marker length and the cutting length) with various size combinations, an expanded integer programming (IP) model is developed to generate a cutting order plan with the lowest overall cutting cost (including the costs of fabric, spreading operation, and cutting operation) for the proposed sizing system. This MC-oriented production planning system has been validated with the performance of personalization (fit) and economy (cutting cost) through a case study on a women's basic straight skirt. The experimental results show that the proposed system enables a considerable improvement of custom-fit at the expense of a very limited amount of extra cutting cost. Nevertheless, the cutting cost can fluctuate with the increasing number of extra sizes rather than increase monotonically with it. This study illustrates that these optimization approaches which support the garment sizing and COP for MC can help to gain a high customer satisfaction in terms of the garment fit and the cutting cost. More precisely, a GA is capable of rapidly finding the globally optimal sizing scenario, and an IP is able to work out the corresponding best cutting order plan. Furthermore, these proposed approaches can ultimately facilitate the evolution of garment production from mass production (MP) to MC.

Keywords Sizing · Cutting order planning · Genetic algorithm · Integer programming · Mass customization

1 Introduction

Throughout the history of apparel production, there has been a transition from earliest craft production (CP) to conventional mass production (MP), and nowadays there is the tendency of mass customization (MC) which is an integration of MP and CP [8], providing both cost benefit and products satisfying personal needs [55].

Mass customization (MC) is an opportunity but also a great challenge for the garment industry. It is dedicated to providing personalized products at acceptable prices [8, 55]. The personalization and the cost both are crucial points that should be considered in garment MC. With the concept of "design-to-cost," we consider costs to be designed early in product development and manufacturing processes [11, 17].

Customized products in the apparel industry mainly deal with the issues of fit [29, 43, 48] and design [49]. Pursuing a satisfactory fit is an essential issue and gains much concern in MC [29, 43], since it is a fundamental need of users. Garment sizing systems are developed to standardize garment sizing [28] and enhance customer satisfaction with the garment fit [45]. In garment cutting process, garment patterns are cut out based on the standard sizes generated from sizing systems, where the majority of the garment manufacturing cost occurs [6, 50]. The sizing and cutting processes are respectively crucial for the garment fit and the manufacturing cost, so the customization can be realized with fully automatic systems.

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However, the automation of sizing and cutting processes in the context of MC, i.e., small series production, is still a challenging issue to resolve. Researchers have attempted advanced technologies in this regard, such as recommendation systems, virtual reality, 3D body scanning, and CAD automatic patternmaking systems, to realize the personalized pattern design and the automatic single-ply cutting [19, 36, 39, 48]. So far, the costs are still high because advanced technologies always work with the support of expensive equipment. As a matter of fact, Duray [9] has demonstrated that the MC process that more closely resembles the corresponding MP process will lead to superior financial performance. It is not necessary to entirely give up all the classical production practices. Instead, maintaining the methods (e.g., sizing system and batch cutting) in MP configuration to the greatest extent can effectively reduce the manufacturing cost in the new structure. Consequently, the sizing system and the batch cutting are considered in this study.

Limited and outdated sizes for ready-to-wear garments are usually considered as the primary source of ill fitting. Developed from MP, MC aims to solve this problem. Introducing additional garment sizes has been mentioned as a proper approach of garment MC to provide better-fitting products in the literature [14] that it enables to establish a new MC sizing system. A variation of pattern induced by the enlarged size quantity in MC has a great impact on the cutting process. To specify, the increased size number in MC makes for variety in marker. The cutting cost accounts for a dominant fraction in the garment manufacturing cost, because the fabric cost is generally taken as the major contributor in the total garment cost and that the fabric consumption occurs mainly in the cutting process [6, 30, 53]. However, to the best of our knowledge, investigations concerning the cutting cost regarding MC are rarely reported. Out of economic concern, batch cutting is adopted in practice. The whole cutting process consists of the operations of spreading, cutting, as well as sorting and bundling, where the lays and the markers are the operated objects. A lay is a stack composed of plies of fabric pieces, of which pattern pieces can be cut out on the basis of the corresponding marker. A marker is a special kind of stencil that specifies how pattern pieces of one or more garments

should be cut out of a lay. In the spreading operation, fabric pieces are superimposed to become a fabric lay on a cutting table. In the cutting process, cut pieces are cut out of the lays according to the outlines of garment patterns on the marker. Finally, in the sorting and bundling operation, cut pieces are checked and sorted into batches and then transported into the following sewing process. A cutting order plan determines the set of lays and the correspondent markers used in the batch cutting. Marker variations mainly exist in the differences in marker lengths and in marker cutting lengths [26] and have an economic impact on the cutting order planning (COP). A precise cutting order plan can be made by using the actual values of the marker length and the marker cutting length. In the previous study, however, the lay planning is accomplished with the ignorance of marker variations [6, 15, 47]. Nevertheless, especially for small series production, marker variations should be taken into consideration in COP to measure the cutting cost.

The personalization and the cost are essential criteria in MC. There is hardly any simple relation between them. However, both of them are tightly related to the manufacturing process, referring primarily to the sizing and the cutting, which offers the feasibility to build an indirect relation; see Fig. 1. The solid-dot lines represent the known direct relation between the sizing and the fit and the relation between the cutting and the cutting cost, while the red-dot line represents the indirect relation between the fit and the cutting cost. The indirect relation is addressed in this study.

In our study, due to a reduction of difficulty and a limitation of extra cost in the pattern development and the garment manufacturing of MC, we propose a method of building an optimized MC sizing system by adopting additional sizes and retaining classical MP sizes. In addition, we establish a COP model with marker variations considered to evaluate the MC sizing system in terms of the cutting cost. In practice, genetic algorithms (GAs) are usually taken as efficient tools for dealing with the complex scheduling and sequencing problems in apparel production due to its rapid convergence and simple encoding [21, 22, 25, 42, 56]. In an MC system, the possibilities of sizing scenarios grow exponentially with the number of

Fig. 1 Relation among personalization, cost, sizing, and cutting
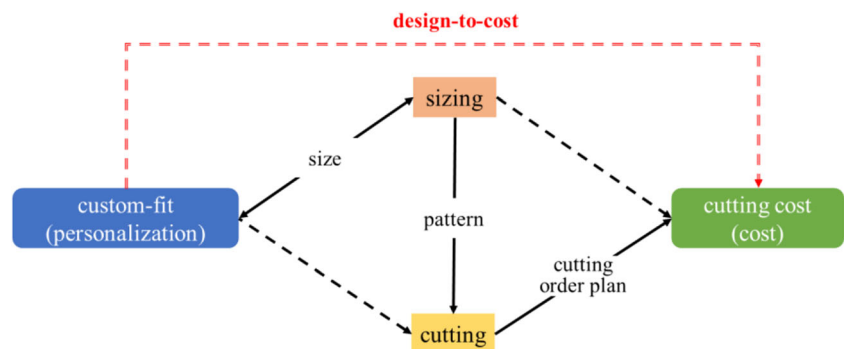
additional sizes. In terms of the big solution population, we also use a GA to work out the optimal sizing scenario, where the comprehensive fit (CF), a criterion representing the total fit degree of the target population, is taken as the fitness function. Moreover, according to the literatures [6, 7, 10], integer programming (IP) is a suitable tool for solving lay planning problems with small-size orders. In this context, we expand the IP model to solve the COP problem, with marker variations (i.e., the individual difference of marker length among markers) considered, according to three key cutting-related factors: fabric price, cutting speed, and operator cost [7, 34]. We use a case study to implement the MC-oriented garment sizing and COP system, in which the indirect relation between the fit and the cutting cost is analyzed. In conclusion, our innovative contributions in this paper include (1) the establishment of an MC sizing system with appropriate additional sizes created by a GA and classical MP sizes retained, (2) an expansion of the lay planning IP model which is implemented on specific lays and markers, and (3) a quantitative analysis of the impact of fit enhancement by additional garment sizes on the cutting cost in order to figure out the underlying relation between the fit and the cutting cost and further master the concept of "design-to-cost" in the garment manufacturing.

This paper is presented as follows. In Section 2, the two-step mass customization (MC)-oriented garment production planning system is demonstrated. We first introduce the concept and structure of the GA-based fit-oriented sizing system with additional sizes by adaptation from a traditional MP sizing system. Next, the COP problem is defined, and the related optimized IP mathematical model with marker variations considered is formulated. A case study of a basic straight skirt is then given in Section 3 to validate the effectiveness of the proposed system. In Section 3, we analyze the relations between the garment fit and the cutting cost for a varying number of sizes in order to reveal the underlying relationship between the personalization and the cost. The paper finally concludes with a summary and overall insights detailed in Section 5.

2 Optimized production planning system for garment mass customization

In order to find the best solution to small series garment production planning problems, we propose a new planning system centered on sizing and cutting (Fig. 2), permitting to combine (1) a mass customization (MC) sizing system adapted from the standard sizing chart used in mass production (MP) and anthropometric data of the target population and (2) an optimized cutting-order-planning (COP) system adapted to customized garment patterns generated from the previous MC sizing system in order to meet specific orders sent by consumers. The proposed sizing system enables to improve the satisfaction of garment fit, while the proposed COP model is specifically developed for identifying the lowest cutting cost towards a given fit level, and afterwards, with various scenarios of MC, the relations between the garment fit and the cutting cost are analyzed.

2.1 Fit-oriented sizing system for garment mass customization

As mentioned earlier, to develop a cost-efficient MC strategy, it is recommended to adapt a classical MP process [9]. Accordingly, the proposed fit-oriented sizing system for MC, illustrated in Fig. 3, is established by developing a series of additional sizes based on an MP sizing system with standard sizes. The upper portion of Fig. 3 shows the flowchart of establishing a garment sizing system in MP [24], and the lower portion gives the adaptation procedure to generate MC sizes, in which the classical MP sizes are also retained.

The inputs of this sizing system are taken from the following main sources: the target population, the garment, the company, as well as the sizing standard as references. Initially, the

Fig. 2 Structure of proposed garment production planning system
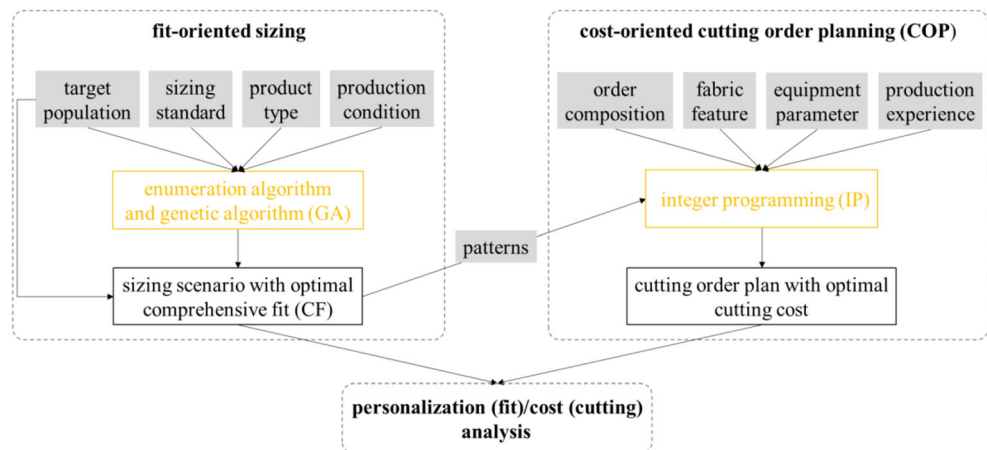
Fig. 3 Flowchart of proposed fit-oriented sizing system
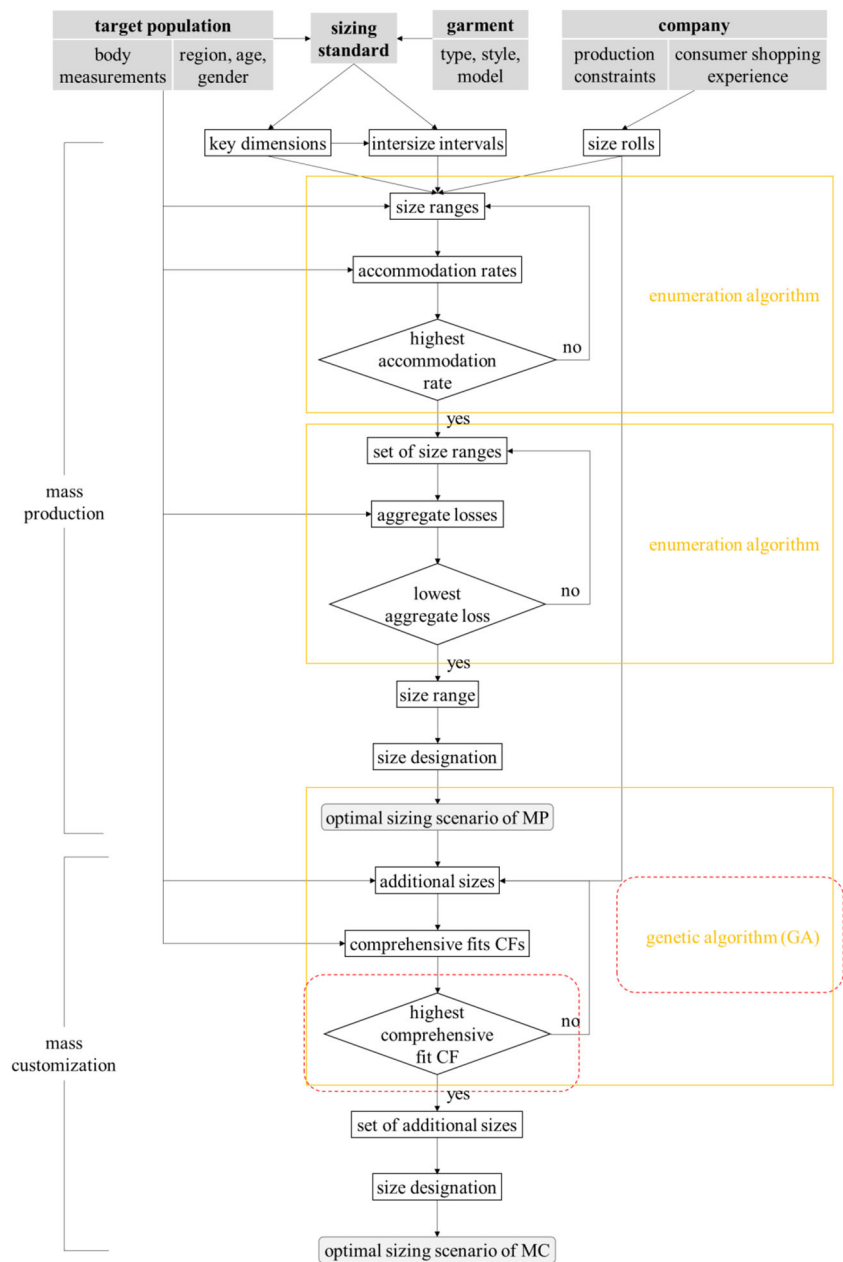
key body (control) dimensions and the corresponding intersize intervals are determined (size step is the increment between adjacent sizes). For any fixed size roll, a size range achieving the highest accommodation rate is determined. That is, for the total number of garment sizes, the system determines the largest set of values along that key dimension to be covered in the size chart to maximize the portion of the population provided for by the sizing system. Generally, there would be more than one solution. Therefore, an aggregate loss (i.e., the quadratic average of log differences between the body dimensions of customers and the assigned garment size dimensions) is used as a criterion for evaluating these size ranges, and the solution with the lowest aggregate loss is adopted. Finally, after

designation (i.e., the set of descriptions or names of garment sizes), the optimal size scenario for this size roll can be determined. In the same way, the output provides the optimal MP size scenarios for all defined size rolls. On the basis of the produced classical sizes from the MP sizing system, the proposed MC sizing system permits improving the garment fit by applying additional sizes. At this stage, the key issue is the selection of the most relevant additional sizes. Adding one size in the sizing system will certainly give rise to additional costs in the garment manufacturing, especially in the cutting process. Therefore, it is crucial that each added size provides the highest profit in terms of fit. In this system, the optimization of adding sizes is performed using a genetic algorithm

(GA), where the comprehensive fit (CF) is taken as the fitness function. The set of additional sizes which has the highest CF is selected for the next step (size designation). At this point, the optimal MC size scenario is generated.

Section 2.1.1 and Section 2.1.2 present the steps and algorithms adopted for standardizing garment sizing (considering the portion of the MP sizing system and the portion of the MC sizing system, respectively).

2.1.1 Sizing system development

In this section, procedures of building an MP sizing system as well as building an MC sizing system on the basis of classical MP sizes are demonstrated as follows:

(1) Sizing system development for mass production

An MP sizing procedure can be realized by performing the following steps:

- Key dimension (D) identification

    Two key body dimensions are selected, considering a specific target population, characterized by its region, age and gender, and a required garment, represented by its type, style, and model. These key dimensions are denoted as primary dimension (D_p) and secondary dimension (D_s). Height (H), chest/bust girth (CG/BG), waist girth (WG), and hip girth (HG) are the commonly used key body dimensions in garment sizing standards (EN 13402–2, [4, 33]).

- Intersize interval (IntD) determination

    The distance between two neighboring size values is called intersize interval and is used in the determination of the size range (see Fig. 4). Based on experience and the concept of "interval of indifference" [35], for each key dimension, we can first get the value range of its intersize interval, usually composed of a set of specific integer numbers [20].

    Then, the interval values ($IntD_i$, $i = s$ or p) are evaluated with a linear regression [46] of the two key dimensions ($D_s = \alpha + D_p * \beta$) by this Equation, namely:

$$\min[abs(\beta - IntDs/IntDp)] \tag{1}$$

    when the proportion of the key dimensions is the closest to the slope β, which indicates that the vast majority of the target population is accommodated by the sizing system.

- Size roll (S) determination

    A suitable number of sizes, namely, size roll, are responsible for a good compromise between the company and consumer in terms of the personalization and the cost

[57]. More precisely, the size roll in MP should be neither too small nor too large in order to control the production and the distribution costs, meanwhile enhancing satisfaction of shopping experience.

- Size range (R) determination

    The range, $Ri = [minR_i, maxR_i]$ ($i = s$ or p), covers all feasible values of the key dimension. As shown in Fig. 4, a standard size range linearly varies from very small to very large [31] and is determined when the maximum portion of target population is accommodated by a fixed size roll S and intersize interval IntDi, namely:

$$maxR_i - minR_i = IntD_i \times S \tag{2}$$

- Coverage range/accommodation rate calculation

    Coverage range refers to the number of samples whose measurements are within the size range. Similarly, the accommodation rate refers to these samples in the percentage of the whole population, and the value is typically between 65% and 85% [20].

- Aggregate loss calculation

    As the general criterion evaluating sizing systems [23], the aggregate loss represents the averaged distance between the body dimensions of the instances D_i and the dimensions of the assigned garment sizes, A_i. The following equation explains how to calculate this average Euclidian distance (d):

$$d = \sqrt{\sum (D_i - A_i)^2} \tag{3}$$

Gupta and Zakaria [24] define the ideal aggregate loss (i.e., the benchmark for an accurate size) as follows: $\sqrt{2} * 2.54 = 3.58$ cm. A smaller aggregate loss means a shorter distance between the body and the assigned garment size, in which
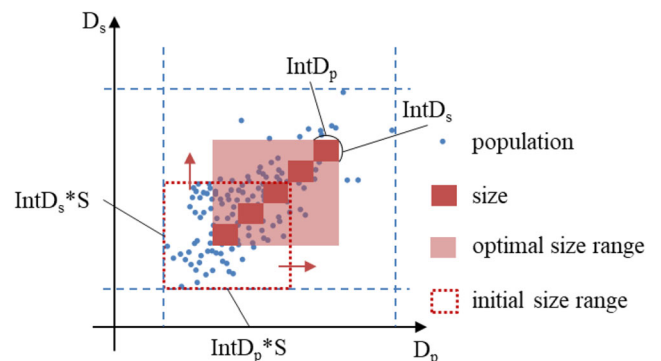

Fig. 4 Sketch of size range determination

case the garment is expected to have a better fit and therefore the performance of the sizing system can be validated.

- Size designation

    This is the final step in the sizing system development procedure, aiming to transmit the size information expressed by codes which provide the best selection of the garment fit to the customers. Arabic numerals or alphabet are common codes used in size designation. The corresponding codes and the body dimensions are defined for each garment size in order to compose a size chart (EN 13402–3, [5, 32]).

    According to the size range and the interval, the garment size dimensions (A_p, A_s) are defined as follows:

$$\left(minR_p + (2N_s-1) \times IntD_p/2, minR_s + (2N_s-1) \times IntD_s/2\right) \tag{4}$$

where N_s refers to the sequence number of sizes in the size roll.

    The median size (e.g., M) is set in accordance with the median instance of the population, when the Euclidian distances of garment size dimensions A_i to the median values of body dimensions D_i (medium) of the target population are minimized, namely:

$$min\sum[(minR_i + (2N_s-1) \times IntD_i/2)-D_i(medium)]^2 \tag{5}$$

(2) Sizing system development for mass customization

A newly proposed MC sizing system is realized with a series of additional sizes generated on the basis of the classical MP sizes by performing the following steps:

- Size roll determination

    In order to provide an appropriate customization and meanwhile limit the rise of complexity mainly in the

manufacturing and the pattern-developing process as well, we consider that the maximal number of additional sizes in MC equals the size roll in MP. Thus, in our case study, the size rolls are 7 and 14, respectively, in the MP and the MC sizing systems.

- Additional size generation

    With consideration of the feasibility and the efficiency in the pattern-developing and the garment manufacturing process, the additional sizes are set by remaining the primary dimension the same and only varying the secondary dimension of the corresponding MP sizes. Concretely, the additional sizes are created through a translation of classical MP sizes along the secondary dimension (see Fig. 5a). The MC method of setting additional sizes enables to obtain various value combinations of key dimensions in order to permit the variety of figure types in the target population, namely, the variation of ratios between key body dimensions [12]. In contrast, MP sizing systems based on proportional sizing cannot reflect the variety of body shapes within a single garment size in a target market [2].

- Comprehensive fit (CF) calculation

    The comprehensive garment fit is the criterion used for the optimization and the evaluation of the MC sizing system in this study. The garment fit is in general associated with diverse factors (i.e., garment material, garment type, customer body size, customer age, and customer gender) and has impact on consumers' psychological comfort and physical comfort [12]. The physical comfort, a provision of simple comforts, heading the list that the garment fit, is generally defined in accordance with the relation between garment size dimensions and body dimensions [1]. The aggregate loss used for sizing system evaluation in MP (as mentioned above) is the most commonly used criterion to represent the garment fit in the literature [1, 24, 57]. However, customers' subjective feeling on fit may not necessarily be in a simple linear correlation with the average distance between the garment size dimensions and the body dimensions, and the importance of key dimensions to fit varies with individual opinions as well. Regarding this, we define the criterion CF to assess the overall fit

Fig. 5 (a) Sketch of additional size generation; (b) example of fit definition
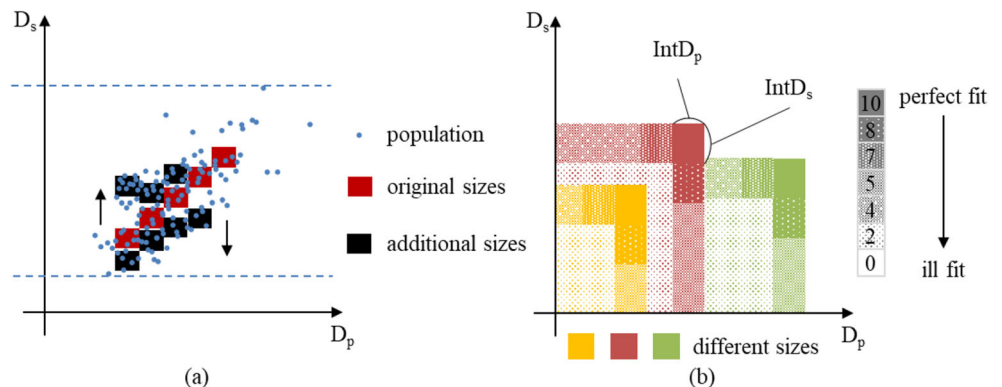
impact of the MC sizing system on the target population. The graph (b) in Fig. 5 gives an example of the fit definition with seven fit levels from ill-fit to perfect-fit and the correspondent weights from 0 to 10 according to consumers' subjective common satisfaction of fit with that specific garment size. CF is defined as the weighted average of the whole target population's satisfaction on garment fit:

$$CF = \sum P_z \times W_z \qquad (6)$$

where z is the specific fit level and the corresponding weight is W_z, P_z refers to the percentage of the target population that is accommodated in the area with the fit level z.

- Size designation

    As additional sizes may not have the same isometric change in key body dimensions as classical MP sizes, we propose to use the exact values of the key body dimensions in the format D_p/D_s to offer customers directly the information about the corresponding body dimensions for this specific garment size.

2.1.2 Algorithm applications in sizing systems

In this study, we apply two enumeration algorithms and a genetic algorithm in solving the sizing problems for MP and MC, respectively (see Fig. 3).

(1) Enumeration algorithm for mass production
        Enumeration algorithms are used in the development of an MP sizing system by listing all the possible items

when calculating the accommodation rate and the aggregate loss in order to find the best sizing scenario [24].

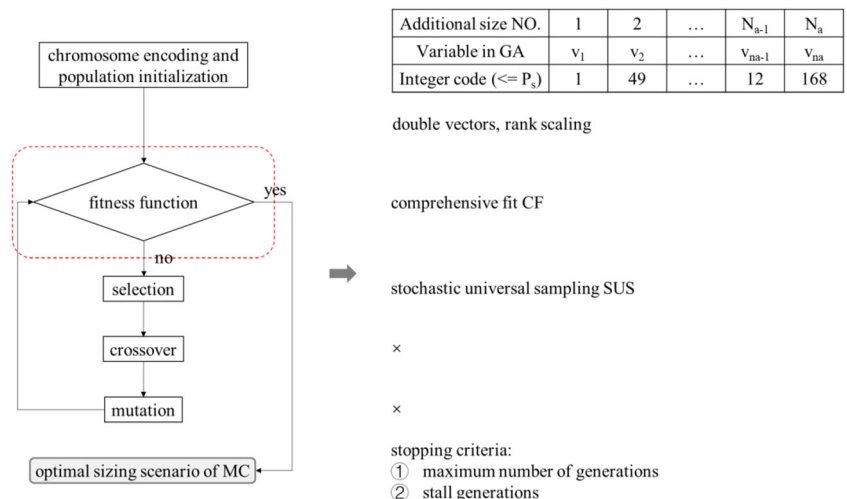(2) Genetic algorithm for mass customization
        Enumeration algorithms perform well for MP due to a small computational load. However, when applying them to build MC sizing systems, it becomes more complicated because finding the best set of additional garment sizes is a combinatorial optimization problem and that the computational load grows exponentially with the number of additional garment size. In this case, GA developed by [27]) is considered as an efficient tool with a high local and global searching ability used for modeling and solving complex discrete optimization problems. The application of GAs has the advantage of easy implementation and quick convergence to a global optimum by evaluating only a small fraction of the design domain [38]. In our study, the procedure of the GA used to generate the optimal additional size combination for MC is demonstrated in Fig. 6, and the specific steps are described as follows:

where P_s is the maximal integer number presenting the possibilities of additional sizes, V_{na} is the design variable representing a specific additional garment size, and N_a is the sequence number of this additional size.

- Encoding

    In general, the real-encoding method is adopted for solving constrained optimization problems, while the integer-encoding method is for combinatorial optimization problems. For this combinatorial optimization problem, a problem of searching for the best set of additional garment sizes, each design variable (V_{na}), representing a specific possible additional garment size, is coded on a specific integer number. The GA decodes the chromosome of individuals in order to obtain its phenotypic

Fig. 6 Flowchart of applied genetic algorithm

Additional size NO.	1	2	…	N_{a-1}	N_a
Variable in GA	v_1	v_2	…	v_{na-1}	v_{na}
Integer code (<= P_s)	1	49	…	12	168

double vectors, rank scaling

comprehensive fit CF

stochastic universal sampling SUS

×

×

stopping criteria:
① maximum number of generations
② stall generations

values (i.e., the exact set of additional garment sizes) corresponding to the decision variable values (see Fig. 6). Having decoded the chromosome representation into the decision variable domain, the set of additional sizes is known so that the fitness of each individual can be evaluated.

- Initial population

    An initial population of certain amount (e.g., *max* (min (10 × N$_a$, 100), 40)) individuals is generated randomly in a double vector form. Rank scaling is selected for more diverse populations because it removes the effect of the spread of the raw scores.

- Constraints

    The constraints of variables in the GA enable defining the upper and lower bounds of the predicted number of possible additional garment sizes. Each of the variables is in the range of 1 to P$_s$ (see Fig. 6).

- Fitness function

    The CF is taken as the fitness function of the GA in our study.

- Operators

    The selection of the individuals is realized with a stochastic universal sampling (SUS) strategy. SUS uses a single random value to sample all of the solutions by choosing them at evenly spaced intervals and thus reduces the unfair nature of fitness-proportional selection methods ([3], July). Crossover and mutation are likely to produce illegal solutions. To simplify, we do not use crossover rate, or mutation rate, with this integer problem for the results obtained in this paper. And it is proved workable with a good performance of the GA.

- Termination criteria

    Under some trial tests, the stopping criteria for this GA are set. First, the GA is allowed to run at a maximum number of iterations (e.g., 300). Second, if the average change in the fitness function values over certain number of generations (e.g., 50) is less than a pre-defined threshold (tolerance), the algorithm stops.

2.2 Cost-oriented cutting-order-planning system for garment mass customization

The garment production planning in the cutting room, an NP (non-deterministic polynomial-time) hard problem [41, 44], mainly deals with lays and markers in the context of layout and sequence. The aim of the cutting order planning (COP) is to find an optimal layout subject to the constraints, in terms of order, fabric, equipment, and pattern, permitting to minimize a number of cutting-related costs. In the MP domain, each ply of lays is complete that residual products (i.e., the cut pieces of clothing articles) are inevitable, and the COP is made by using

the estimated values of marker lengths and marker cutting lengths. As the standard costs in MP are not available in MC, the economic profit is strongly related to the complexity of the production plan and the accuracy of cost estimation. In this context, excess garment products are not expected, and step lays are implemented to reach an explicit low cutting cost. As shown in Fig. 7, in the proposed cost-oriented COP model, lay planning is complemented with specific markers considered in order to obtain the optimal cutting plan with the lowest cutting cost.

Section 2.2.1 and Section 2.2.2 respectively present the three modules in the cost-oriented COP model (i.e., lay planning, marker making, and calculation of cutting-related costs) and the establishment of a corresponding expanded integer programming (IP) model to work out the optimal cutting order plan for MC.

2.2.1 Modules of the proposed cutting-order-planning model

The three modules (i.e., lay planning, marker making, and calculation of cutting-related costs) in the COP model are detailed as below:

(1) Lay planning

    Lay planning determines parameters (i.e., the contained clothing articles, the ply number) of lays for an order. The order is produced either by forecast or by demand, indicating the required quantity of clothing articles to produce for each garment size with different fabrics. It is taken as one of the constraints to satisfy in the lay planning process that the clothing articles that are cut out of lays should be adequate to the order demand. The ply number is limited by the operational cutting height (H$_c$) and fabric thickness (T$_f$). This constraint is shown in eq. (7):

$$maxPN_l = \lfloor H_c/T_f \rfloor \tag{7}$$

where maxPN$_l$ represents the maximum ply number per lay.

Lay planning and marker making are both interrelated (see Fig. 7 and Fig. 8a). Spreading surface is in line with marker surface. Their widths and lengths are subject to fabric width, ease allowance, cutting window length, and pattern attributes. Size combinations in lays, also considered in the marker making module, should be subject to these side-length restrictions. Lay planning without regard to actual markers is a rough cost estimation, and the optimal layout can be hardly found. As shown in the literature, the lay planning problem can be solved assuming that the marker length and the cutting length are constant for each clothing article, while in fact, these values differ
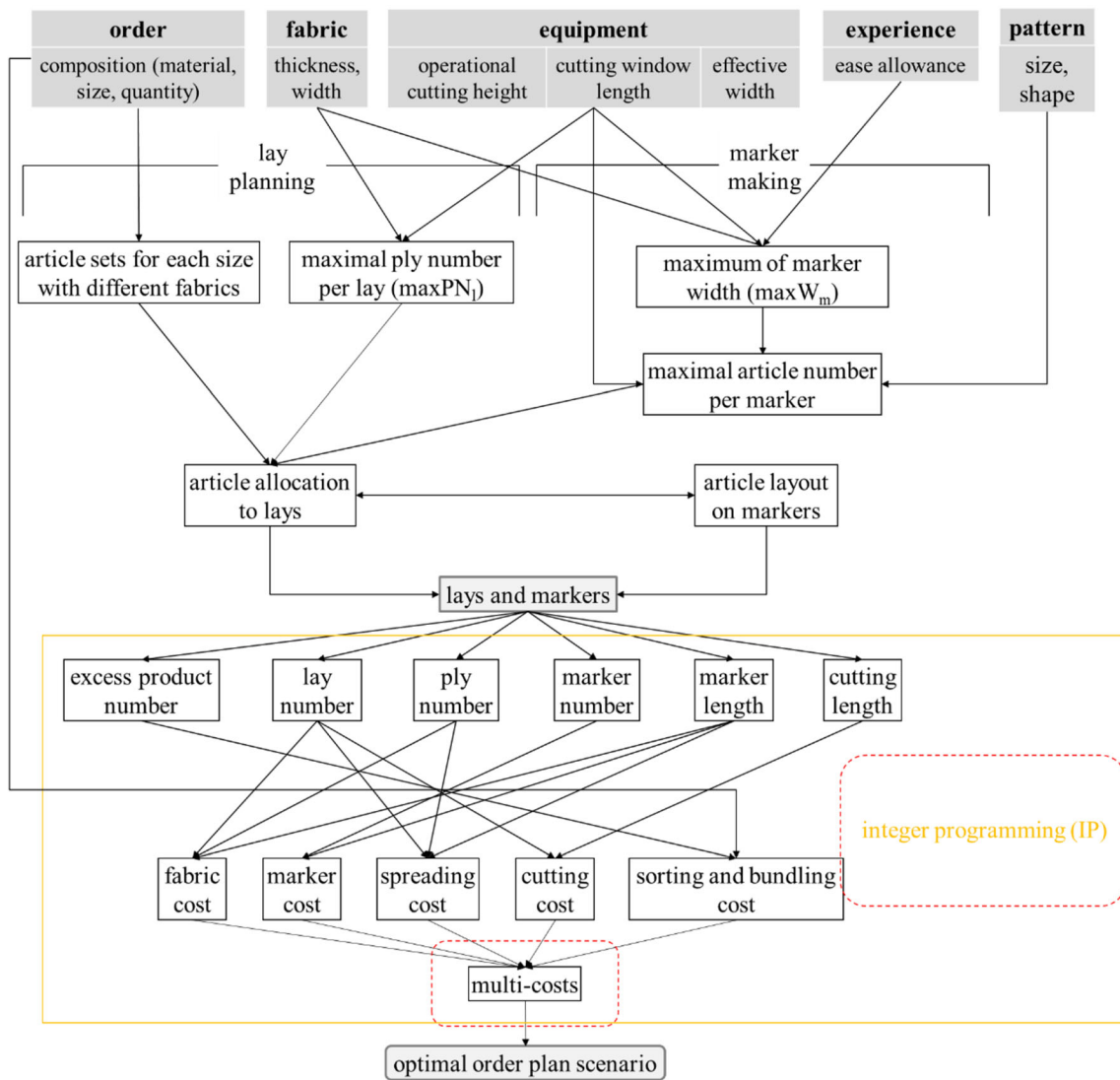
Fig. 7 Flowchart of proposed cost-oriented cutting-order-planning model

considerably between markers. The marker variation and the industrial application are explained in detail in the following marker making module in this section.

For large order sizes in an MP situation, each ply tends to use the whole length of the marker, and it is easy to reach a high marker utilization and gain economy in scale. Nevertheless, the ladder-shaped step lay [13] is preferred when it comes to quite small order sizes like in an MC situation, in which excess garment products are not expected.

(2) Marker making

A marker determines the length and the width of the fabric pieces in the corresponding lays for cutting out the patterns of the contained clothing articles. The marker size depends mainly on the fabric width and the cutting window length of the cutting table. The maximal marker width is relative to the effective width of the cutting table, the fabric width, and the

fabric ease allowance [50], where usually enough fabric allowance is made among patterns and slice sections. Indeed, effective width always exceeds the fabric width; thus, the calculation of the maximal marker width ($maxW_m$) is determined by fabric width (W_f) and fabric allowance (E_a) according to the following equation:

$$maxW_m = W_f - E_a \tag{8}$$

There are various marker types in garment production [26]. Each type of marker has its own advantages and disadvantages, which should be noticed for a proper implementation in COP. For instance, for the same size combination, the mixed marker, patterns of all garment articles contained are mixed on the marker, is generally better in terms of efficiency than the group marker, in which patterns of each clothing article are arranged in an individual section of the marker.

Fig. 8 (a) Sketch of lay and corresponding marker; (b) sketch of different lays and markers
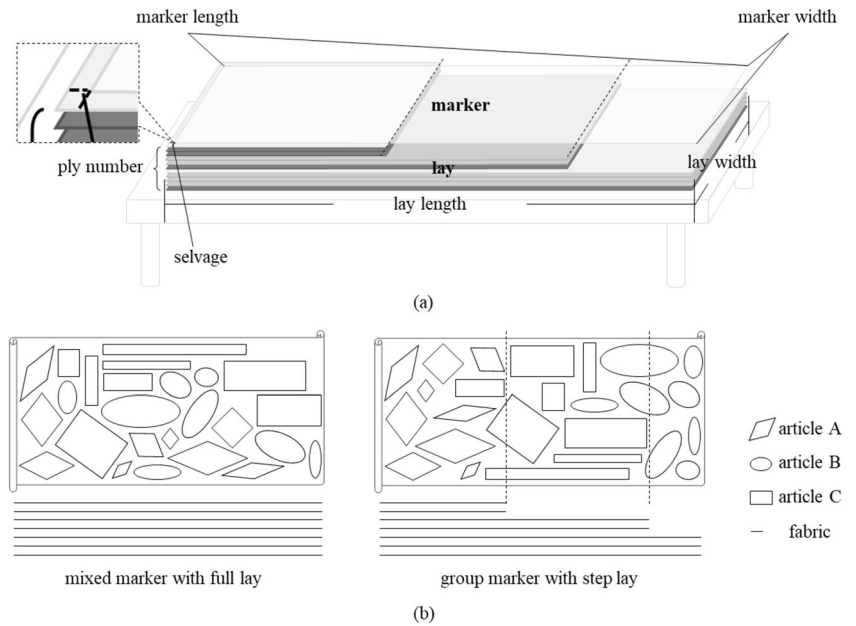
Mixed markers are commonly applied in MP due to the high efficiency. In small series production, excess products are undesired, group markers used with step lays. The sketches of these two types of markers are shown in Fig. 8b.

(3) Cutting-cost calculation

The costs in respect of the cutting process can be classified into two types: one (including fabric and marker costs) is relative to the consumption of materials, and the other (including spreading, cutting, as well as sorting and bundling costs) is relative to operations. Of all the five costs arising from the cutting process, the marker cost will become evidently low with automation of production, and the sorting and bundling cost is considerably lower than the others. In this study, we consider that the total cutting-related cost mainly concerns the fabric consumption and the operations of spreading and cutting.

The COP-related parameters are necessary in the calculation of the cutting related cost, as shown in the lower half portion of Fig. 7. The production size, the lay number, and the ply number are available in the lay plan, while the marker number, the marker length, and the marker cutting length can be extracted from the marker parameters. The corresponding computational formulas concerning the fabric consumption and the operations of spreading and cutting are given below.

1) Fabric cost (C_f):

$$C_f = \sum P_f \times L_f \tag{9}$$

where P_f is the fabric price per unit length and L_f is the used fabric length.

2) Spreading cost (C_s):

$$\begin{aligned} C_s &= (P_o + P_{sm}) \times T_s \\ T_s &= \sum L_f / V_s + N_p \times T_{sp} \end{aligned} \tag{10}$$

where P_o stands for the operator cost per hour, P_{sm} the spreading machine cost per hour, T_s the number of hours for spreading, V_s the spreading speed, N_p the ply number, and T_{sp} the number of hours for each pause during spreading.

3) Cutting cost (C_c):

$$\begin{aligned} C_c &= (P_o + P_{cm}) \times T_c \\ T_c &= \sum L_c / V_c + T_{cp} \end{aligned} \tag{11}$$

where P_{cm} stands for the cutting machine cost per hour, T_c the number of hours for cutting, which is determined by the cutting length (L_c) and the cutting speed (V_c), and T_{cp} the number of hours for the pause during cutting.

2.2.2 Formulation of the cutting-order-planning problem in mass customization

Lay planning is one part of the cutting stock problem [13] and can be solved by mathematical methods [6, 7, 13] with the aid of soft computing technologies [16, 40, 54]. Considering the

previous described differences of COP in MP and MC, we propose an expanded IP model on the basis of the Zeger Degraeve's mixed integer programming model (MIP) [6] in order to tackle the lay planning problem with both step lays and full lays. The additional value of the expanded IP model lies in that the specific marker lengths and cutting lengths of the actual markers are taken into consideration. A comprehensive cutting cost, composed of various costs (i.e., fabric consumption, operations of spreading and cutting), is taken as the objective of this COP model. Below is the detailed IP model for solving this COP problem under an MC environment:

Notations:

S	set of sizes
OD_s	order demand for size s, $s \in S$
M	set of markers
SN_{sm}	copies of size s in marker m, $s \in S$, $m \in M$
$maxSN_m$	maximum number of sizes in marker m, $s \in S$, $m \in M$, is constant
SN_{ssm}	existence of size S in subsection of marker m, $m \in M$, $= 1$, when exists, $= 0$, otherwise
L_m	length of marker m, $m \in M$
L_{sm}	length of each subsection of marker m, $m \in M$
L_s	length of selvage, is constant, 0.02–0.04 cm [18]
CL_m	cutting length of marker m, $m \in M$
L	set of lays
$maxPN_l$	maximum ply number of lay l, $l \in L$ is constant
PN_l	ply number of lay l, $l \in L$, $\leq maxPN_l$, $= TPN_m/U_m$, PN_{m1}/U_m, $m \in M$
TPN_m	total ply number of lays with marker m, $m \in M$
PN_{sm}	ply number of subsections with marker m, $m \in M$, on a downward trend
U_m	copies of lays with marker m, $m \in M$, $U_m - 1 \leq TPN_m/maxPN_l \leq U_m$, $U_m - 1 \leq PN_{m1}/maxPN_l \leq U_m$
V_m	existence of marker m, $m \in M$, $= 0$, $TPN_m = 0$, $PN_{m1} = 0$, $= 1$, otherwise

Assumption:

Equipment investment cost is not included in the calculation because it is relatively small in comparison with other costs.

Constraints:

1) Satisfaction of demands for each size

$$\sum_{m \in M} SN_{sm}TPN_m + \sum_{m \in M}\sum_{1}^{maxSN_m} SN_{ssm}PN_{sm} \geq OD_s \qquad (12)$$

2) Lay number determined by ply number

$$U_m - 1 \leq TPN_m/maxPN_l \leq U_m \qquad (13)$$
$$U_m - 1 \leq PN_{m1}/maxPN_l \leq U_m \qquad (14)$$

3) Diminishing subsection heights in step lays

$$PN_{m1} \geq PN_{m2} \geq \ldots \geq PN_{mmaxSN_m} \qquad (15)$$

Objective function:

$$\text{Min} \sum_{m \in M}\left(w_u \times U_m + W_{tpn} \times TPN_m + W_{pn} \times \sum_{1}^{maxSN_m} PN_{sm}\right)W_e$$
$$= f\left(SN_{sm}, L_m, CL_m, SN_{ssm}, L_{sm}, L_s, P_f, P_o, V_s, V_c, T_{sp}, T_{cp}\right) \qquad (16)$$

where W_e refers to weight in the objective function and W_u, W_{tpn}, and W_{pn} are the weights for each specific variable.

3 A case study

Customer satisfaction with the overall fit at the lower body (e.g., a skirt) is generally lower than that at the upper body and at the total body [37]. The basic straight skirt is a clinging skirt type commonly used on formal occasion, which elicits a more stringent evaluation of fit at the lower body. In this context, this garment type has the motivation of generating more sizes for a better fit. As it has just several simple pieces of patterns, it is relatively more feasible and more realistic in the product development and the manufacturing process. In this section, a case study of the women's basic skirt production is used to validate the proposed system as well as to analyze the relation between the personalization and the cost. The key body dimensions are the waist girth (WG) and the hip girth (HG), where the latter is the primary dimension. We first perform a sizing treatment for different production modes (i.e., mass production (MP), craft production (CP), and mass customization (MC)) and calculate the corresponding cutting costs. Then, an analysis of the fit and the cutting cost is made to evaluate the performance of MC supported by the proposed optimization methods under the concept of "design-to-cost."

Table 1 Parameter setting in relevance with spreading and cutting operations

Parameter in cutting order planning	Set value				
Fabric price P_f (€/m)	0.2	1	5	10	20
Length of selvage l_s (m)	0.02				
Operator cost P_o (€/h)	5		10	20	
Spreading speed V_s (m/h)	2400				
Time per spreading pause T_{sp} (h)	1/60				
Cutting speed V_c (m/h)	2400	400			
Time per cutting pause T_{cp} (h)	0				

3.1 Experiment design

The size charts are designed for MP and MC, while CP uses personalized patterns that each individual is served with a specific size. The unit cutting costs for MP and MC are figured out by using the proposed cost-oriented cutting-order-planning (COP) model, while for CP, the cost is estimated in the single-piece manufacturing environment. In regard to the experiment design, the data collection and the parameter setting and the used analytical methods are described as follows:

1) Data collection

   The anthropometric measurements used in sizing come from a population of 451 French women aging from 20 to 40. To evaluate our system in a scenario close to reality, the data sample is split into two datasets:

   – A training dataset is composed of 301 instances randomly selected from the population. Both the sizing systems for MP and MC are built using this dataset. Also, this training dataset is used for the forecasting of the order quantity by sizes, which is taken as a constraint of the IP model in the COP of the MP scenario.
   – A testing dataset, composed of the remaining 150 instances, serves as the real consumer demand in the COP of the MC and the CF scenarios.

   In addition, the real patterns for all garment sizes are developed, and markers for all the size combinations are drawn using the software of Lectra Modaris and Lectra Diamino Fashion, respectively. The data extracted (including the marker length and the cutting length) from these markers are used in COP of all scenarios in this study.

2) Parameter setting

   Parameter setting in sizing is mainly based on the industrial practice. The intersize interval can be the same magnitude across all the sizes or vary across the size range [51]. Based on the intersize intervals in the European standard (EN 13402–3, [5]) and the binary linear

regression analysis of relationship between the two key body dimensions (viz., HG and WG), where β equals to 1.13, to simplify the operation, in this case study, IntHG is determined as 5, IntWG as 6.

Parameter setting in COP is based on the related literature and the production experience. In our experience, we take a Vector 2500 Techtex produced by Lectra as the cutting equipment. The parameters associated with the cutting operation are: the effective width is 1.80 m, the cutting window length is 1.75 m, and the operational cutting height is 2.5 cm. The values of parameters on spreading and cutting operations that set in our experiment are given in Table 1. There are five classes of fabric whose prices vary from the low cost of 0.2 €/m to the luxury cost of 20 €/m. The length of selvage is 0.02 m for each lay. We set three levels of operator cost: 5 €/h, 10 €/h, and 20 €/h. The spreading operation is automatic with the speed of 2400 m/h, and the time for each spreading pause is 1/60 h. Two modes of cutting process are considered: the automatic cutting with a speed of 2400 m/h and the manual cutting with 400 m/h. As the cutting pause is relatively short compared with the time consumed in the entire cutting operation, it is considered as null in our experiment.

3) Analytical methods

   The analytical methodologies applied in our study contain comparative analysis and descriptive statistical analysis. Comparisons regarding the personalization and the cost were made among the three different production modes, i.e., CP, MP, and MC. The variation tendencies of unit cutting cost with additional size number in MC and CP, unit cutting cost in MP with order size, and comprehensive fit with additional size number were described using mean values, stable values, as well as mode, respectively. For enhancement, related analysis has been conducted to unveil the relations (between the comprehensive fit and the additional size number, between the unit

Table 2 Size chart with size roll of seven in mass production

Size	HG (cm)	R HG (cm)	IntHG (cm)	WG (cm)	R WG (cm)	IntWG (cm)
XXS	89	[86.5, 91.5]	5	67	[64, 70]	6
XS	94	[91.5, 96.5]		73	[70, 76]	
S	99	[96.5, 101.5]		79	[76, 82]	
M	104	[101.5, 106.5]		85	[82, 88]	
L	109	[106.5, 111.5]		91	[88, 94]	
XL	114	[111.5, 116.5]		97	[94, 100]	
XXL	119	[116.5, 121.5]		103	[100, 106]	

Fig. 9 Size distributions with additional size number ranging from 0 to 7
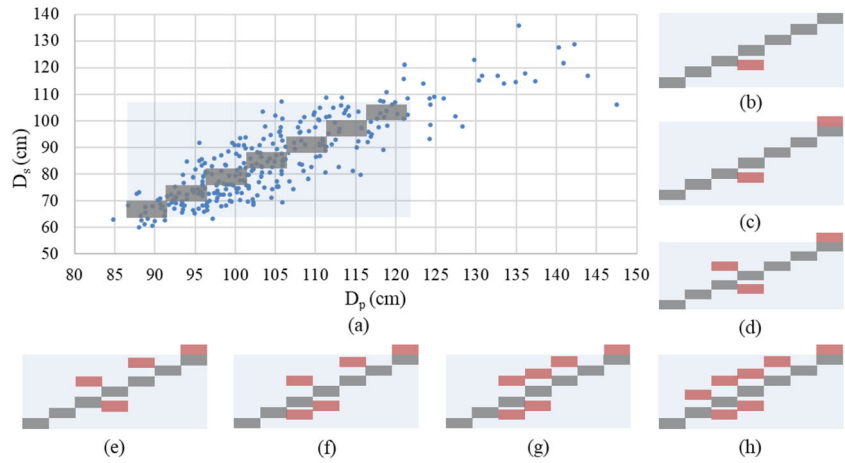
cutting cost and the additional size number, and between the unit cutting cost and the comprehensive fit).

3.2 Results and discussion

For MP and MC, we produce sets of sizes and calculate the comprehensive fits (CF) by using the proposed fit-oriented sizing system and then use the proposed IP model to figure out the corresponding unit cutting costs. For CP, as specific garment patterns are generated for each personalized individual, and the value of CF is regarded as 10; the single-piece cutting is applied in the cutting process, and therefore, we take the average value of marker-related parameters (i.e., the marker length and the cutting length) in MC as the estimated values in CP to calculate the corresponding unit costs.

The following section illustrates the results of sizing, the CFs, and the unit cutting costs and gives an analysis of the relation of the fit and the cutting cost with different garment production modes (viz., MP, MC, and CP).

**Table 3** Size chart with size roll of 14 in mass customization

HG (cm)	Original waist		Larger waist		Smaller waist	
	WG= (cm)	Size code	WG+ (cm)	Size code	WG- (cm)	Size code
89	67	1	–	–	–	–
94	73	2	83	7*	–	–
99	79	3	91	3*	72	5*
104	85	4	95	6*	77	1*
109	91	5	102	4*	–	–
114	97	6	–	–	–	–
119	103	7	109	2*	–	–

3.2.1 Sizing and fit

Two sizing systems are respectively applied in the MP and the MC environments. In the CP environment, patterns are made for each individual using measured personal body dimensions of the instances. In the MP environment, we introduce a number of different size rolls and select the one which provides the best performance according to the indices of accommodation rate and aggregate loss. Then, in order to establish the MC sizing system, we introduce a number of additional sizes to the previous MP sizing system in order to obtain the highest value of CF.

For MP, the reasonable accommodation rate between 65% and 85% is obtained with size rolls, i.e., 5, 6 and 7. The sizing system with a size roll of seven corresponds to the highest accommodation rate, and thus it is used to represent the performance of MP in our analysis and for the comparison. With the exact size ranges and intervals, the size dimensions of each size are calculated by using eq. (4). We define the size whose dimensions are the closest to the median dimension values as size M, referring to eq. (5). Table 2 shows the MP size chart with a size roll of seven.

As aforementioned, additional sizes for MC can be made by varying the secondary dimension (WG) of the classical MP sizes while keeping the same in their primary dimension
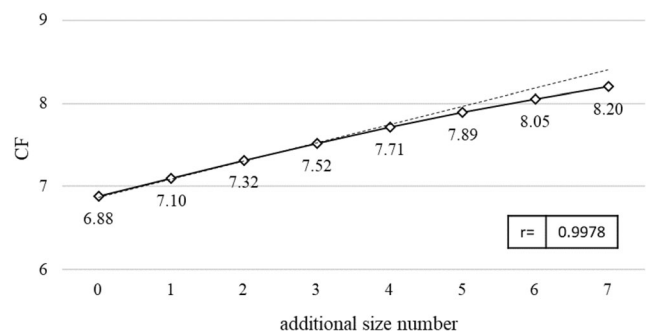
Fig. 10 Comprehensive-fit trend with additional size number ranging from 0 to 7

Table 4 Sizing system evaluation results with various size rolls in mass customization

Size roll	Comprehensive fit CF	Size range R (cm)		Accommodation rate (%)	Aggregate loss (cm)
		RHG (cm)	RWG (cm)		
7	6.8804	[86.5, 121.5]	[64, 106]	86.05	5.55
8	7.0997	[86.5, 121.5]	[64, 106]	86.05	5.07
9	7.3156	[86.5, 121.5]	[64, 112]	88.70	5.05
10	7.5183	[86.5, 121.5]	[64, 112]	88.70	4.88
11	7.7143	[86.5, 121.5]	[64, 112]	88.70	4.58
12	7.8904	[86.5, 121.5]	[64, 112]	88.70	4.18
13	8.0498	[86.5, 121.5]	[64, 112]	88.70	4.01
14	8.1993	[86.5, 121.5]	[64, 112]	88.70	3.91

(HG). The body dimensions of the instances on the left and bottom decide the limitations of WG for a given HG range. The experiments end with the maximal additional size number of seven applied to the original MP sizing system (the black rectangles in Fig. 9a. Figure 9b–h gives the distributions of additional sizes determined (red rectangles) by using a genetic algorithm (GA) with an increasing additional size number ranging from 1 to 7.

Table 3 shows the MC size chart with a size roll of 14. The size codes of the additional sizes are marked with *.

The same fit level definition as demonstrated in Fig. 5b and CF calculation by eq. (6) is used in MP as well as in MC. In this case, a total of seven fit levels named unfit, ill-fit, minus medium-fit, medium-fit, minus good-fit, good-fit, and perfect-fit are assigned with the weights of 0, 2, 4, 5, 7, 8, and 10, respectively (see Fig. 5b). Then, the CFs are calculated by eq. (6). The CF of MP is 6.88. The CF of MC increases from 7.10 to 8.20 when adding new sizes, and its increasing rate progressively decreases with the number of additional sizes (see Fig. 10). The high correlation coefficient (r) of 0.9978 indicates that there is a perfect uphill linear relationship between the CF and the additional size number.

Table 4 gives the evaluation results of the MC sizing systems with various size rolls. It shows that adding more sizes brings not only an increase of the CF but also a decrease of the aggregate loss. However, the accommodation rate can be further improved with the size roll or maintain a stable value. For

instance, the sizing system can improve the accommodation rate when the size roll is maintained to be higher than nine.

According to the changing values of the three indices for the sizing system evaluation (CF, aggregate loss, and accommodation rate), it is demonstrated that the CF increases, the aggregate loss decreases, and a higher percentage of the population can be achieved when the size roll grows. The changes of the CF are more sensitive than those of the aggregate loss. Therefore, the proposed criterion, the CF, is proved to be capable of representing the performance of fit correctly and accurately.

In summary, the additional sizes mainly provide a better garment fit towards the consumer population and can support additional consumers to some extent as well. Furthermore, the proposed CF has a good performance in representing the fit with the whole target population.

3.2.2 Cutting order planning and cutting cost

The production mode differs, and the cutting order plan varies. The proposed integer programming (IP) model is conducted to find appropriate combinations of lays and markers and to figure out the unit cutting costs for MP and MC scenarios. With the order size of MP ranging from 0 to 13,400, in which the maximal value 13,400 is determined by 100 times 134 (the basic forecasted order size according to the size distribution in MP with a roll

Fig. 11 Cutting cost trend in MP (manual cutting, fabric price = 5 €/m, operator cost = 10 €/h)
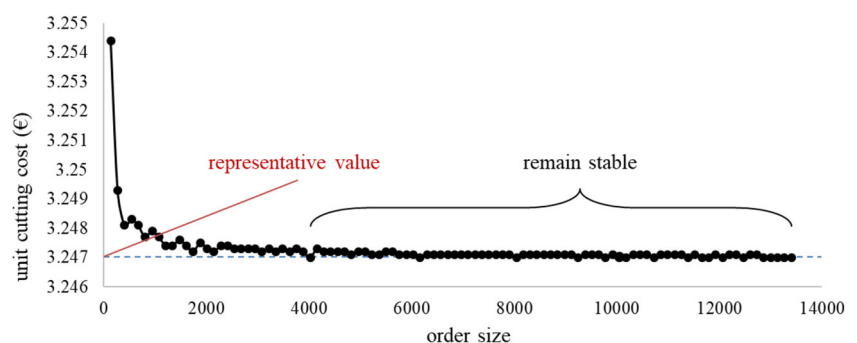
Table 5 Cutting costs in mass production

Cutting speed (m/h)	Operator cost P_o (€/h)	Unit cutting cost (€) Fabric price P_f (€/m)				
		0.2	1	5	10	20
2400	5	0.17	0.67	3.20	6.35	12.66
	10	0.21	0.72	3.24	6.40	12.71
	20	0.30	0.80	3.33	6.48	12.79
400	5	0.17	0.68	3.20	6.36	12.67
	10	0.22	0.72	3.25	6.40	12.71
	20	0.31	0.81	3.34	6.49	12.80

size of 7), the COP results (Fig. 11) show that the larger the order size is, the lower the cutting cost will be. However, when the order size is large enough (above 4000 in our experiments), the cutting cost tends to be stable at a specific value. We use the cutting-cost values of the order size 10,000 to represent the cutting costs in MP. In MC, the order size is the exact number of 150, and the cutting cost changes with the increase of additional sizes from 1 to 7. For CP, we use the average marker length of a single clothing article and regard the cutting operation as a simple-ply cutting in COP during the cutting-cost calculation.

Table 5 indicates the cutting costs in MP. The manual cutting and a higher operator cost result in increases of the cutting cost, but a higher fabric price is obviously much more effective, and a strong positive correlation between the fabric price and the unit cutting cost can be found.

Table 6 gives the estimated unit cutting costs of CP. The costs in CP are much higher than those in MP (Table 5) due to the manual operation and short markers. It is shown that fabric price plays an absolutely important role on the unit cutting cost.

In the MC environment, there are some turns of trends (Fig. 12) in the corresponding unit cutting-cost curves when applying various values of production parameters, i.e., the fabric price and the cutting speed, while the operator cost has no impact on this trend.

The trend of the unit cutting cost varies when the cutting speed differs or fabric price varies. When the number of additional sizes increases, the unit cutting cost decreases if the cutting operation is automatic (Fig. 12a) or fabric is expensive (Fig. 12d). Otherwise, when the cutting operation is manual and fabric is at a quite low price, the unit cutting cost increases (see Fig. 12b). As a high fabric price has a significant impact while a low cutting speed has a slight effect on raising the weight of fabric price in the objective function of the COP model, the above phenomenon, in fact, results from the decrease of

fabric usage when more additional garment sizes are adopted. One reason for this decrease is that the newly generated additional sizes would occupy less area on markers than the original sizes, resulting in a reduction in fabric usage. The other reason is that the additional sizes bring more possible size combinations with shorter markers and finally reduce the fabric usage. A higher operator cost also causes a small increase of unit cutting cost, but does not affect its variation trend (see Fig. 12c). This is because the operator cost accounts for a small weight in the objective function of the overall cutting cost.

The correlation coefficients show a strong linear relationship between the unit cutting cost and the additional size number in MC. Moreover, in each of all the curves, the fourth point is special for its lower value. Applying four additional garment sizes allows more customers to be accommodated (see Table 4). Therefore, the cutting cost can be divided by a larger order size, and then a much lower unit cutting cost can be obtained.

To summarize, if a manual cutting operation is applied and the used fabric is cheap, the unit cutting cost will increase with additional sizes. Otherwise, if the cutting operations are automatic, the cost of cutting operation will decrease so that the proportion of fabric usage is relatively much larger, and therefore, the unit cutting cost has a strong positive correlation with the fabric cost. Especially for MC, it is meaningful that at a certain point, the unit cutting cost decreases when the additional size quantity slightly increases, which is economically beneficial in garment MC. Additionally, MC can enlarge the user population at some extent.

3.2.3 Analysis of relation between comprehensive fit and unit cutting cost

The idea is to gain the fit and cost tradeoff under the concept of "design-to-cost" by using the proposed system that enables to control the garment manufacturing cost, especially the cutting

Table 6 Cutting costs in craft production

Cutting speed (m/h)	Operator cost P_o (€/h)	Unit cutting cost (€) Fabric price P_f (€/m)				
		0.2	1	5	10	20
2400	5	0.29	1.07	4.94	9.79	19.47
	10	0.40	1.17	5.05	9.89	19.58
	20	0.60	1.37	5.25	10.09	19.78
400	5	0.37	1.15	5.02	9.87	19.55
	10	0.55	1.33	5.20	10.05	19.73
	20	0.91	1.69	5.56	10.40	20.09

Fig. 12 Partial results of cutting cost in MC with testing dataset (a population of 150)
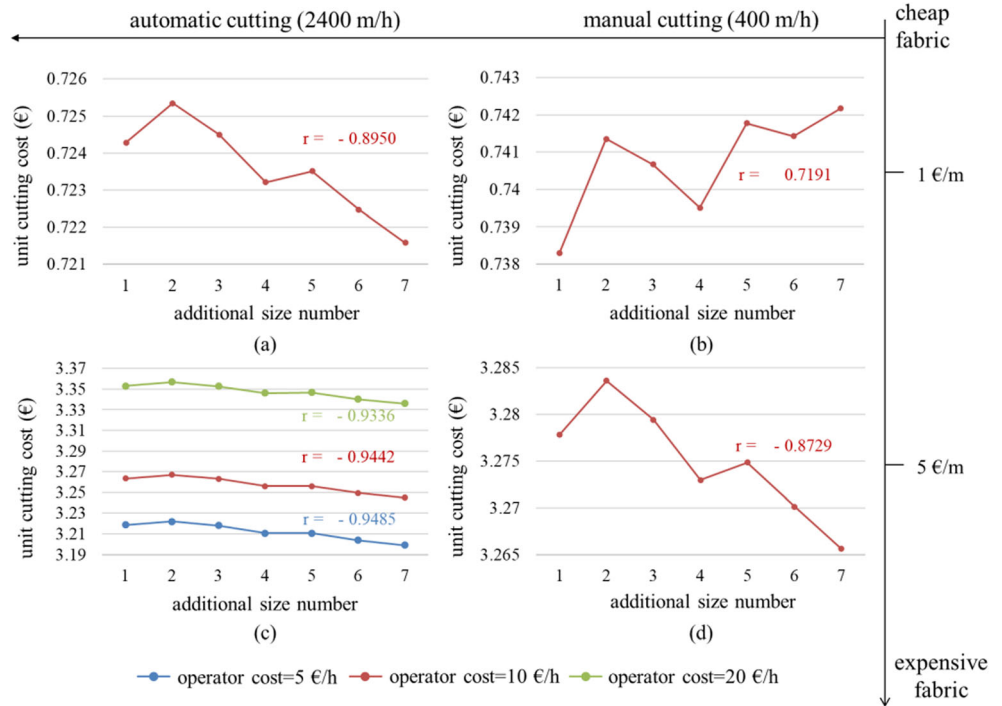
cost, during the design stage. An analysis of the unit cost variation with the CF in MC is described in this section.

The correlation coefficients indicate that the CF has a strong linear relationship with the unit cutting cost in MC. Similar with the tends of the unit cutting cost when the number of additional sizes increases, there are two opposite trends of the unit cutting cost when CF increases (see Fig. 13). Figure 13a is with an automatic cutting and Fig. 13b with a manual cutting. The appropriate sizing scenarios (red points) which are lower in the unit cutting cost but higher in CF can be found in these curves.

With a comparison of MP, MC, and CP on the CF and the unit cutting cost (Fig. 14), we find that the MC method can efficiently improve the CF with a slight increase in unit cutting cost related to CP instead of a significant cost increase. In the current industrial and business situation, automation in production has been widely accepted by companies, and luxury fabrics are largely preferred by more customers, so the

proposed system is extremely significant to the garment MC tendency.

Having mastered how the cutting cost varies with the fit, we can select appropriate sizing scenarios according to a compromise between the unit cutting cost and the CF, which evolve in the two opposite trends. In practice, compared with the significant high unit cutting cost in CP, a slight increase of unit cutting cost brought by MC can be much more acceptable for garment manufacturers, and also customers can get benefit from this in the end.

4 Conclusion

In our study, optimizations have been made for the sizing and the cutting order planning (COP) of the garment manufacturing process by applications of advanced computing techniques, and a cost-benefit analysis has been provided for

Fig. 13 Opposite cutting cost trends when comprehensive fit increases for two different cutting speeds (fabric price = 20 €/m, operator cost = 10 €/h)
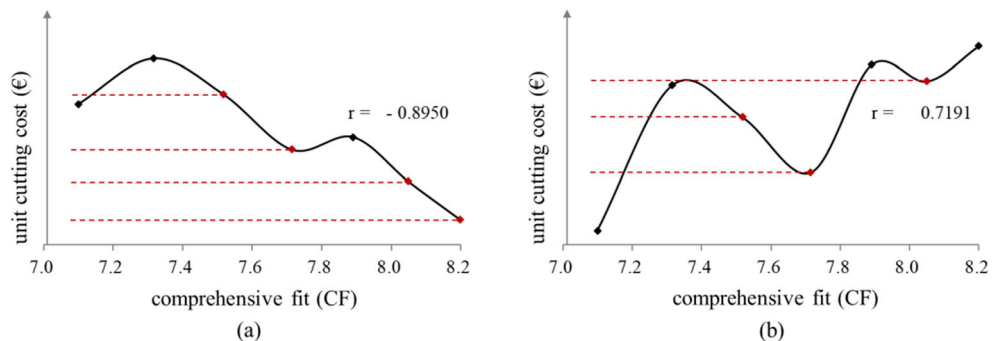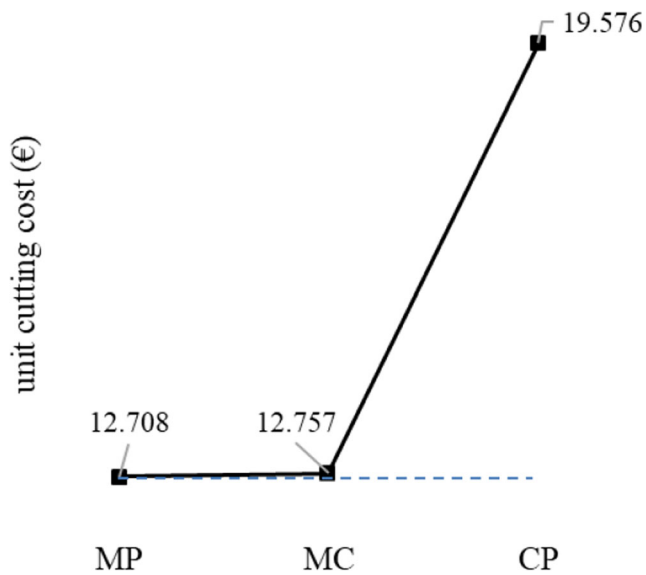
Fig. 14 Cutting cost for various production modes (automatic cutting, fabric price = 2 €/m, operator cost = 10 €/h)

decision-makers in the garment industry towards mass customization (MC). To be more specific, we propose a two-stage system, composed of a sizing system and a COP model, and evaluate the cost/personalization ratio. The sizing strategy for MC is to create additional garment sizes based on the mass production (MP) sizing system due to a reduction of difficulty and a limitation of extra cost in new pattern development and manufacturing processes. A genetic algorithm (GA) has been applied to locate the appropriate additional garment sizes, the comprehensive fit (CF) defined as the fitness function. The expanded integer programming (IP) model has been built to determine the COP solution yielding the least costly cutting process using precise data of marker parameters (i.e., the marker length and the cutting length).

To demonstrate the efficiency of the proposed system, we present a specific case study of women's straight skirt in a real industrial environment, in which the underlying relationship between the personalization and the cost was explored. The results show that the system can effectively improve the garment fit for a target population with a limited increase of cutting cost. The relationship between the cutting cost and the number of additional garment sizes is nonlinear and is fluctuating, strongly influenced by a combination of different factors such as fabric price, labor cost, and cutting speed. Local optima can arise that the identification of these local optima is crucial for developing MC by obtaining a better compromise between the personalization (e.g., the fit) and the cost (e.g., the cutting cost).

Thereupon, with the concept of "design-to-cost," the proposed system provides an attractive reference for the garment industry to handle the tradeoff between the personalization and the cost in MC so as to meet customers' growing demand of personalization at an acceptable cost. It provides garment

manufacturers with the guidance on developing effective manufacturing strategies for the production mode transformation from MP to MC. Additionally, as an attempt of the automation and intellectualization in garment manufacturing, it is in the spectrum of Industry 4.0.

The proposed system can be further improved and extended. For the sizing system, a fit-related pricing strategy can be developed in order to provide customers with accurate prices for each specific personalization. For the COP, it is significant to apply artificial intelligence techniques to predict accurate data of markers due to the complexity of the relation with the size combination. From an industrial point of view, a multi-material case for the customization of co-design will be conducted, and the time, another important criterion for production [52] besides the cost, also will be considered in the next step.

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