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Optimization of the cutting-related processes for consumer-centered garment manufacturing

Optimisation des processus liés à la coupe pour la fabrication de vêtements centrée sur le consommateur

Soutenue le 26 Juin 2020 devant la Commission d'Examen :

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Introduction

The fashion industry plays a vital role in daily life since it produces what people wear. Likewise, it makes a substantial contribution to global economics since the entire industry is very large which is related to the international clothing supply chain from raw materials to garments.

In the mass production era, a great quantity of garments has been produced in batch for a large population rather than meeting the requirements of a specific consumer in terms of individual body characteristics and personal fashion preferences, as what occurs in the craft production era. Craft production, mainly targeting individuals, performs a perfect fit, and allows any desired designs manually with very high costs, while mass production, serving a large population, features a low cost but a poor fit and very limited variants. Due to the ever-changing fashion trend and consumers' increasing personal demands, mass customization has become a promising strategy in the garment industry by combining mass production and craft production modes. It can improve the personalization level towards craft production, and meanwhile, control the manufacturing cost, the production speed, and the product quality towards mass production (Yang, Kincade & Chen-Yu, 2015).

To the best of our knowledge, there have been numerous scientific reports on mass customization in the garment industry. The majority of the current work deals with garment design (Ulrich, Jo Anderson-Connell & Wu, 2003; Dai et al., 2006; Lee & Park, 2009; Satam, Liu & Lee, 2011; Vogiatzis et al., 2012; Xu et al., 2017), while the minority concerns garment manufacturing (Lu et al., 2010; Watcharapanyawong, Sirisoponsilp & Sophatsathit, 2011). As pointed out by Jiao, Zhang & Pokharel (2007), mass customization increases the number of variants in production, also decreases the number of items produced per variant, with significant impacts on garment manufacturing. In the whole garment manufacturing, cutting is the initial and one of the most complicated stages. It seriously affects the downstream links, i.e., sewing, finishing, and packaging. The cost that occurs in cutting is critical, as fabric usually occupies more than 50% of the total manufacturing cost (Wong & Leung, 2008). In addition, cutting can be considered as the decoupling point in the customized garment production, that a garment customization in manufacturing is essentially realized through patterns variations, directly conducted by the cutting-related processes (e.g., sizing, cutting order planning, and marker making). In this research, focusing on the garment cutting-related processes, we propose several mass customization strategies, and then apply some appropriate optimizations techniques in order to make the customization more efficient, and finally validate the proposed strategies and techniques through representative case studies. The proposed strategies and techniques can effectively facilitate the implementation and development of garment mass customization by taking into account the criteria of personalization levels and manufacturing costs.

In this context, **Chapter 1** provides the state of the art, which is composed of two parts. The first part begins with garment manufacturing, including concepts and current status of garment manufacturing and garment mass customization. It especially focuses on the garment cutting process and the cutting-related processes, i.e., sizing, cutting order planning, and marker making. The second part describes various optimization techniques applied to garment manufacturing, including operation research methods, heuristics, meta-heuristics, and hybrid techniques, where the three popular soft computing technologies (namely, genetic algorithm, fuzzy logic, and neural network) and hybrid intelligence are addressed in detail. Based on the literature survey, we identify the main drawbacks of the current methods in garment mass customization and set up new orientations for developing more appropriate and effective methods.

Taking into account the state of the art, we give the general structure of the thesis as follows (see Figure 0.1).

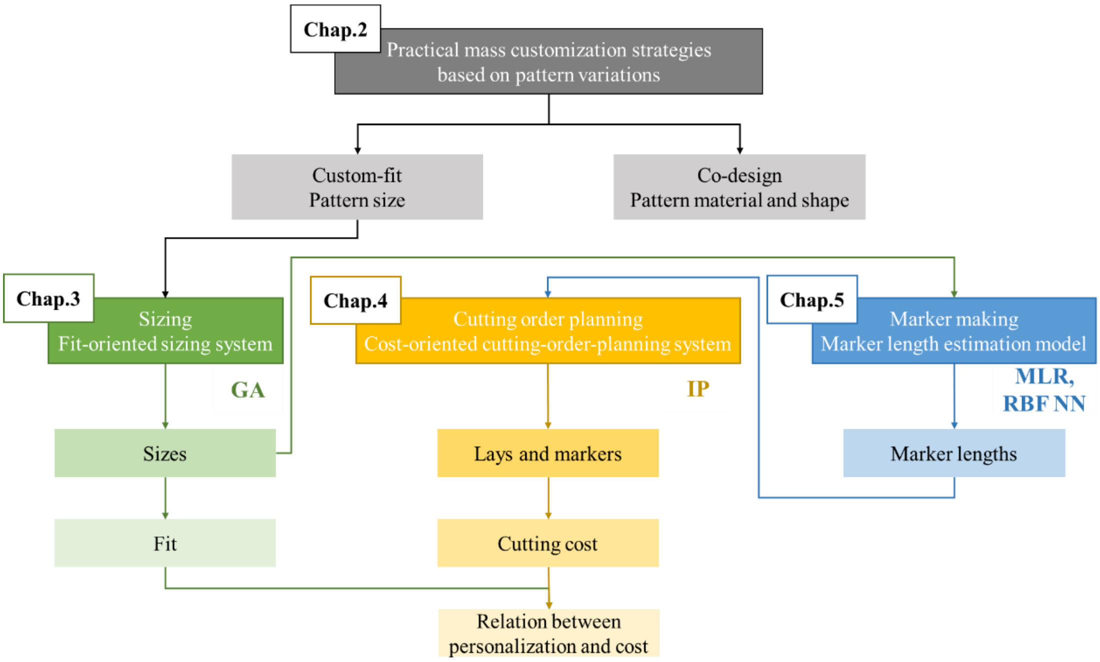

Figure 0.1 General structure of **Chapters 2-5**.

In **Chapter 2**, from the perspective of pattern variations, several practical mass customization strategies on custom-fit (pattern size) and co-design (pattern material and shape), namely, the two main categories of garment customization (Yang, Kincade & Chen-Yu, 2015), are developed from classical production practices in mass production. An analysis of the personalization levels and the cutting-related costs is demonstrated for evaluating the efficiency of these strategies. The analysis result can be considered as a reference for apparel companies to make their mass customization plans according to their specific conditions.

In **Chapters 3, 4,** and **5,** we propose several optimization techniques for improving three vital cutting-related processes, i.e., sizing, cutting order planning, and marker making, respectively. Considering that the fit customization is a fundamental need for users, and the simplicity and cost minimization in the course of pattern development and garment manufacturing, we use additional sizes for the customization in the three chapters. The mass customization strategies proposed in **Chapter 2** and the optimized processes shown in **Chapters 3, 4,** and **5** have all been validated through a case study of women's basic straight skirt manufacturing.

Chapter 3 presents a fit-oriented sizing system with additional sizes adapted from a traditional mass production sizing system. In this system, a Genetic Algorithm (GA) is used to find the global optimum within an acceptable computation time. The objective function is a newly proposed criterion comprehensive fit (CF) representing the overall garment fit of the whole target population.

In cutting, a cutting order plan determines the set of lays and corresponding markers used in batch cutting. As a classical cutting approach that is widely employed in mass production due to its high efficiency, batch cutting is herein adopted in mass customization by considering marker variations. Marker variations mainly exist in the differences in marker lengths and marker cutting lengths (Haque, 2016), and have an economic impact on the cutting order planning. However, in the previous study, the cutting order planning is accomplished with the ignorance of marker variations (Degraeve & Vandebroek, 1998; Rose & Shier, 2007; Fister, Mernik & Filipic, 2008). Consequently, in **Chapters 4**, a cost-oriented cutting order planning system with marker variations is established for an accurate economy performance (cost) evaluation of the proposed mass customization sizing system. 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). Moreover, by applying the sizing system and the cutting order planning system to the case study of **Chapter 4**, the indirect relation between the fit (personalization) and the overall cutting cost (cost) is revealed through the direct relations between sizing and fit, and between cutting and cost. The relation is discerned and a better compromise between personalization (i.e., the fit) and the cost (i.e., the cutting cost) can be obtained.

Adding more garment sizes in mass customization will lead to an exponential increase of marker number, which is determined by the possible garment size combinations. It induces a heavy and complex workload of marker making, because, in the current garment production, markers are generally made in a semi-automatic way with commercialized software. In addition, there exist some implicit relation between the overall marker length of a given size combination and that of each contained garment size, due to the geometrical arrangement. Therefore, a marker length estimation model is built in **Chapter 5**, where the Multiple Linear Regression (MLR) and Radial Basis Function Neural Network (RBF NN) have been applied to estimate the most appropriate marker lengths considering different sets of garment sizes (regarding mass production and mass customization) and different marker types (namely, mixed marker and group marker). The theoretical maker lengths can be used as the target values for the guidance and evaluation of marker making and the input of the cutting order planning system for cutting cost estimation.

Chapter I:

State of the Art

Chapter 1 State of the Art

In this chapter, we first give a comprehensive literature survey on the development of modern garment manufacturing, including its basic concepts, industrial practice, related bottle-necks, and potential opportunities. The key issues and trends of mass customization in the complex garment manufacturing have been systematically analyzed. Especially, we focus on the cutting process and cutting-related processes, including sizing, cutting order planning, and marker making.

Next, we review the potential optimization techniques that can be used for improving the current garment manufacturing. These optimization techniques can be classified into three main categories, i.e., exact methods, approximate techniques, and hybrid approaches. Considering that soft computing technologies have been successfully applied to different industrial sectors, we mainly focus on the three most popular techniques (i.e., genetic algorithm, fuzzy logic, and neural network) and their hybrid applications in garment manufacturing.

In order to realize mass customization meeting consumers' personalized and diversified requirements with a quick reactivity and minimal cost/price, practical mass customization strategies regarding garment manufacturing should be developed based on the industrial practice. Furthermore, garment manufacturing processes should be largely improved by massively applying optimization techniques. Especially, the most complex processes related to fabric cutting, i.e., sizing, cutting order planning, and marker making, that are determinative to the cost, should be optimized in the context of mass customization.

1.1 Garment manufacturing

Garment manufacturing contains a set of processes permitting transforming fabrics into garments. Facing consumers' strong demands on higher personalization, lower cost, and sound quality, there is an emerging trend of garment mass customization because it enables the personalized products offering at an acceptable price. The two cutting-related processes, i.e., the cutting order planning and marker making, are usually considered as the most complicated processes in the whole garment manufacturing. Therefore, significant mass customization progress in these processes is highly expected. Besides, the sizing process, which determines the development and production of garment patterns, should be addressed forward.

1.1.1 Garment manufacturing processes

The garment manufacturing is usually considered as a lengthy and complicated process (Nayak & Padhye, 2017). Consequently, the breakthrough in garment production at technical and organizational levels can ultimately help mass customization in this industrial sector in both theory and practice.

1.1.1.1 Content of garment manufacturing processes

Considering that (natural or synthetic) fibers, yarns, fabrics, and garments constitute four product stages of the textile manufacturing processes, we study in this thesis the garment manufacturing processes only, namely, the transformation of two-dimensional fabrics into three-dimensional garments. It consists of four main sequential processes, i.e., fabric cutting, sewing, finishing/ironing, and packing (Figure 1.1).

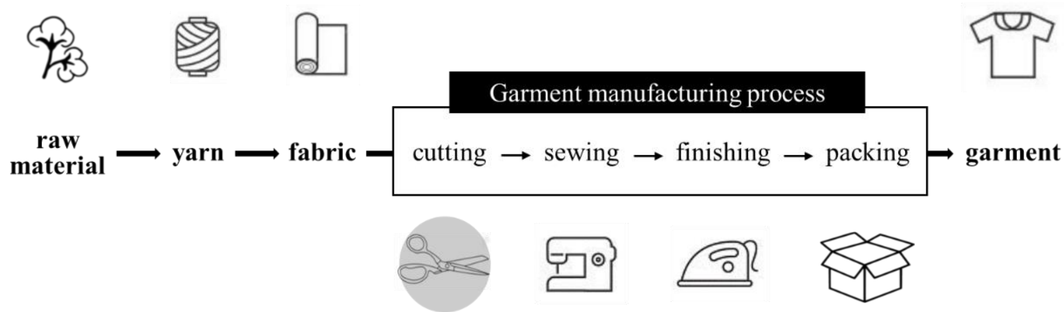

Figure 1.1 Workflow of the garment manufacturing processes.

The processes of cutting and sewing are the two key elements in garment manufacturing due to their relatively complex technologies and long time-consuming compared with the other two processes. Cutting is the upstream process of sewing, and sewing is served by cutting. In terms of work division, cutting is to cut cut-pieces from fabric rolls, while sewing is to assembly cut-pieces into a garment. Then the garment will be delivered from the final workstation of the assembly line in sewing to the finishing station for ironing processing, and finally, be packed into boxes in the last packaging process. In industrial practice, finishing and packing are placed in the same working area.

1.1.1.2 *Research issues on garment manufacturing*

Each process of garment manufacturing is composed of several steps. Table 1.1 is a classification scheme illustrating all the steps and corresponding technical details.

Table 1.1 Classification scheme of technical details in garment manufacturing.

<table>
<tr><th>Process</th><th>Step</th><th colspan="2">Technical detail</th></tr>
<tr><td rowspan="6">Cutting</td><td rowspan="3">production planning</td><td rowspan="2">cutting order planning</td><td>lay planning</td></tr>
<tr><td>marker making</td></tr>
<tr><td colspan="2">spreading and cutting sequencing</td></tr>
<tr><td>spreading operation</td><td colspan="2">roll sequencing</td></tr>
<tr><td>cutting operation</td><td colspan="2">-</td></tr>
<tr><td>sorting and bundling</td><td colspan="2">-</td></tr>
<tr><td rowspan="6">Sewing</td><td rowspan="3">production planning</td><td colspan="2">sewing order planning</td></tr>
<tr><td rowspan="2">sewing line design</td><td>layout design</td></tr>
<tr><td>sewing assembly line</td></tr>
<tr><td rowspan="2">quality control</td><td colspan="2">product inspection</td></tr>
<tr><td colspan="2">defect prediction</td></tr>
<tr><td>sewing operation</td><td colspan="2">fabric handling</td></tr>
<tr><td>Finishing</td><td>finishing operation</td><td colspan="2">fabric folding</td></tr>
<tr><td>Packing</td><td>packing operation</td><td colspan="2">product packaging</td></tr>
<tr><td rowspan="3">Management</td><td rowspan="2">production planning</td><td colspan="2">order planning</td></tr>
<tr><td colspan="2">resource allocation</td></tr>
<tr><td>quality control</td><td colspan="2">production monitoring</td></tr>
</table>

1.1.1.2.1 Cutting

Cutting has a crucial impact on garment manufacturing that it is the first and leading process of all manufacturing processes affecting the following processes (Vilumsone-Nemes, 2018). The cutting cost accounts for a dominant fraction in the total garment manufacturing cost, because the fabric cost is usually more expensive than the other expenses and that the fabric consumption mainly occurs in the cutting process. The main work in cutting contains a set of operations including spreading, cutting, as well as sorting and bundling, which is guided by a good production plan. The Cutting Order Planning (COP), and the Spreading and Cutting Sequencing (SCS) constitute the production planning of cutting. The COP determines the layouts of lays and corresponding markers (M'Hallah & Bouziri, 2016), while SCS defines the working sequencing of the spreading and cutting operations (Wong, Chan & Ip, 2000a). During the spreading operation, the sequencing of fabric rolls is also an important issue to be determined for fabric saving (Hui, Ng & Chan, 2000).

1.1.1.2.2 Sewing

Sewing is the most critical and intricacy process of garment manufacturing, which deals with a number of various operations, operators, and machines. It is manual work in most of the factories (Zoumponos & Aspragathos, 2008). The production planning in the sewing process consists of the sewing order planning and sewing assembly line design. The sewing order planning provides a production schedule for sewing orders to be put into production in turns within a limited time with the least inventory. The design of an assembly line considers two parts, i.e., the layout design and Sewing Assembly Line Balancing (SALB). An assembly line is a sequence of workstations equipped by operators who have the required skills and technological capabilities and machines with the required functions and connected by means of conveyance. The shape, the direction, the conveyor, the system type are elements considered in terms of the layout design. Garment assembly lines could be in different shapes like straight line, Z-shaped line, U-shaped line, or in a loop (Lin, 2009). Operators could face the same or opposite direction. Center tables or tools like trolley, basket, or hanger are used for material handling in different sewing systems, for example, the Progressive Bundle System (PBS) and the Unit Production System (UPS). Line balancing is to distribute tasks evenly to workstations with machines equipped, which is vital for efficiency (Hui *et al.*, 2002; Wong, Mok & Leung, 2006; Eryuruk, Kalaoglu & Baskak, 2008; Guo *et al.*, 2008a, 2008b, 2008c; Zeng, Wong & Leung, 2012). In a sewing line, each operator operates the given tasks in workstations equipped with machines for sewing or ironing as materials moving across the workstations. Before putting into production, the sewing line supervisors tackle the resources allocation problem with material, operator and machine to achieve a balanced loading. Since cut-pieces are assembled into garments in this process, a strict quality monitoring should be conducted here. Therefore, the product inspection and defect prediction are used for quality control.

1.1.1.2.3 Finishing and packing

Finishing, also called ironing, enables to straighten garments for packing. The main issue of the finishing process is fabric folding (Dai *et al.*, 2004).

Packing consists of a series of actions, i.e., sorting, piling, and packing. The product packaging is the main issue of the packing process.

1.1.1.2.4 Management

The order planning, resource allocation, and production monitoring of overall management are performed for a smooth workflow and a stable product quality.

Some trends occurring in the garment manufacturing processes can be summarized using three keywords, i.e., “customized”, “agile”, and “green”. Facing the ever-increasing demand on customization from consumers, the proposed concept “mass customization” is to introduce customized products into the production processes which previously were designed for mass production (Zulch, Koruca & Borkircher, 2011). Advanced techniques like artificial intelligences have become attractive and powerful tools (Guo *et al.*, 2011) having a great impact on automation and computerization of the garment industry (Nayak & Padhye, 2018). Emerging mobile technologies, such as Radio Frequency Identification (RFID), wireless sensor networks, as well as cloud computing are applied to enhance communications in supply chains, or even between and in manufacturing departments (Ngai *et al.*, 2014). Sustainability is a hot topic that efforts are made for increasing the usage of renewable sources and reducing water waste and carbon emission (Nayak, Akbari & Far, 2019).

1.1.2 Mass customization in garment manufacturing

There is an emerging trend of garment mass customization facing to consumers' strong demands on higher personalization, lower cost, and sound quality (Anderson-Connell, Ulrich & Brannon, 2002; Fogliatto, Da Silveira, & Borenstein, 2012; Nayak *et al.*, 2015).

1.1.2.1 *Evolvement and features of garment production paradigm*

The oxymoron "mass customization" was first coined by Davis (1987) in his book *Future Perfect* and popularized by the seminal work of Pine (1993).

It is well known that "economy of scale" and "economy of scope" is a pair of conflicts. It has been well documented in the existing literature that mass customization provides significant strategic advantages in price and customization (Kumar, 2004; Alptekinoglu & Corbett, 2008). Mass customization is established by combining mass production and craft production, as shown in Figure 1.2. The former features the high production efficiency and the latter represents the high degree of product variety, aiming to produce adequately diversified products at reasonable prices.

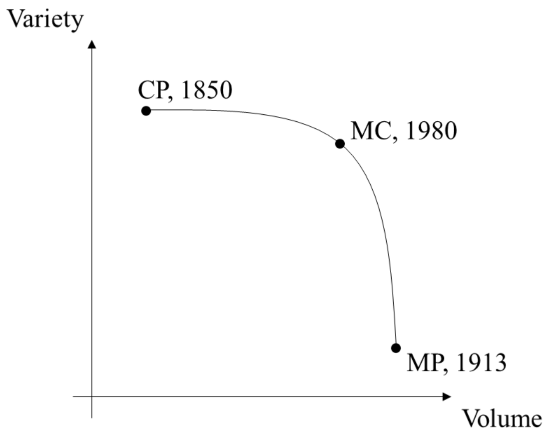

Figure 1.2 Relation of the three production paradigms.

Due to the increasing consumers' demand for product variation, the garment industry like other classical industrial sectors is undergoing a revolution from mass production to mass customization (Dong *et al.*, 2012; Hu, 2013; Nayak & Padhye, 2015). Features of the three production paradigms in the garment industry are displayed in Table 1.2. Craft production mainly targets individuals for "economy of scope". It performs a perfect fit and allows any wanted designs but costs high. Mass production serves a large population for "economy of scale". It brings low cost but a poor fit and lack of wanted designs. Mass customization allows personalization towards craft production. Meanwhile it can control cost, speed, and quality towards mass production. In other words, mass customization provides both cost advantages and satisfaction of consumers' personalized needs at the same time (Yang, Kincade & Chen-Yu, 2015).

Table 1.2 Differences among various production paradigms

Production paradigm	**Manufacturing strategy**	**Personalization Degree**	**Cost**
mass production	made-to-order/stock	common	cheap
mass customization	made-to-measure/ configurate-to-order	customized	acceptable
craft production	bespoke	individualized	expensive

1.1.2.2 Content of garment customization

Customization of garment includes two aspects, namely, custom-fit (Hu *et al.*, 2009; Mpampa, Azariadis & Sapidis, 2010; Tao *et al.*, 2018) and co-design (Teichmann, Scholl-Grissemann & Stokburger-Sauer, 2016; Li & Chen, 2018), as shown in Figure 1.3. The fit-related customization refers to adjusting the pattern size using key dimensions, in order to close the gap between individual body dimensions and dimensions of the assigned garment size, and the design-related customization refers to satisfying personalization demands through changes of fabric materials or construction of new pattern shapes.

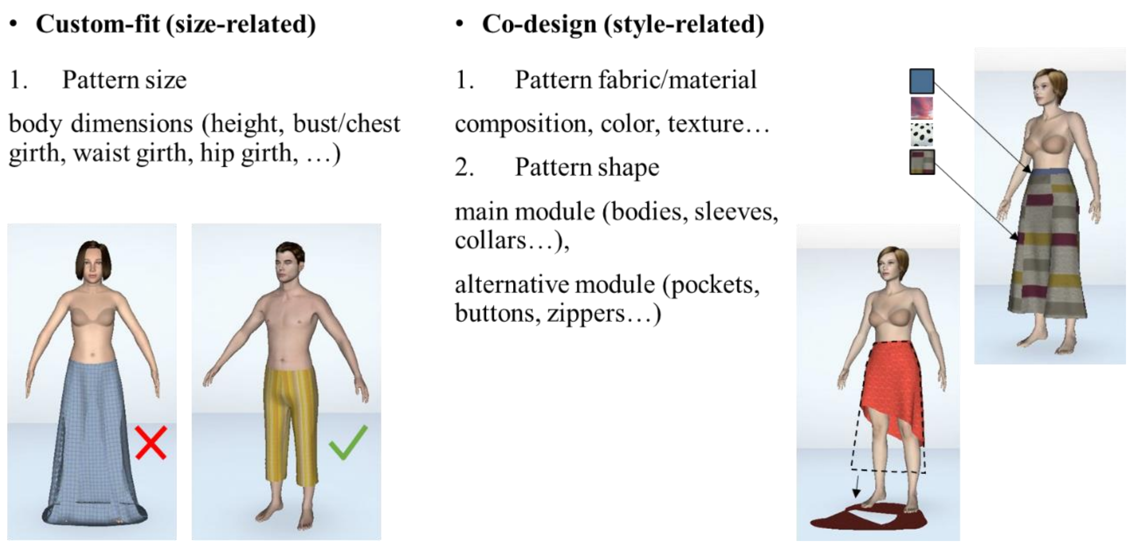

Figure 1.3 Specific contents of garment customization.

1.1.2.3 Research issues on garment mass customization

From the beginning of the 21st century, mass customization of garments has become a very popular topic and attracted great attention from academic researchers to industrial companies (Senanayake & Little, 2010). Researches have been made in various aspects of garment mass customization, including customer relationship, customized product design, production process, supply chain management, and price issue. The key issues are demonstrated in Table 1.3.

Table 1.3 Classification scheme of issues on garment mass customization.

Issue	Sub-issue
Customer relationship	customer perspective (preference, willingness, motivation, satisfaction)
	e-commerce (user-interface/web design, co-design system, recommendation system)
Product design	advanced design technologies (3D scan, VR, CAD, AI)
	customization design system
Production process	advanced manufacturing technologies (CAM, digital printing)
	production methods (postponement, modularity/product family, batch/mass manufacturing, concurrent engineering)
Supply chain management	information network
	logistics
Price	personalization and cost analysis
	pricing strategy

1.1.2.3.1 Customer relationship

Western societies now have entered an "experience economy" (Pine & Gilmore, 1999) that consumers increasingly derive value from experiences. Companies should emphasize not only on product and production, but also improving customer satisfaction and safeguarding a tight customer relationship. Accordingly, on one hand, investigations have been implemented on customer perspectives to explore customer motivations, willingness (Fiore, Lee & Kunz, 2004) and preferences (Lee *et al.*, 2002; Deng, Hui & Hutchinson, 2010) to mass customized garments. On the other hand, to promote consumers' participation in product design in e-commerce, research attention is laid on user-interface (Hankammer *et al.*, 2016; Tangchaiburana & Techametheekul, 2017) and recommendation function (Vogiatzis *et al.*, 2012) of customer-interaction web-designs. These works could aid in the development of more effective marketing efforts, a better understanding of consumers' needs and ideas, and gaining a rich customer experience in the application of mass customization in the garment industry.

1.1.2.3.2 Product design

Advanced design technologies including 3D anthropometry/scan, Virtual Reality

(VR), Computer-Aided-Design (CAD), and Artificial Intelligence (AI) have been widely applied in the product design process in order to satisfy consumers' needs, especially for fit satisfaction.

Anthropometric data automatically derived from a 3D scan (Daanen & Hong, 2008; Su, Liu & Xu, 2015) are used to produce individual patterns for improving the garment fit. VR is employed to build 3D body models (Cho *et al.*, 2005; Zhou *et al.*, 2016) and 3D garment models (Cho *et al.*, 2005; Au & Ma, 2010; Tao & Bruniaux, 2013; Thomassey & Bruniaux, 2013; Zhu *et al.*, 2017; Tao *et al.*, 2018) especially for displaying the wearing effect in a collaborative design process. The product design with CAD tools allows mass customization through automatic alteration of patterns based on individual body measurements (Istook, 2002; Yang, Zhang & Shan, 2007; Huang *et al.*, 2012; Han, Kim & Park, 2015). Two AI applications have been found in the product design of mass customization, that Fuzzy Logic (FL) was used in a method of ease allowance generation for garment personalized design in (Chen *et al.*, 2008) and a GA was proposed for the production decision making in (Xu *et al.*, 2017).

Establishing customized design systems is another hot issue during product development. These proposed systems deal with customer integration (May-Plumlee & Little, 2006; Li & Chen, 2018), the adaptation of advanced technologies like 3D scan, CAD, and laser-cutting machine (Lu *et al.*, 2010, Satam, Liu & Lee, 2011), and product modularity (Pan, 2016).

1.1.2.3.3 Production process

The optimization of manufacturing in garment mass customization has not been holistically tackled in industrial and academic practices.

Advanced technologies such as CAM (Dong *et al.*, 2012), and digital printing (Ren, Chen & Li, 2017) are mentioned to be used in the implementation of garment mass customization.

Duray (2002) suggested that mass customization processes, which are designed to be close to the existing mass production processes, usually lead to a good financial performance. Thus, mass production cost-effective expertise and methods of production should be considered, like the batch manufacturing and sizing systems (Duray, 2002; Mpampa, Azariadis & Sapidis, 2010). Additionally, postponement (Weskamp *et al.*, 2019), and modularity (Wang *et al.*, 2014) are two effective strategies to achieve mass customized garments. Postponement customizes products by delaying product differentiation. In garment mass production, it is an efficient way to make a pattern quickly by controlling an underlying the structure identified as a foundation for multiple styles. Thus, in garment mass customization, for each model, the variations can be made based on foundation. Modularity-based manufacturing is the application of unit standardization or substitution principles to create modular components and processes that can be configured into a wide range of end products to meet specific consumer needs (Tu *et al.*, 2004). In garment mass customization, modularity is the use of pre-cut and pre-assembled pieces, i.e., modules, for production (Yang, Kincade & Chen-Yu, 2015).

1.1.2.3.4 Supply chain

Setting up smooth flows of information and goods is a key research emphasis in garment manufacturing supply chain in the context of mass customization.

Shang *et al.* (2013) created a communication platform using the network, cloud technology, and other technologies to meet the demands of information flow and logistics in garment mass customization. Yinan, Tang & Zhang (2014) proposed that organizational flatness should facilitate effective lateral communication among supply chain partners in order to increase coproduction capacity.

1.1.2.3.5 Cost and selling price

Cost/price is a vital topic in mass customization strategy. The variety and depth of customizations determine the manufacturing complexity, which affects the manufacturing cost. The related work includes handling the le dilemma between personalization and cost, as well as setting a proper pricing strategy. As such, the relation between personalization level and cost are discussed in (Jost & Susser, 2019).

1.1.3 Cutting process

The cutting process is in the first phase of garment production, in which the production cost is the highest. The corresponding production methods and techniques need to be adjusted or even changed for mass customization.

1.1.3.1 Content of the garment cutting process

In a garment-cutting process, the garment patterns are cut out based on the standard sizes generated from a sizing system. As shown in Figure 1.4, cutting contains a series of steps starting with the production planning which includes the Cutting Order Planning (COP) and Spreading and Cutting Sequencing (SCS). The COP consists of lay planning and marker making, followed by the spreading operation, the cutting operation, and the sorting and bundling operations.

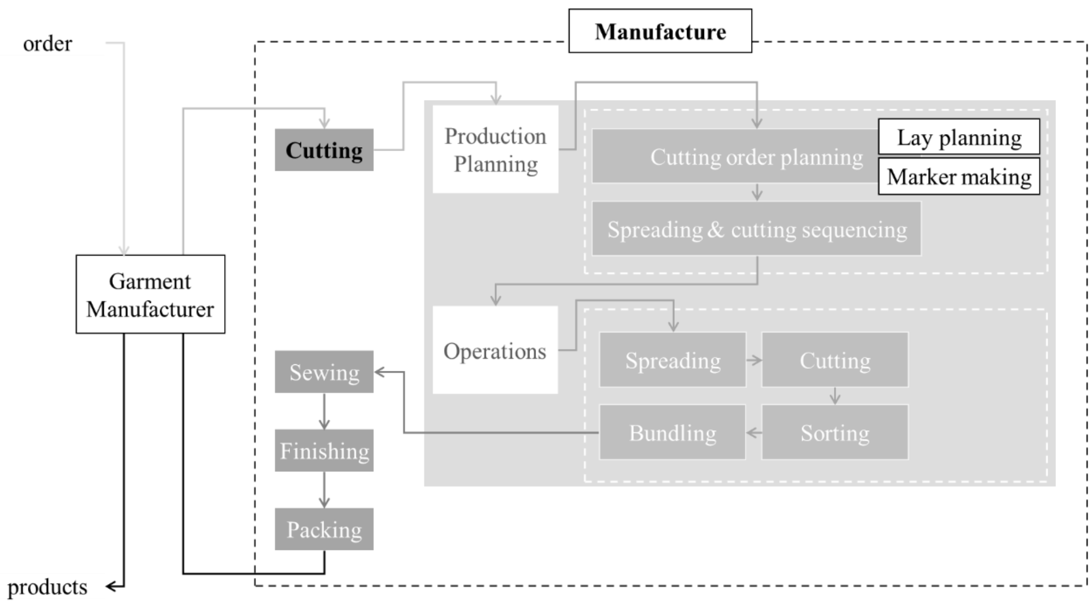

Figure 1.4 Workflow of the cutting process of garment manufacture.

The COP (or also called the cutting scheduling) is conducted once production orders are received. It is a basic and crucial step of the cutting process and the premise of Spreading and Cutting Sequencing (SCS). The COP and the SCS provide a guidance of the following operations: spreading, cutting, sorting and bundling. The purpose of the COP is to propose an optimal lay plan and its corresponding markers satisfying the constraints of order content, production conditions, delivery time, etc. A lay/stack consists of a certain number of fabric plies. A maker shows the layout of patterns which will be cut out from the lay.

The SCS refers to the balancing of spreading and cutting operations aiming to eliminate the idle time and satisfy the time constraint within the spreading and cutting capacity.

As the setup option of the cutting process, the spreading operation contains several actions: spread fabric rolls, cut fabric into pieces, superpose these pieces into lays on a cutting table, and finally spread the marker across the top fabric ply.

Following the cutting route generated according to the pattern layout on the marker, cut-pieces are cut out from fabric lays and then sorted and bundled for assembling use.

The cutting process should first fulfill the quantities of the cut-pieces required by the orders. In addition, it is subject to physical constraints in terms of fabrics and cutting devices: the fabric type/the cloth thickness and the cutting knife depth that determine the maximum ply count, the cutting table length that determines the maximum marker length, as well as the fabric width that determines the marker width.

Figure 1.5 gives a sketch showing all the steps included in the garment cutting process. First, in the cutting production planning step, we generate a lay plan and a marker of COP, a Gantt chart of the SCS. Under these three instructions, the cutting related operations (i.e., spreading, cutting, sorting and bundling) are then performed.

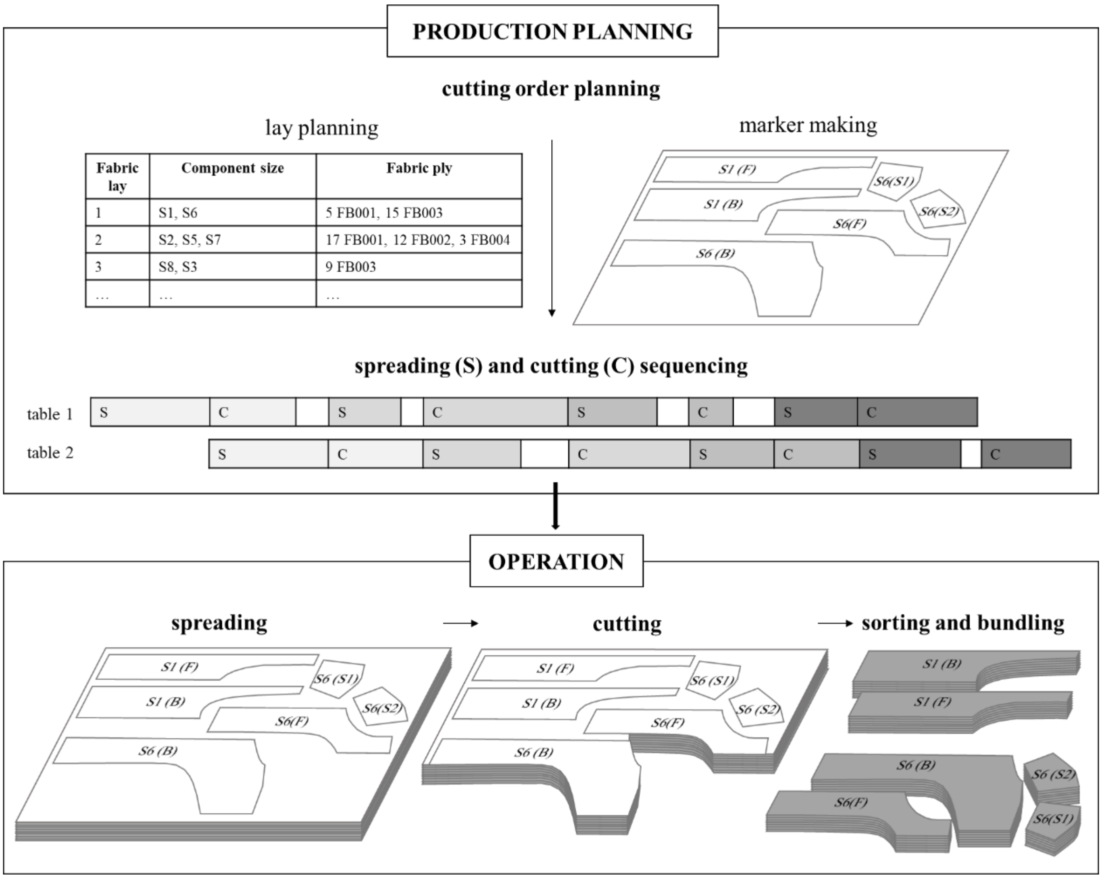

Figure 1.5 Sketch of the key steps in the garment cutting process.

1.1.3.2 Research subjects of garment cutting process

Table 1.4 Subjects and corresponding objectives on improvement of garment cutting process.

Step/subject			Objective
production planning	COP	lay planning	overproduction, setup cost, fabric cost, marker cost, machine and labor cost
		marker making	marker length, cutting length
	SCS		makespan
operations	spreading	fabric roll sequencing	fabric consumption
	cutting		-
	sorting and bundling		-

Researchers have paid much attention to the steps and related objectives of the cutting process listed in Table 1.4.

1.1.3.2.1 Lay planning

This is a step for planning lays with specific ply numbers for cutting out the required garment pieces satisfying orders while minimizing the total cost. The most concerned cost-related factors include fabric, spreading and cutting operations, and excess production.

In the past 30 years, lay planning has received continuous attention. Exact methods, i.e., enumeration (Rose & Shier, 2007), Integer Programming (IP) (Degraeve & Vandebroek, 1998; Degraeve, Gochet & Jans, 2002), and artificial intelligence-based algorithms, i.e., heuristics (Jacobs-Blecha *et al.*, 1997), meta-heuristics (Martens, 2004; Fister, Mernik & Filipic, 2008; Wong & Leung, 2008), and hybrids (Fister, Mernik & Filipic, 2010), were used to solve this cutting stock problem. One of the earliest researches was conducted by Farley (1988). He utilized an Integer Programming (IP) and a Quadratic Programming (QP), in which the sewing capacity constraint was considered. Publications boomed between 1995 and 2010. Degraeve & Vandebroek (1998) proposed a Mixed Integer Programming (MIP), based on which, IP models were introduced in (Degraeve, Gochet & Jans, 2002) and a GA was applied afterward in (Martens, 2004). Apart from IP, an exact enumerative approach (Rose & Shier, 2007) was another developed exact method. Evolutionary algorithms were the most employed algorithm (Fister, Mernik & Filipic, 2008; Wong & Leung, 2008; Fister, Mernik & Filipic, 2010). Besides, Ant Colony algorithm (ACO) and Simulated Annealing (SA) were also adopted in (Yang, Huang & Huang, 2011) and (M'Hallah & Bouziri, 2016) respectively.

1.1.3.2.2 Marker making

The fabric cost comprises a great part of the production cost in garment manufacturing, while maker making is always the major determinant of fabric utilization. Marker making aims to pack a given set of patterns within a rectangular surface of a fixed width in such a way as to minimize the length required.

Since the 1990s the problem of marker making has attracted considerable attention. The irregular garment patterns are represented first by a geometric approach (Heckmann & Lengauer, 1995) and later by a digitized approach (Wong & Leung, 2009). The placements of irregular shapes representing garment patterns are produced and optimized by using computer graphics techniques (Ko & Kim, 2013), exact algorithm (Heckmann & Lengauer, 1998), heuristics (Amaral, Bernardo & Jorge, 1990; Jaidormrong, Chaiyaratana & Hassamontr, 2003, July; Awais & Naveed, 2015), and meta-heuristics including Simulated Annealing (SA) (Heckmann & Lengauer, 1995; Javanshir *et al.*, 2010), Genetic Algorithms (GAs) (Bounsaythip & Maouche, 1997, October), and Neural Networks (NNs) (Wong & Guo, 2009).

1.1.3.2.3 Spreading and cutting sequencing

The cutting process has to fulfill the quantities of the cut-pieces required by the downstream sewing lines in time, in which the optimal schedule of the spreading and cutting operations is a key issue. Otherwise, a bad schedule will lead to a poor work balance with an idle time of spreading and cutting machines.

Wong and his partners made efforts for dealing with the spreading and cutting problem in the first decade of the 21st century. In an endeavor to achieve a full utilization of the spreading and cutting capacity, they formulated a spreading and cutting sequencing model and applied GAs to search for the optimal configuration (Wong, Chan & Ip, 2000a, 2000b; Wong, 2003c; Wong *et al.*, 2005, 2006; Kwong, Mok & Wong, 2006; Mok, Kwong & Wong, 2007) and used a queue theory which could achieve similar results (Wong, 2003a). Additionally, they adopted a fuzzy set theory for uncertainties in the real-life manufacturing environment (Wong, 2003b; Wong *et al.*, 2005; Kwong, Mok & Wong, 2006; Mok, Kwong & Wong, 2007).

1.1.3.2.4 Fabric roll sequencing

The variance of fabric yardage between fabric rolls induce the fabric loss during fabric spreading. Therefore, more attempts have been made to handle the fabric-roll sequencing for each cutting lay.

A few studies were made for sequencing the fabric rolls around the year of 2000. Ng, S. F. first presented a theoretical model using exact methods (Ng, Hui & Leaf, 1998) to calculate the fabric loss and conducted a comprehensive survey of the actual loss incurred in practice later (Ng *et al.*, 2001). Based on Ng's work (Ng, Hui, Lo & Chan, 2001), Hui, afterward, applied Genetic Algorithms (GA) to search for an optimal fabric-roll plan (Hui, Ng & Chan, 2000).

1.1.4 Sizing

Sizing aims at generating standard garment sizes. It is a link in the production design and development section, preceding cutting. A garment sizing system facilitates pattern development in both design and manufacturing processes and size assignments to individuals.

1.1.4.1 Overview of sizing

Garment sizing systems are constructed for the development of standard garments used in mass production. The standard sizes generated from sizing systems provide guidance when garment patterns are cut out in the garment cutting process. Sizing means deriving a set of sizing systems according to anthropometric data of the population in order to standardize garment sizes, and hence consumer satisfaction with garment fit. The garment fit is determined by the correspondence of certain body measurements to values for which the garment is intended. Objectives of sizing mainly concern the improvement of garment fit and the control of production cost including increasing the population accommodation rate, reducing the size number, or improving the overall fit in accommodated individuals. Efforts to advanced sizing system development are made for solving problems like improper fit for consumers, inconvenient for production, and endless trails for finding the right size.

The construction of garment sizing systems is composed of three steps (Gupta & Gangadhar, 2004): 1) the development of sizing systems based on population groups,

2) the validation of sizing systems, and 3) the designation of garment sizes. Figure 1.6 demonstrates the traditional processes of building sizing systems in mass production.

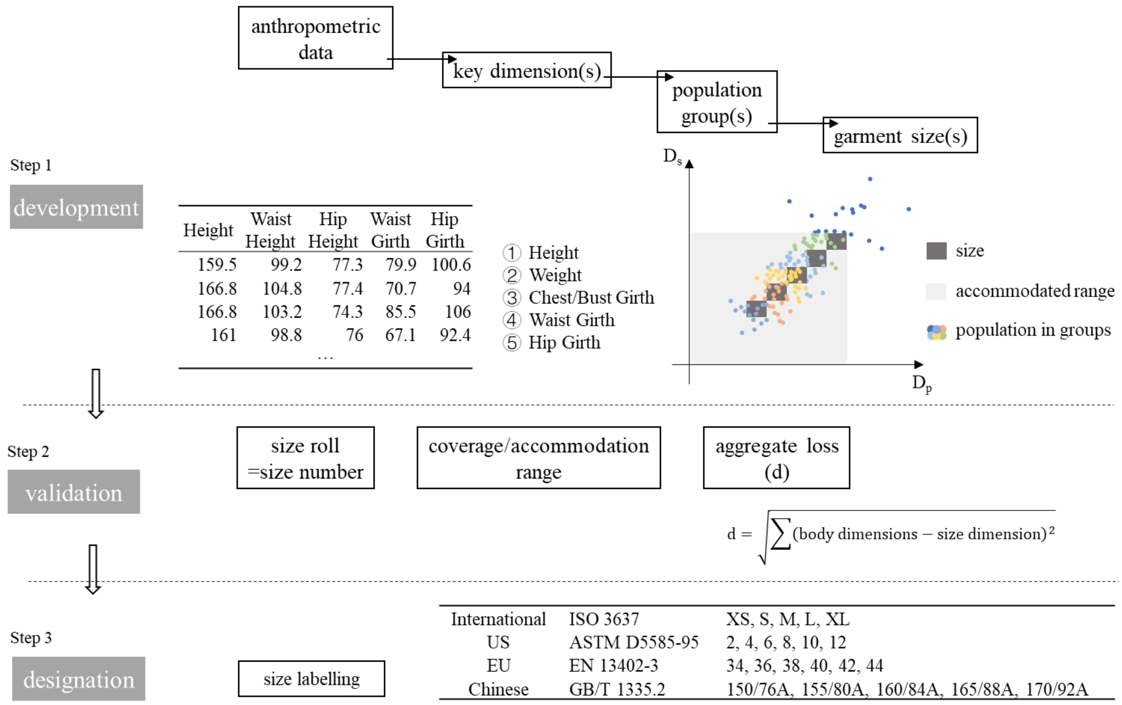

Figure 1.6 Flowchart of building sizing systems in traditional garment mass production.

In the developing phase, garment sizes are generated in four steps. The first is the collection of anthropometric data including important dimensions for pattern making like height, waist height, hip height, waist girth, and so forth. The second is the determination of key dimensions, i.e., primary and secondary dimensions. The third is the division of the population into homogenous groups according to body characteristics, i.e., key dimension measurements and figure types. And the final step is the generation of linear size systems that range from very small to very large for population groups. In the validation phase, the evaluation of garment sizes regarding size number, accommodation, and fit satisfaction is facilitated with parameters of size roll, coverage/accommodation range, and aggregate loss respectively. In the designation phase, the labeling of garment sizes is conducted by using Arabic numerals, English letters, or their combinations.

1.1.4.2 *Research progress of sizing*

The research on garment sizing started early from the 1950s (Staples & DeLury, 1949; Emanuel *et al.*, 1959) and continues with now (Hu *et al.*, 2019). In the beginning, the studies dealt with military uniforms (Emanuel *et al.*, 1959; Robinette, Churchill & McConville, 1981; Mellian, Erwin & Robinette, 1990; Robinette, Mellian & Ervin, 1991). Sizing standards, for instance ISO 3637, ASTM D5585, BS EN 13402, etc., were made to provide scientifically derived reliable information on body shapes and sizes for producers in order to develop patterns in garment manufacturing. To achieve an improved sizing methodology, various technologies were applied in the literature like exact methods (Tryfos, 1986; Gupta & Gangadhar, 2004; Gupta *et al.*, 2006; Mpampa, Azariadis & Sapidis, 2010), data mining (Ibanez *et al.*, 2012; Hsu & Wang, 2004; Hrzenjak, Dolezal & Ujevic, 2014), and soft computing (Vadood, Esfandarani & Johari, 2015; Hu *et al.*, 2019).

The linear structure is considered as the traditional layout of sizes widely applied in garment manufacturing practice. The comparison with other structures, i.e., two-tiered and unconstrained structures, was made in (Ashdown, 1998). Due to the various body proportions, linear sizing systems that range from very small to very large sizes cannot accommodate all body types. The unconstrained sizing systems bring a larger coverage and a better fit but usually cause difficulties in pattern grading and size designation.

The performance of sizing systems was evaluated in various aspects in terms of accommodation, size number, fit, and population distribution related to sizes. The aggregate loss (Tryfos, 1986) became a commonly used criterion for evaluation of garment sizing systems (McCulloch, Paal & Ashdown, 1998; Gupta & Gangadhar, 2004; Chung, Lin & Wang, 2007; Ibanez *et al.*, 2012; Vadood, Esfandarani & Johari, 2015). A garment sizing system with a higher coverage rate and a smaller size number was preferred. McCulloch, Paal & Ashdown (1998) proposed a nonlinear programming approach that was able to identify the accommodated individuals simultaneously with the selection of the prototype body size. Pei *et al.* (2017)

proposed a complete workflow to improve body size charts without changing the number of sizes in the range, namely, equalizing the number of people accommodated by each size within the range. In addition, an even population distribution to sizes is regarded as a good performance in sizing (Ashdown, 1998).

Some optimization techniques were proposed to create a sizing system for a better fit, such as integer programming (Tryfos, 1986), and a nonlinear optimization approach (McCulloch, Paal & Ashdown, 1998).

Statistical analysis methods, i.e., multivariate analysis (Xia & Istook, 2017), Principal Component Analysis (PCA) (Zakaria *et al.* 2008; Salehi Esfandarani & Shahrabi, 2012; Hrzenjak, Dolezal & Ujevic, 2014; Widyanti *et al.*, 2017), Factor Analysis (FA) (Zakaria *et al.* 2008; Hrzenjak, Dolezal & Ujevic, 2014), and Analysis of Variance (ANOVA) (Hsu, 2009; Hsu & Wang, 2004), were most widely employed for analyzing body dimensions.

The classification issue of dividing the population into homogeneous subgroups based on some key body dimensions was widely discussed in the literature. Emanuel *et al.* (1959) formulated standard sizes for all body types by first classifying bodies having similar body weight and height into different categories. Hsu (2008) proposed a bust-to-waist girth ratio approach for identifying female body shapes in order to develop body measurement charts. Data mining technologies were applied especially during this decade. In (Hsu & Wang, 2004), the classification and regression tree (CART) technology was used to mine data in order to identify and classify significant patterns in the body shapes of soldiers and establish standard-sizing systems. A two-stage cluster analysis approach was used to develop sizing systems (Chung, Lin & Wang, 2007; Hsu, 2009). The approach used the Ward's minimum variance method to determine the number of figure types, and subsequently, applied the K-means cluster analysis to group the homogeneous individuals into each figure type. In (Zakaria *et al.* 2008), the K-means cluster method was used to segment the children into distinct clusters, which were validated by a decision tree. These segmented groups were then converted into size tables for a certain group of girls aged between 7 and 12 years old. A K-mean algorithm was also used in (Salehi Esfandarani & Shahrabi, 2012) to change the heterogeneous population to a homogenous population in building sizing systems for Iranian males. A trimmed version of the Partitioning Around Medoids (PAM) algorithm jointly with Weighted Averaging Operators (OWA) was proposed to develop an efficient apparel sizing system (Ibanez *et al.*, 2012). With applications of artificial intelligence in the garment industry, neural networks were also widely used for building sizing systems in recent studies. Vadood, Esfandarani & Johari (2015) presented a sizing chart for Iranian male suites where different body types are clustered using the Kohonen neural network. Hu *et al.* (2019) applied a GA with the Support Vector Clustering (SVC) model to develop an upper garment size system with an increased fit and a reduced size number. The SVC technique was used to classify sizes, and the GA technique determines the optimal parameter values of the model.

1.1.5 Cutting order planning

The cutting order planning includes lay planning and marker making. Usually addressed in the literature is the lay planning problem only, taking identical marker lengths. Lay planning aims at arranging garment patterns in layers of fabrics with limited height. The optimization of lay plans is beneficial to the minimization of the total garment manufacturing cost in terms of cutting, i.e., fabric, spreading and cutting operations, and excessive production.

1.1.5.1 *Overview of cutting order planning*

The research on cutting order planning from the earliest study to the present has lasted for about thirty years. More attention has been made to made-to-order production. Unlike those with large quantities in mass production, there is a significant trend of fast fashion orders with small lot sizes. Integer programming, heuristics, enumeration, and graph theory are the approaches applied in the literature for solving the NP-hard problems, among which IP and heuristic algorithms are especially attracted by scholars. In this area, some classical work provided a solid foundation. The studies of Farley, Elomri, and Degraeve first introduced IPs to solve the cutting order planning problem, while heuristic algorithms were earliest used by Jacobs-Blecha. An IP is appropriate to represent the problem at a basic level (Figure 1.7). The main objective to achieve was to reduce various costs, i.e., fabric cost, labor cost, and machine cost, or cost-related components: number of markers, number of lays, and number of excessive products. The assumptions made in the modeling process either considered setting some parameters with different specific values as constants, such as material price and length of different markers, or required certain markers or lays to be full. For certain specific situations, modifying the model and adding more constraints can be conducted for finding the solutions. Additionally, for a shorter computation time, heuristics, and AIs can be applied. Among all the contributors, researchers from KU Leuven have a significant contribution with three representative papers (Degraeve & Vandebroek, 1998; Degraeve, Gochet & Jans, 2002; Martens, 2004) published in high-impact journals. “European Journal of Operational Research” and “International Journal of Production Economics” are the top most relevant journals in this area (Martens, 2004, Wong & Leung, 2008).

Notations:

S	set of sizes, $S = \{1,\ldots, s\}$
d_s	demand for size s
L	length of the cutting table
H	maximal ply number of a lay
l_{sm}	pattern length of size s on marker m
M	set of markers $M = \{1,\ldots, m\}$
a_{sm}	number of copies of size s in marker m, $s \in S$, $m \in M$
y_m	=1 if marker m is used, 0, otherwise, $m \in M$
z_m	ply number of marker m; $m \in M$
C	the cutting cost
E	excess products

Main constraints:

1. satisfy the order demand for each size

$$\sum_{1}^{m} a_{sm} z_m y_m \geq d_s$$

2. do not exceed the length of the cutting table

$$\sum_{1}^{s} l_{sm} a_{sm} y_m \leq L$$

3. do not exceed the maximal height of a lay

$$z_m y_m \leq H$$

4. some integrality constraints

a_{sm} is integer, z_m is integer

Main objective functions:

1. minimum the cutting cost

$$C = f\,(l_{sm}, a_{sm}, y_m, z_m)$$

2. minimum excess products

$$E = \min(\sum a_{sm} y_m z_m - d_s)$$

Figure 1.7 Frame of an integer programming model for the cutting order planning.

1.1.5.2 *Research progress of cutting order planning*

One of the first initial attempts of developing mathematical-programming models for solving the cutting stock problem in the garment industry was presented by Farley (1988). Both integer and quadratic formulations were introduced under the constraints with unique characteristics that occur in the laying, cutting and sewing operations to satisfy the objective of maximizing the annual contribution margin accruing from its production and sale of garments. The quadratic model is made for eliminating the integer variables and reducing the problem to a manageable size but it cannot guarantee the global optimum. Both models include various parameters that must be selected by the user and determined by practical experience. Especially, an explicit distinction between two broad garments categories (i.e., stock garments and made-to-order garments), was made and two kinds of fabric lay (i.e., step lay and rainbow lay) are discussed and analyzed in this study. For stock garments, holding stock is allowable, and for made-to-order garments, overproduction should be kept at a minimum. A step lay is possible to combine into one lay stack of different heights, and a rainbow lay is also possible for one stencil cut in different colors or of different fabric types.

Elomri *et al.* (1994) and Degraeve & Vandebroek (1998) separately made further studies on the same topic afterward.

In 1994, Elomri combined linear and non-linear programming in order to obtain sufficient precision in a very short time and with small memory requirements when solving the cutting problem which consists of choosing the patterns in the library, permitting to satisfy the client order with minimum cutting operating cost. The problem was solved by building the matrix form of the system constraints and putting the discontinuous economic function between two linear functions. The economic function defined in this study is a sum of several values related to the various operations of the cutting process, namely, costs regarding laying, cutting, fabric and material wastage, the time spent at the beginning and end of each laying, as well as the cost for taking away the cut-pieces and so forth. Some steps with low costs, such as costs for separating lots of articles and changing rolls, can be neglected.

In Degraeve's paper, a Mixed Integer Programming (MIP) model was proposed. It searched for an optimal set of markers, each giving a combination of articles to be cut in one operation and the corresponding stack heights, in which the total production costs can be optimized by minimizing the number of the cutting operations without performing excessive production. In order to restrict the solution space, the objective function was altered by fixing the number of different markers. It is the first paper from KU Leuven on the cutting order planning problem.

Later in 2002 and 2004, the research team of KU Leuven published the other two papers. One proposed two new IP models, and the other applied GAs to solve large real-life problems. Both studies extended the objective function to the total cost.

In (Degraeve, Gochet & Jans, 2002), two improved alternative IP models were proposed for the same layout problem described in (Degraeve & Vandebroek, 1998). The objective is to minimize the total production quantity with a fixed number of markers. One of the new models eliminated alternative optima among markers by imposing an ordering of the sizes within each marker. The other imposed a lower bound on the number of stencils needed in one marker in order to eliminate unnecessary variables. The computational results indicated a general outperformance of the alternative models compared with the originally proposed model. In addition, the model has been extended to a case with the objective of minimizing total cost, which is composed of fabric cost, spreading cost, cutting cost, and setup cost.

Martens (2004) built two GAs based on two alternative IPs, including NLIP and LIP models, proposed in (Degraeve & Vandebroek, 1998) that generate optimal or near-optimal solutions on small problem instances and solve large, real-life layout cases in an acceptable amount of time. The evaluation result showed that GA1 can find better solutions for a wide number of layout problems in a much smaller amount of time than GA2.

Heuristics were first mentioned to solve the garment cutting stock problem in 1997 (Jacobs-Blecha *et al.*, 1997). Jacobs-Blecha proposed a mathematic model aiming to minimize the total cost regarding fabric, cutting, spreading, and marker making that the addressed COP problem was performed independently of the downstream production considerations. Three greedy heuristics, including two constructive: Savings and Cherry Picking, and one improvement algorithm, were developed as computationally efficient procedures solving the COP problem to figure out size combination of markers and find low fabric cost solutions because of the significantly large impact of the cost of fabric on the total cost of the cut order planning process. Among the heuristics, Savings performed better than the Cherry-Picking algorithm and at least as good as the commercial packages, the improvement algorithm helped to optimize fabric utilization when applied to all solutions.

Algorithms of EAs (excluding GAs) and other meta-heuristics or hybrid algorithms were developed afterward.

Wong & Leung (2008) proposed a genetic optimization approach using adaptive ESs in order to genetically synthesize the cutting order plan and complete the order with minimized total cost which emphasizes on fabric cost and extra products under the time constraint predetermined by the downstream assembly departments.

This paper focused on transforming marker optimization into the 0/1 knapsack problem and designed evolutionary algorithms searching for an optimal minimum combination of markers to accomplish a work order which outperformed those existing deterministic algorithms, i.e., greedy heuristics. There lied a premise of this study that in practice, the minimum number of markers was the most often used optimization criterion that could be used as an approximation for minimizing real costs and was suitable for mathematical treatment.

Two years later in (Fister, Mernik & Filipic, 2010), Fister proposed a Hybrid Self-Adaptive Evolutionary Algorithm (HSA-EA) which improves the results of the previous simple evolutionary algorithms (Fister, Mernik & Filipic, 2008). In contrast, it successfully dealt with the objective of minimum preparation cost representing material, marker making, spreading and cutting costs which was identified and mathematically expressed instead of the minimum number of markers. The HAS-EA was a self-adaptive evolutionary algorithm hybridized using construction heuristics and improved with local search heuristics where the former solves the problem traditionally and the latter directs each solution into a local optimum. As especially shown in numerical experiments in this study, the material cost was much higher than the costs of marker making, spreading and cutting combined that it was the crucial objective for this production.

In the study of (Yang, Huang & Huang, 2011), Yang proposed a heuristic model considering setup, excess, and cloth layer costs. The ACIP model was a combination of Ant Colony Optimization (ACO) and an Integer Programming (IP) that ACO was applied for selecting the appropriate combination of cutting patterns and an IP model was developed for identifying the number of layers of cloth for each cutting pattern and computing the total cost.

In (M'Hallah & Bouziri, 2016), lay planning and marker making was combined into a single problem with the objective of minimizing fabric length solved using five constructive heuristics, and three meta-heuristics (i.e., a stochastic local improvement heuristic based on Simulated Annealing (SA), a global improvement heuristic based on Genetic Algorithms (GA), and a hybrid heuristic denoted genetic annealing. Different from current industrial practice, the study regarded the length of the layout of a section was known in advance, and it did depend on its combination of sizes.

In addition to mainstream integer programming methods and heuristic algorithms, enumeration and graph theory have also been applied in some research projects.

Rose presented a practical two-stage enumerative approach satisfying all demands exactly with the minimum number of lays (Rose & Shier, 2007). One variation of the two-stage approach would place a limit on the number of unique optimal solutions generated for consideration that for some instances, the number of optimal solutions could be prohibitively large. Besides, the hypothesis that all multiple-ply markers are full should be made to guarantee an optimal solution.

In (Nascimento *et al.*, 2010), the cutting order planning problem was modeled with the non-convex objective function including the various cost components including setup cost of lays, spreading setup cost, spreading cost, cutting cost, cost of folding losses, cost of imperfect template fit, inventory cost and markdown or obsolescence costs. So, an innovative state-space approach using heuristic rules was proposed to solve the problem where each possible schedule is modeled as a node in an initially unknown graph, the objective is to search for the lowest-cost schedule, and heuristic procedures are used for shortening processing times.

1.1.6 Marker making

The fabric cost is the major cost item in clothing products, while maker making is always the major determinant of material utilization. Additionally, considering the marker variances (i.e., maker length and cutting length) in cutting order planning can comparatively lead to a low-cost cutting plan. Thus, the optimization of marker making proves effective.

1.1.6.1 Overview of marker making

The marker making is laying out garment patterns within a rectangular surface with a fixed width, which is determined by equipment effective width, fabric width, and ease allowance. In the literature, the marker making problem is regarded as a Cutting Stock Problem (CSP), also is called an irregular object packing problem, an irregular nesting problem, or, to specify, a Two-Dimensional Layout (TDL) optimization problem. The principal purpose is to gain the best fabric utilization without overlap. The efficiency of a marker is therefore represented by the required marker length. The most restrictive constraint is the limitation of allowed rotation angles for the stencils. If needed, the symmetry and rapport constraints should be obeyed that a dependency between the placement positions of different patterns will be created. In the marker making process, there are three steps, i.e., pattern presentation, layout determination, and pattern compaction (Jaidormrong, Chaiyaratana & Hassamontr, 2003). As shown in Figure 1.8, in the first step, patterns in irregular shapes are represented by polygons, namely, the geometric representation, or by two-dimensional matrices, namely, the digitized representation, the next step is to generate layouts for these patterns, and finally adjust each pattern position and maximize the fabric utilization further.

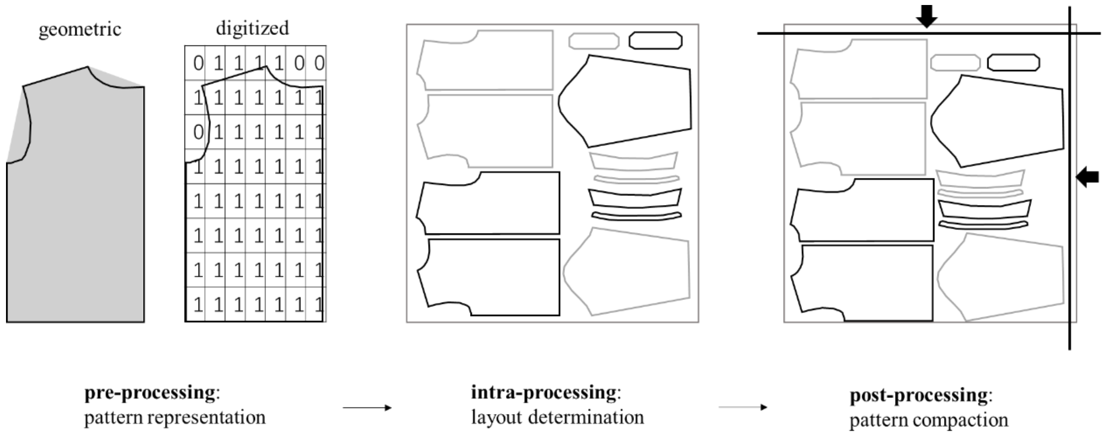

Figure 1.8 Sketch of steps in the marker making process.

1.1.6.2 Research progress of marker making

One of the earliest studies was made by Amaral, Bernardo & Jorge (1990). Since then, continuous researches for solving the complex garment marker making problem have been conducted. The pattern representation and layout optimization are the two key sub-problems in this domain. Patterns in irregular shapes were mainly enclosed by geometric shapes at the beginning. Later with the development of digital technologies, the grid approximation was introduced by Wong. Under this technique, each garment pattern is divided into a finite number of equalized cells. The layouts were produced and optimized by using exact methods and advanced computing algorithms for a reduction of the overall calculation time. The most adopted algorithms are heuristics and evolutionary algorithms. Besides, simulated annealing, neural networks are mentioned as well. In the literature, Wong from the Hong Kong Polytechnic University made a relatively in-depth study using the proposed grid approximation-based representation and meta-heuristics, i.e., Evolutionary Strategy (ES) and Neural Network (NN).

Amaral is one of the first to take the step of realizing the fully automatic placement of garment patterns. In the study (Amaral, Bernardo & Jorge, 1990), he proposed a sliding algorithm for the interactive placement of irregular shapes used in the GIZ graphic editor and developed a heuristic approach which uses the sliding algorithm for an automatic marker making. All the garment patterns in irregular-shapes are circumscribed by polygons with fewer points and placed following a greedy strategy by the sliding algorithm to achieve considerable material savings. The described algorithms were indicated to be applicable in a general way to the irregular shapes in the garment industry. Another attempt made with heuristics was reported in a conference paper (Jaidormrong, Chaiyaratana & Hassamontr, 2003, July). The design and development of a software tool using a top-down design paradigm was described where a heuristic search strategy is developed for layout determination on plain fabric, fabric with horizontal or vertical stripes, and fabric with checkered patterns.

In (Heckmann & Lengauer, 1995), Heckmann introduced a meta-heuristic: a Simulated Annealing (SA)with a fully dynamic statistical cooling schedule to solve this layout problem. For each garment pattern, a polygonal enclosure was calculated and used to represent it. Three years later in (Heckmann & Lengauer, 1998), he proposed two upper-bound procedures, where original garment patterns were represented by polygonal approximations. For the upper bounds he used greedy strategies based on hodographs and a global optimization based on simulated annealing. For the lower bounds he used branch-and-bound methods for computing optimal solutions of placement subproblems that determine the performance of the overall subproblem. There was room for improvement in the runtime and the outputs.

Another usage of SA in solving this problem was described in (Hwan & Jin, 2002). In this study, the rectilinear polygon approximation technique was used that fabric patterns, usually in non-convex shapes, were approximated as rectilinear polygons and at first allocated in random positions using the Multi-BSG algorithm (Sakanushi, Nakatake & Kajitani, 1998). Then, the most efficient marker was searched fast using a stochastic simulated annealing method.

In 1995 and 1997 IEEE conferences of International Conference on Systems, Man, and Cybernetics, Bounsaythip first used evolutionary algorithms (EA) to deal with the cutting nesting problem where patterns in polygons were circumscribed by bounding rectangles. The reduced-combs encoding method was used to find the smallest enclosing rectangles conveniently.

In (Yeung & Tang, 2003), Yeung used a combination of a Genetic Algorithm (GA) and the novel heuristic "Lowest-Fit-Left-Aligned" (LFLA) heuristic approach with which the complex two-dimensional strip-packing problem was transformed into a simple permutation problem to be effectively solved and the searching domain was reduced. It was shown from the simulation results that the optimal results could be obtained in a reasonably short period.

Vorasitchai tried to improve applications of GAs to solve the nesting problem by finding good parameter settings for the specific garment cutting layout problem (Vorasitchai & Madarasmi, 2003).

Between 2009 and 2010, Wong proposed to use the grid approximation (Ismail & Hon, 1992) instead of the traditional geometric approach for pattern representation, and concentrated on the application of meta-heuristics, i.e., Evolutionary Algorithms (EAs) and Neural Network (NNs), to the irregular garment patterns packing problem. Wong & Leung (2009) hybridized a Heuristic packing (HP) approach based on the grid approximation with an integer representation-based (μ+λ) evolutionary strategy (ES). Wong *et al.* (2009) hybridized a two-stage packing approach based on grid approximation with an integer representation-based Genetic Algorithm (GA). Wong & Guo (2009) proposed a hybrid approach combining a grid approximation-based representation, a learning vector quantization Neural Network (NN), a heuristic placement strategy, and an integer representation-based (μ+λ) Evolutionary Strategy (ES).

The other methods were also proposed. Especially, image processing, 3D simulation, computer graphics techniques have been used for solving cutting nesting problems. In Ko's work (Ko & Kim, 2013), a pattern nesting process for garments made of fabrics with complex figures was developed. In this study, image processing techniques were used to detect repeated graphical units from digitalized images of fabrics. Then, a three-dimensional simulation was used to design garments by taking these graphical units as texture maps. Next, a simple nesting method was used for placing patterns one by one according to their sizes. Finally, the patterns of garments were arranged on the fabric automatically so that the continuity of the graphical figures can be preserved while minimizing the loss of fabrics.

In addition, a linear programming approach was mentioned in (Awais & Naveed, 2015). In the study, a width-packing heuristic was used for shapes grouping, a column generation method was introduced for mapping groups onto the stock, and a linear programming approach was applied for selecting the minimum number of stock sheet layouts.

1.2 Optimization techniques in garment manufacturing

In the previous section, research progresses made in garment manufacturing processes, i.e., sizing, cutting order planning, and marker making, have been reviewed in detail. In this section, we first summarize the commonly used optimization techniques by category and emphasis on the most popular ones and their classic applications in garment manufacturing.

1.2.1 Overview of optimization techniques

The application of optimization techniques plays an increasingly critical role in industry development, including fashion sector as well (Majumdar *et al.*, 2010; Guo *et al.*, 2011; Hui, Fun & Ip, 2011; Gersak, 2013; Ngai *et al.*, 2014; Nayak & Padhye, 2015; Xu, Thomassey & Zeng, 2018, 2020). Through analysis of the literature, the commonly used types of optimization techniques are demonstrated in Figure 1.9.

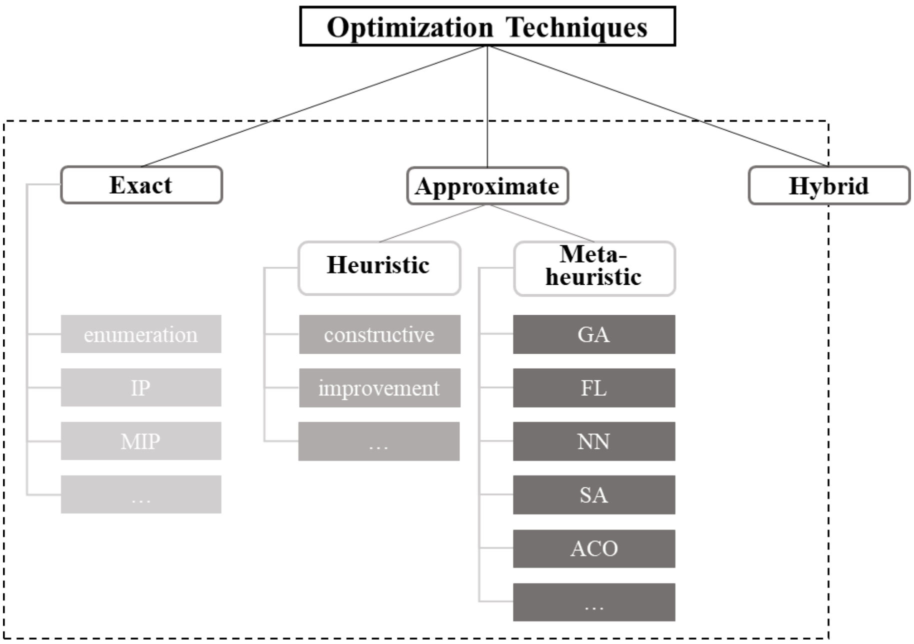

Figure 1.9 Classification of optimization techniques.

The optimization techniques used in the literature include exact methods, heuristics, meta-heuristics, and hybrid techniques. Exact methods are always the initial choices for solving problems with an optimal solution, among which, integer programming (IP) tends to be the most widely used. Enumerative approach has been adopted as well. Heuristics, including constructive and improvement are employed for searching for a satisfactory solution. A heuristic technique is any approach to problem-solving, learning, or discovery that employs a practical method not guaranteed to be optimal or perfect, but sufficient for the immediate goals. Where finding an optimal solution is impossible or impractical, heuristic methods can be used to speed up the process of finding a satisfactory solution. Soft computing, belonging to meta-heuristics, is widely applied for finding a good solution with less computational effort by searching over a large set of feasible solutions. Genetic Algorithm (GA), Fuzzy Logic (FL), and Neural Network (NN) are the most mentioned optimization techniques in the literature. Besides, Simulated Annealing (SA) and Ant Colony algorithm (ACO) are also popular. In addition, hybrid methods integrating the former technologies are favored by many researchers in recent years.

1.2.2 Application of specific optimization techniques in garment manufacturing

The applications of several specific optimization techniques are demonstrated as follows. Among these methods, three soft computing methods, i.e., genetic algorithm, fuzzy logic, and neural network are discussed in detail separately due to their outstanding performances.

1.2.2.1 *Exact methods*

According to the literature, exact methods are applied for solving various garment manufacturing issues. The initial and wide usage is in the cutting order planning.

Regarding the cutting order planning, IP is the first and most employed mathematical technology. Farley made integer and quadratic formulations with the overall objective to maximize long-run profitability (Farley, 1988). Elomri used a combined linear/non-linear programming approach which consists of choosing the patterns in the library with the objective of minimizing cutting operating cost (Elomri *et al.*, 1994). Degraeve proposed a mixed integer programming model and based on which he produced the other two alternative IPs (Degraeve & Vandebroek, 1998;

Degraeve, Gochet & Jans, 2002). Yang used IP in a combination with ACO considering setup, excess, and cloth layer costs (Yang, Huang & Huang, 2011). Besides IP, Rose & Shier (2007) developed an enumerative approach, and Nascimento *et al.* (2010) adopted graph theory.

For marker making problem, branch-and-bound methods were used for computing optimal solutions of placement subproblems that determine the performance of the overall subproblem in (Heckmann & Lengauer, 1998) to minimize the length of the marker surface.

For solving SCS problem, IP and queue theory were mentioned in (Wong *et al.*, 2001; Wong, 2003a) to evaluate the configuration of spreading and cutting machines installed in the cutting department.

Recursion and logarithm regression were used for QC in the garment sewing process. Lee used a recursive process mining algorithm to obtain a set of decision rules for fuzzy association rule mining, where the rules are used for determining the related product quality production process parameters (Lee *et al.*, 2013b).

Hui used multiple regression with a common logarithm method and a NN to predict the seam performance of woven fabrics (Hui & Ng, 2009). Compared with the NN, the regression models were found quicker to construct, more transparent, and less likely to overfit the minimal amount of data available.

1.2.2.2 *Heuristics*

The majority application of heuristics regarding garment manufacturing is found in COP problems, i.e., lay planning and marker making.

Heuristics were firstly used by Jacobs-Blecha to solve the cutting order planning problem (Jacobs-Blecha *et al.*, 1997). He proposed three greedy heuristics including two constructive, i.e., Savings and Cherry Picking, and one improvement. These heuristics have been proved to be computationally efficient procedures to figure out the size combination of markers and find low fabric cost solutions. Among the heuristics, Savings performed better than the Cherry-Picking algorithm and at least as good as the commercial packages, while the improvement algorithm helped to improve fabric utilization when applied to all solutions. Nascimento *et al.* (2010) developed an innovative state-space approach to solve the cutting order planning problem with graph theory where heuristic rules were introduced to select the most promising color-size combination for expansion so that processing durations were shortened. The other application of heuristics to the cutting order planning was mentioned in (M'Hallah & Bouziri, 2016), where lay planning and marker making were combined into a single problem to minimize fabric length. The problem was solved by using constructive heuristics with metaheuristics, i.e., a stochastic local improvement heuristic based on SA, a global improvement heuristic based on GA, and a hybrid heuristic denoted genetic annealing.

Amaral proposed a heuristic approach for the automatic placement of garment patterns (Amaral, Bernardo & Jorge, 1990), where garment patterns were placed following a greedy strategy by the sliding algorithm to achieve considerable material. Fabric patterns approximated as rectilinear polygons were allocated in random positions using the Multi-BSG algorithm (Sakanushi, Nakatake & Kajitani, 1998), which is a heuristic, and then, the most efficient marker was searched using a stochastic SA (Hwan & Jin, 2002). In (Yeung & Tang, 2003), Yeung used a combination of a GA with the novel heuristic approach “Lowest-Fit-Left-Aligned” with which the complex marker making problem was transformed into a simple permutation problem that the searching domain was reduced. The design and development of a software tool using a top-down design paradigm was described in (Jaidormrong, Chaiyaratana & Hassamontr, 2003, July), where a heuristic search strategy is developed for layout determination on various special fabrics like plain fabric, fabric with horizontal or vertical stripes, and fabric with checkered patterns. In (Wong & Leung, 2009), they hybridized a heuristic grid approximation-based packing approach with an integer representation-based ($\mu+\lambda$) evolutionary strategy (ES) to obtain the optimal marker with the minimal marker length. The heuristic pattern classification approach, inspired by experienced packing planners, was proposed for reducing the search space size. In addition, to solve the two-dimensional irregular shapes cutting stock problem a width-packing heuristic was used for shapes grouping, a column generation method for mapping groups onto the stock in (Awais & Naveed, 2015), then, a linear programming approach was used for selecting the minimum number of stock sheet layouts.

For predicting seam quality, Pavlinic used regression trees, where heuristic was applied for smaller and more accurate trees (Pavlinic *et al.*, 2006).

1.2.2.3 *Genetic algorithm*

Genetic Algorithm (GA), developed by Holland (1992) in 1975, is based on the principle of the natural evolution of species. By exchanging intergroup information, GA is powerful for its high ability in both local and global searching. It generates a whole population instead of just one possible solution in order to avoid getting stuck within a local optimum. Due to its advantage of easy implementation with optional coding methods and quick convergence by evaluating only a small fraction of the design domain, GA is always used to solve intractable discrete optimization problems.

A GA works on a population of so-called chromosomes which represent possible solutions to a specific optimization problem (Martens, 2004). As can be seen, a general GA is displayed in Figure 1.10. In the first step, the initial population of chromosomes is generated and coded as parent chromosomes. The fitness function or a penalty function is used for the determination of suitable chromosomes. Then, operators, i.e., crossover and mutation are employed for the creation of offspring chromosomes. It turns to the second step until the stop criteria are reached. Finally, chromosomes with a superior fit are returned as the optimal solution.

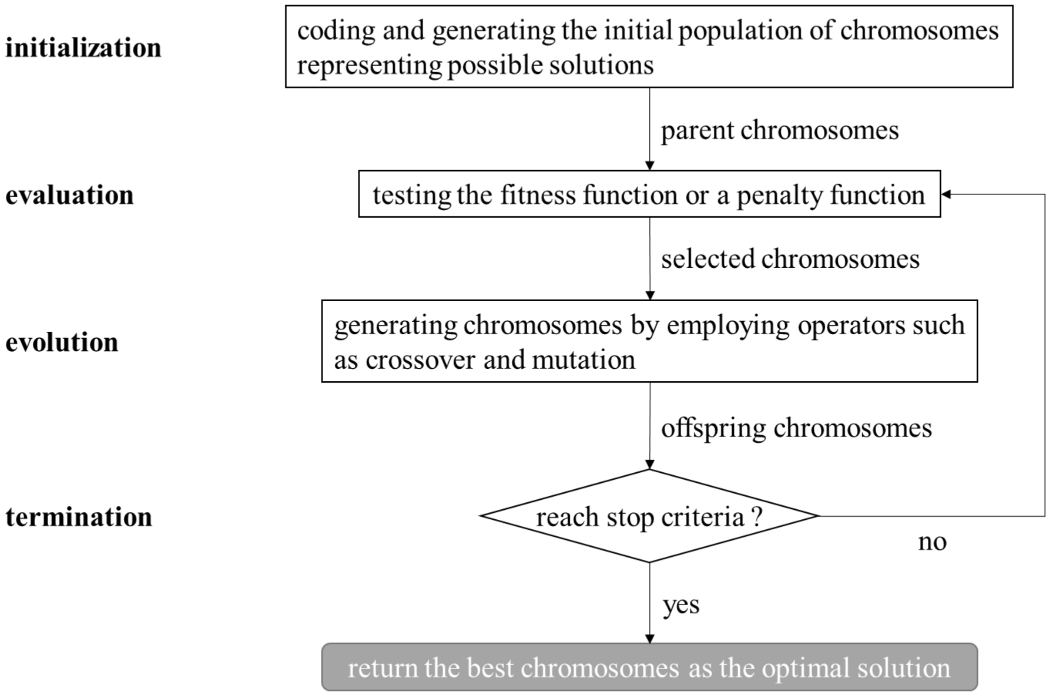

Figure 1.10 Sketch of a general genetic algorithm.

There has been an increasing trend of GA applications in dealing with the production scheduling and sequencing problems in the garment manufacturing process, especially in the cutting and the sewing processes.

In the decade from 2000 to 2010, there were considerable GAs applied to the cutting process.

Martens made an early attempt of applying GA in the cutting order planning (Martens, 2004). Based on two alternative integer programming (IP) models, a pair of GAs was proposed for minimizing the computation time. The good usage of EAs in finding the optimal cutting lay plan was proved in later continuous researches (Fister, Mernik & Filipic, 2008; Wong & Leung, 2008; Fister, Mernik & Filipic, 2010).

Yeung LHW proposed a hybrid method combining GA and the "Lowest-Fit-Left-Aligned" algorithm (LFLA) with which maker making of garment cutting process was converted into a simple permutation problem and the optimal results can be obtained in a reasonably short period (Yeung & Tang, 2003). Vorasitchai emphasized the parameter setting in the GA specific to the marker making (Vorasitchai & Madarasmi, 2003, May). An integer-representation based GA was proposed for an optimal marker (Wong *et al.*, 2009).

Between 2000 and 2007, Wong and his team made applications of GA to balance the SCS and minimize the makespan. GA was applied to determine the number of spreading tables to be installed in a computerized fabric-cutting system (Wong, Chan & Ip, 2000b). GA was afterward employed to obtain a shorter completion time, a higher machine utilization, and higher cut-piece fulfillment rates in a traditional manual system, a computerized system and a manual–computerized system (Wong, Chan & Ip, 2000a; Wong, 2003a, 2003c; Wong *et al.*, 2005), with the JIT philosophy (Wong, Chan & Ip, 2001; Kwong, Mok & Wong, 2006) or considering different types of existing uncertainties (Wong, 2003b). Moreover, Wong, Leung & Au (2004) proposed a GA for a Real-time Segmentation Rescheduling (RSR) of cutting related operations including marker-making, spreading, cutting, and bundling in a dynamic apparel manufacturing environment. Some partners addressed fault-tolerant fabric cutting schedules using this AI technology to satisfy resource-competing requests from downstream operating units to minimize the makespan (Kwong, Mok & Wong, 2006, Mok, Kwong & Wong, 2007).

GA was also applied to determine an optimal sequence of fabric rolls for each cutting lay during the fabric spreading operation to maximize the fabric saving in (Hui, Ng & Chan, 2000).

GAs have been widely applied to the sewing process as well.

Lin (2009) used a hierarchical order-based GA to quickly identify an optimal layout in a U-shaped sewing line with a single-row machine layout for effective moving distance of cut-pieces at lower production costs.

The Sewing Assembly Line Balancing (SALB) problem was addressed by researchers using EAs to minimize makespan and idle time. GAs were used to solve flexible assembly lines balancing problem where the flexible operation assignment is allowed, that one operation can be assigned to multiple workstations or multiple operations can be assigned to one workstation (Hajri-Gabouj, 2003; Guo *et al.*, 2008a, 2008b; Guo *et al.*, 2009). A GA was adopted to solve the SALB problem in UPS by periodically re-adjusting operator assignment and found the optimal number of task skills that each sewing operator should possess was three (Wong, Mok & Leung, 2006). GAs were developed in (Chen *et al.*, 2012; Mok *et al.*, 2013) for the automatic job allocation which can make an even workload allocation among machines based on the difference between labor skill levels. By applying an EA, Zeng investigated the operator allocation problems with job sharing and operator revisiting for the balance control of a complicated hybrid assembly line (Zeng, Wong & Leung, 2012).

The early completed jobs should be kept in a finished goods inventory before the delivery dates, while jobs that are completed after their due dates may incur penalty costs. Therefore, in a Just-In-Time (JIT) manufacturing environment, jobs are preferred to be completed in time. A GA was used to achieve an ideal schedule in which all jobs are finished exactly on the assigned due dates (Wong & Chan, 2001). To generate the optimal order scheduling solution in a real-life, make-to-order production with various uncertainties, Guo proposed a GA-based approach with the objectives to maximize the total satisfaction level of all orders and minimize their total throughput time (Guo *et al.*, 2008c).

1.2.2.4 *Fuzzy logic*

Fuzzy Logic (FL) (Zadeh, 1965, 1996, 1997), opposite to Boolean logic, in which the truth values of variables may only be the integer values 0 or 1, is a form of many-valued logic in which the truth values of variables may be any real number between 0 and 1 both inclusive. It has become a successful modeling tool for complex problems that can be controlled by humans but difficult to define precisely. Imprecise information as those resulting from inexact measurements or gained from imperfectly codifying expert knowledge can be incorporated into a fuzzy modeling. FL systems possess characteristics of simplicity and flexibility that the application of FL is in a simplified platform and takes a relatively short period of development time.

Decision making in manufacturing includes uncertainties and imprecision. FL has the capability of dealing with data that are vague and lack certainty, representing uncertainties such as variations in human operator performance, inaccuracies of process equipment, and volatility of environmental conditions (Azadegan *et al.*, 2011).

FL could deal with the dynamic and fuzzy factors in the real garment manufacturing environment such as machine breakdowns, late receipt of fabric rolls, insertion of rush orders, etc. It helps robotic handling in sewing, SCS in cutting, resource allocation, and QC.

In the sewing department, FL was employed for automatic fabric handling to handle with the varieties during conducting a robot guiding non-rigid fabrics.

Koustoumpardis developed a hierarchical robot control system including a fuzzy decision mechanism where the fuzzy rules and the membership functions are determined according to the experts' knowledge, combined with a neuro-controller to regulate the tensional force applied to the fabric during the robotized sewing process (Koustoumpardis & Aspragathos, 2003). Later, he investigated the robotized sewing of two plies of fabrics (Koustoumpardis & Aspragathos, 2014). Zoumponos presented a robot end-effector path-planning algorithm based on FL for the robotic laying of fabrics on a worktable that possesses the characteristics of flexibility and low computational cost (Zoumponos & Aspragathos, 2008). Later, he introduced visual servoing the he presented a new fuzzy visual servoing strategy based on the knowledge of easily measured fabric shape features for the folding of rectangular fabric strips by robotic manipulators (Zoumponos & Aspragathos, 2010). Also, FL and visual servoing were adopted by Zacharia. Zacharia developed a flexible automation system tolerating deformations that may appear during robot handling of fabrics due to buckling without the need for fabric rigidification based on FL (Zacharia *et al.*, 2009). Zacharia (2009) made an extended research focusing on operations with curved-edge fabrics and correcting the distortions presented during robot handling of fabrics.

The research group of Wong has applied FLs in solving the fabric-cutting balancing problem.

Firstly, a fuzzy capacity-allocation model was proposed to solve the line-balancing problem in a computerized cutting system with consideration of the level of Work-In-Progress (WIP), i.e., number of fabric lays, on each spreading table and the degree of deviation between the planned starting time and actual starting time of spreading of each fabric lay on a particular spreading table as fuzzy input variables (Wong, 2003b). It was indicated that the WIP level could be controlled, and the machine idle-time and makespan could be shortened in a dynamic cutting room.

They used FL for production order fuzzy due time and GA to generate fabric cutting schedules in a just-in-time (JIT) production environment, which improve the internal satisfaction of downstream production departments and reduce production costs through shortening operator idle time (Wong *et al.*, 2006; Mok, Kwong & Wong, 2007). As an extension, they considered three uncertainty factors, i.e., operator skill level, fabric characteristics, cutting pattern on a marker for fuzzy job processing time (Kwong, Mok & Wong, 2006).

Regarding resource allocation, Hui, P. L. proposed a rule-based operator-allocation system using FL where the knowledge of experienced supervisors was captured to determine the right number of operators to be moved in and out of sewing sections to insure overtime balance (Hui *et al.*, 2002). Hajri-Gabouj (2003) relaxed the mathematical model to overcome the nonlinearity and the complexity using fuzzy penalty functions to handle task-operator-machine assignment problem with multilevel objectives, i.e., minimizing the total execution time, neither predefining inter-operator communication costs nor a prefixed number of machines and operators. Lee presented a resource allocation system integrating RFID technology for real-time data capturing and FL concept for machinery resource allocation planning according to expertise knowledge stored as fuzzy rules (Lee *et al.*, 2013a, 2014).

In the QC area, FL was used to find the relationships between production process parameters and product quality, where a set of decision rules was derived for fuzzy logic that will determine the quantitative values of the process parameters (Lee *et al.*, 2013b, 2016). The study provides knowledge support for parameter settings of machinery resources. Shu, M. H. developed a demerit-fuzzy rating mechanism and monitoring scheme to improve online surveillance of manufacturing processes (Shu *et al.*, 2014).

1.2.2.5 *Neural network*

Neural Network (NN) was first introduced in (McCulloch & Pitts, 1943). It was inspired by both biological neural networks that constitute animal brains and mathematical theories of learning, and it can be used as a universal function approximator that learns from observations (training samples), generally without task-specific programming. NN is a highly connected network of processing nodes (artificial neurons) arranged in 3 or more layers. It learns from historical examples known as training data. During the training, the weights connecting the neurons present in different layers are optimized in such a fashion that the error signal reduces in each iterative step. Once sufficiently trained, NN can be used to solve unknown instances of the problem due to its non-parametric nature and ability to describe complex decision regions.

An artificial NN is demonstrated in Figure 1.11, as an interconnected group of nodes, where each circular node represents an artificial neuron and an arrow represents a connection from the output of one artificial neuron to the input of another. NN parameters, i.e., network weights and bias are adapted through a learning process, a continuing process of stimulation by the environment in which the network is embedded (Guo *et al.*, 2011). NN has been used on a variety of tasks in manufacturing, such as prediction, pattern recognition, generalization, fault tolerance, and high-speed information processing.

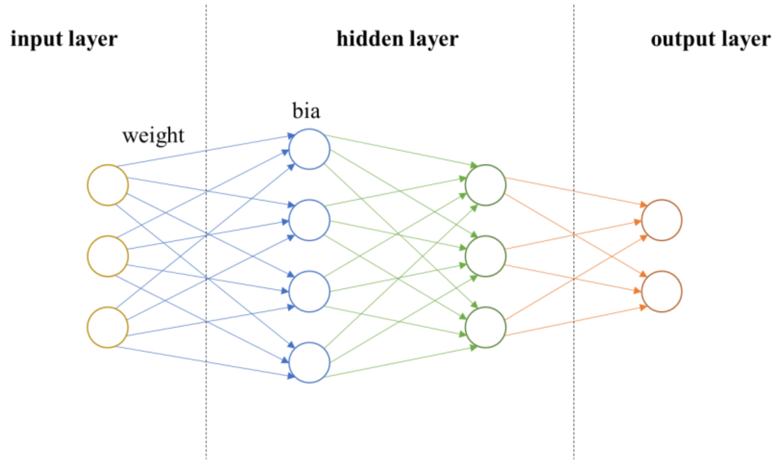

Figure 1.11 Structure of a basic neural network.

In the garment manufacturing process, NN is mainly used for solving prediction problems, process control problems, and model identification problems in Quality Control (QC), robotic fabric handling, maker making, and so forth.

NN has been widely applied for the prediction of fabric sewing performance, seam quality inspection, fabric and garment classification, and sewing thread consumption prediction. In (Lin, 2004), a Back-Propagation (BP) NN was used to establish a translation model between fabric and thread composition properties and sewing quality. Hui investigated the use of extended normalized radial basis function NN to study the correlations between fabric mechanical properties and the seam appearance quality to construct the model for predicting seam, which was proved to outperform the previous BP NN (Hui & Ng, 2005). The same author proposed a BP NN for fabric sewing performance prediction which was classified in terms of four main factors, i.e., pucker, needle damage, fabric distortion, and fabric overfeeding based on 21 physical and mechanical properties (Hui *et al.*, 2007). Afterward, he used a BP NN with a weight decay technique to predict the seam performance of commercial woven fabrics measured by the ratings of three indices, i.e., seam puckering, seam flotation, and seam efficiency (Hui & Ng, 2009). Pavlinic also investigated the relation between fabric mechanical properties and the quality of seam appearance, which was defined by seam puckering and work-piece flotation. Regression trees (CART) and k-Nearest Neighbors (k-NN) were used in the study to construct the predictive model, where the latter method is more appreciate (Pavlinic *et al.*, 2006). Later, the same author developed a subjective evaluation system of garment appearance quality by studying the correlations between fabric mechanical parameters and the grade of garment appearance quality using k-NN (Pavlinic & Gersak, 2009). Especially for knitted fabric, in (Yuen *et al.*, 2009a), four characteristic variables were collected and input into a BPNN to classify the sample images. Similarly, Yuen used a three-layer BPNN to deal with intelligent classification of fabric stitches or seams of semi-finished and finished garments (Yuen *et al.*, 2009b). Besides, NN was employed in sewing thread consumption prediction as well (Jaouadi *et al.*, 2006).

Regarding the robotized sewing issue, Koustoumpardis developed a neuro-controller to regulate the tensional force for the feeding of single-piece fabric to the sewing machine (Koustoumpardis & Aspragathos, 2003). In a latter research (Koustoumpardis & Aspragathos, 2014), he controlled the force applied by the robotic manipulator with NN in order to join two pieces of fabric. Zacharia (2009) dealt with the curved edges of real cloth parts by NN which learns from the information obtained from the fabrics used for the training process and then responds to new fabrics.

To solve the marker making problem, Wong & Guo (2010) constructed an irregular object packing approach where a learning vector quantization NN was developed as a classification heuristic by a set of examples that were inspired by experienced packing planners to diminish the size of a search space by dividing the objects into three classes, i.e., BIG, SMALL and OTHER.

In (Zou *et al.*, 2006), a BP NN was used to simulate the experience and technology of fashion designers for establishing a model to identify body type.

1.2.2.6 *Hybrid methods*

For decision-making in real-world garment production, there are multiple production objectives to achieve simultaneously. There exists a situation that one single technology is not able to fully solve the problem, as such a hybrid intelligence for utilizing an integration of technologies makes sense.

The hybrids mentioned in the literature on the garment manufacturing are demonstrated bellow in terms of these four combinations, i.e., exact method and heuristic, exact method and meta-heuristic, heuristic, and meta-heuristic, and a hybrid of meta-heuristics.

The combinations of exact method and heuristic were found in (Nascimento *et al.*, 2010) and (Lee *et al.*, 2013b). An innovative state-space approach hybridizing a graph theory-based model and a heuristic algorithmic solution to identify the least-cost lay plan was proposed by Nascimento. Lee presented a radio frequency identification-based recursive process mining system using FL to find the relationships between production process parameters and product quality.

A combination of exact method with meta-heuristic, i.e., an IP model with an ACO, was proposed in (Yang, Huang & Huang, 2011) to identify good combinations of markers and determine the number of plies that satisfy demand with the minimal excess production.

Researchers preferred using the combinations of heuristic and meta-heuristic to solve the marker making problem. Hwan Sul, I. first allocated patterns in random positions using the heuristic Multi-BSG algorithm, and then, the optimal marker with the highest efficiency was searched using a SA method (Hwan & Jin, 2002). In (Yeung & Tang, 2003), Yeung used a combination of a "Lowest-Fit-Left-Aligned" heuristic approach with a GA to transform the complex two-dimensional strip-packing problem into a simple permutation problem so that the marker making was effectively solved and the searching domain was reduced. In the study (Wong & Leung, 2009), he hybridized a heuristic packing approach based on grid approximation with an integer representation-based ($\mu+\lambda$) evolutionary strategy (ES). In another study of him (Wong & Guo, 2010), he proposed combined a grid approximation-based representation, a learning vector quantization NN, a heuristic placement strategy, and an integer representation-based ($\mu+\lambda$) ES.

Hybrids of meta-heuristics were adopted in all aspects of the garment manufacturing process, i.e., cutting, sewing, and QC. Bounsaythip hybridized GA with SA to find the optimal pattern layout on the marker (Bounsaythip, Maouche & Neus, 1995, October). The combinations of GA and FL were adopted to solve the spreading and cutting sequencing problem by Wong's research group in (Kwong, Mok & Wong, 2006; Wong *et al.*, 2005; Mok, Kwong & Wong, 2007) with shorter makespans. For the SALB problem, Hajri-Gabouj (2003) developed a GA with fuzzy penalty relaxation to realize flexible assignments in sewing lines with multilevel objectives. The combinations of FL and NN were used by Koustoumpardis to handle fabric handling in sewing operation. He combined a hierarchical robot control system containing a fuzzy decision mechanism with a neuro-controller (Koustoumpardis & Aspragathos, 2003). His extended work on robotized sewing of two-ply fabrics using the same optimization techniques was described in (Koustoumpardis & Aspragathos, 2014). Zacharia (2009) presented the design and tune of the adaptive neuro-fuzzy inference systems for robot guiding fabrics with curved edges based on visual servoing and a learning technique that combines FL, NN, and GA. For QC, Yuen integrated GA and BP NN for knitted garment defects classification (Yuen *et al.*, 2009a). Lee *et al.* (2016) proposed the hybridization of fuzzy association rule mining and variable-length GAs for a better determination of process settings for improving the garment quality.

1.3 Conclusion

Facing the increasing demand of consumers on the product personalization and meanwhile the control of product price, the garment mass customization emerges as the product of the time. The garment mass customization aims to resolve the le dilemme between personalization and cost, and it brings the possibility of offering personalized products at an acceptable price. Nevertheless, the implementation of mass customization in the current production structure is a complex issue but also an opportunity and a challenge to the apparel industry.

There have been a number of reports regarding garment mass customization, of which the majority deals with design, while a few concerns manufacturing. In the long-range garment manufacturing processes, the complicated cutting process plays a key role in cost control, as fabric usually occupies more than 50% of the total manufacturing cost. In addition, cutting can be considered as the decoupling point in the customized garment production, that a garment customization in manufacturing is essentially realized through patterns variations, directly conducted by the cutting-related processes (namely, sizing, cutting order planning, and marker making). Therefore, in this research, we will develop practical mass customization strategies regarding the three cutting-related processes and apply appropriate optimization techniques to enhance the efficiency.

The main idea of this dissertation work is shown in Figure 1.12. The work starts with developing practical mass customization strategies regarding custom-fit and co-design. It then addresses the development of a sizing system and a cutting order planning system (marker making is further studied) for decision making in garment production. In addition, it contains exploring the implicit relationship between the personalization (the fit) and the cost (the cutting cost) through the known relations (Figure 1.13) including the relation between the sizing and the fit, the relation between the cutting and the cutting cost, and the relation between fit and cost.

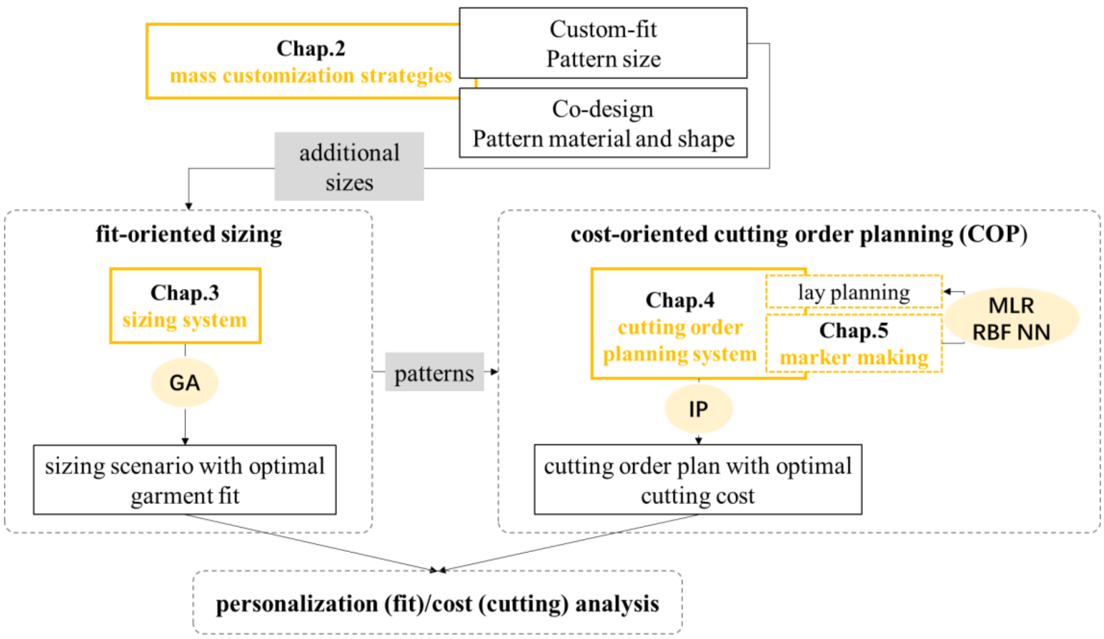

Figure 1.12 Structure of dissertation work.

Customization of garment contains two categories, namely, custom-fit and co-design. The customization of fit should be conducted in the upstream processes (the sizing and the cutting) before sewing, whereas the customization of design can be performed downstream (e.g. postponement strategy). Researchers have attempted advanced technologies in this regard, such as recommendation systems, the virtual reality, the 3D body scanning, and CAD automatic patternmaking systems, to realize the personalized pattern design and the automatic single-ply cutting. So far, the costs are still high because advanced technologies always work with the support of expensive equipment. Duray (2002) suggested that mass customization processes that more closely matched existing mass processes in the plant led to superior financial performance. Thus, the efforts should be made to selectively retain the expertise and methods in cost-effective mass production for mass customization upgrading, like sizing systems and batch manufacturing. In **Chapter 2**, we develop mass customization strategies in the two categories, i.e., co-design and custom-fit, taking into account efficient industrial practices like sizing systems and batch manufacturing in the cutting-related processes.

Compared with the design, the fit is an essential issue of garment customization and gains much concern for it is a fundamental need of users. Limited and outdated sizes for ready-to-wear garments are usually considered as the primary source of ill-fitting in mass production. Introducing additional garment sizes is a feasible solution for fit improvement, which enables to establish a new mass customization sizing system to solve this problem. In **Chapter 3**, we build a fit-oriented sizing system with adding new sizes for the greatest overall fit satisfaction of the target population.

Customization increases the number of material variants in production, significantly affecting the manufacturing process. Specifically, the increased size number in mass customization makes for variety in marker. However, to the best of our knowledge, the cutting order planning is normally accomplished with the ignorance of marker variations. Nevertheless, especially for small series production and mass customization, marker variations should be taken into consideration in the cutting order planning to accurately evaluate the cutting cost. In **Chapter 4**, we build a cost-oriented cutting order planning system with marker variations for the most economical cutting order plan.

Adding more sizes in mass customization leads to an exponential increase of garment size combinations for markers, which induces a heavy and complex workload of marker making. In this context, due to the complexity of the problem, the classical marker making methods using the existing commercialized software are less performant in terms of efficiency and accuracy. Considering that there exists some implicit relation between the overall marker length of a given size combination and that of each contained garment article size, the marker prediction could be simpler and faster. In **Chapter 5**, we build a marker prediction model for the estimation of marker lengths and afterward the estimation of cutting cost.

The personalization and the cost are essential criteria in mass customization. There is hardly any simple or direct relation between them. However, both are tightly related to the manufacturing process, referring primarily to the sizing and the cutting, which offers the feasibility to build an indirect relation, shown in Figure 1.13. The direct relation between the sizing and the fit as well as between the cutting and the cutting cost can be revealed by the establishment of an optimized sizing system and cutting-order-planning system, and is illustrated, by the aid of the black solid line. In addition, the sizing and cutting are interconnected due to the patterns. As a result, the indirect relation can be also built, as indicated by the dotted lines, including the relationship between fit and cost, i.e., design-to-cost relation.

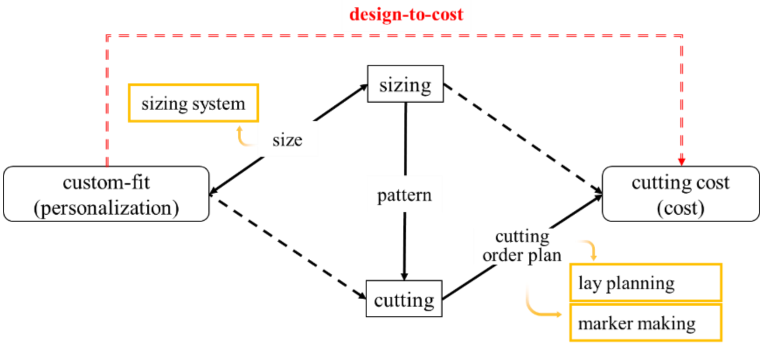

Figure 1.13 Relation among personalization, cost, sizing, and cutting.

The proper operation methods should be found for the research orientations as described above. According to the literature survey, the optimization techniques for garment manufacturing include exact methods, heuristics, meta-heuristics, and hybrid methods. The exact methods are always the first choices for finding out an optimal solution, among which, Integer Programming (IP) tends to be the most widely used. Apart from exact methods, heuristics (constructive and improvement) are also employed for searching for a satisfactory solution. Meta-heuristics are applied for finding a good solution with a less computational effort by searching over a large set of feasible solutions. In detail, Genetic Algorithm (GA), Fuzzy Logic (FL), and

Neural Network (NN) are the most frequently mentioned advanced technologies in the literature. Later, the hybrid methods that combine the aforementioned methods are favored by many researchers due to the outperformance.

In order to further optimize the garment manufacturing process in the context of mass customization, we make efforts to seek the proper application of optimization techniques. 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 terms of the big solution population in the mass customization sizing system, in **Chapter 3** a GA is used due to the advantage of easy implementation and quick convergence to a global optimum. IP was proved to be a suitable tool for solving cutting order planning problems with small-size orders (Elomri, et al. 1994; Degraeve & Vandebroek, 1998; Degraeve, Gochet & Jans, 2002). Based on the previous IPs, an extended IP, in which the marker variations are formulated, is used for working out the cost-oriented cutting order plan in **Chapter 4**. The marker prediction problem can be regarded as a regression problem. It is not dependent on time, and no analytical mathematical model can be available. Multiple Linear Regression (MLR), Radial Basis Function NN (RBF NN) are applied in the marker length estimation model in **Chapter 5**, and their performances are evaluated and compared.

Chapter II:

Garment Mass Customization Strategies for Cutting-related Processes

Chapter 2 Garment Mass Customization Strategies for Cutting-related Processes

This chapter aims to propose several new practical strategies based on pattern variations for upgrading the cutting-related processes (the sizing process and the cutting process) in the garment mass customization environment (Figure 2.1 Topic of **Chapter 2**), in terms of personalization and cost.

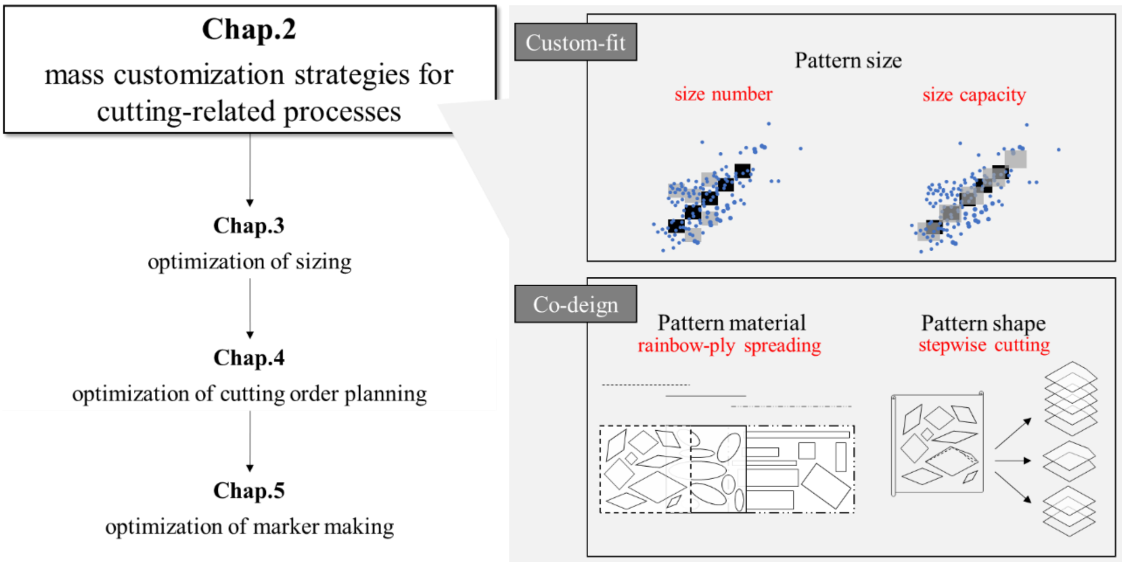

Figure 2.1 Topic of **Chapter 2**.

This chapter is organized as follows. In Section 2.1, the strategies of garment mass customization are presented in two different categories, i.e., custom-fit and co-design. It is followed by the definition of personalization levels, i.e., custom-fit level and co-design level, as well as the calculation of cutting-related costs. Section 2.2 presents the implementation of these strategies through a case study of women's basic straight skirt, and further illustrates the results and related discussions. Finally, Section 2.3 gives a conclusion and perspectives for future work.

2.1 Strategies related to cutting in garment mass customization

As pointed out by Jiao, Zhang & Pokharel (2007), the customization increases the number of variants in production, also decreases the number of items produced per variant, with significant impacts on the manufacturing process. In the context of mass customization for garment manufacturing, we propose four strategies for upgrading the complex cutting-related processes. Two proposed strategies are related to custom-fit and two others to co-design. The criteria of personalization and cutting costs will be formalized and then evaluated in order to make further optimization of the cutting-related processes.

2.1.1 Mass customization strategies based on pattern variations

Four mass customization strategies regarding custom-fit and co-design are developed. Two of them are related to pattern size, and two others to pattern material and pattern shape, centered on the cutting-related processes in the garment manufacturing. The details about these proposed strategies are discussed in the following texts.

2.1.1.1 Strategies for custom-fit

Since fit is a fundamental need for users, a satisfactory fit in mass customization is consequentially of great concern (Hu *et al.*, 2009; Mpampa, Azariadis & Sapidis, 2010). The strategies regarding custom-fit are associated with the pattern sizes, of which the main idea is to enhance the fit satisfaction of the targeted consumers by adjusting the sizing system. Consumers' satisfaction with fit is difficult to reach a higher level due to the limited and outdated sizes of ready-to-wear garments. To generate appropriate sizes for the target population in mass customization, optimization techniques are designed by considering the enhancement of number or the capacity of size (Gill, 2008).

2.1.1.1.1 Increment of size number

The proposed strategy for custom-fit can be realized by updating a sizing system for mass customization containing a larger number of sizes. In this case consumers can be better served with more choices and the garment fit is improved. Considering whether to remain the original mass production sizes in the new sizing system, there are two main strategies: 1) remain original mass production sizes and add additional sizes; 2) completely abandon the existing sizes and use newly generated sizes. The former updating approach is the focus of the research displayed in Figure 2.2, in which a mass customization sizing system is demonstrated with additional sizes (grey rectangles) and the original mass production sizes (black rectangles).

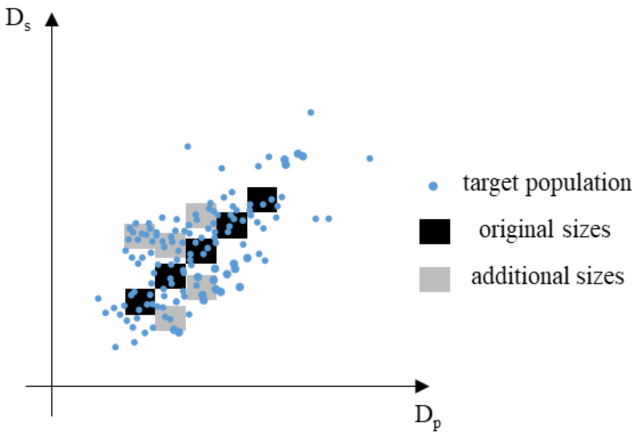

Figure 2.2 Mass customization strategies for custom-fit: Addition of pattern size via additional sizes.

2.1.1.1.2 Expansion of size capacity

In addition, the size capacity can be also increased as the proposed strategy for custom-fit can enhance the fit satisfaction by adjusting the pattern size through a structure processing, for instance, embedding some special structures with high flexibility, including darts, elastic materials, belts and so forth. As depicted in Figure 2.3, the original mass production sizes (black rectangles) are discarded and replaced by the expanded sizes (grey rectangles), which enable the sizes to serve a larger percentage of the target population. However, this strategy can only bring slight and limited effects on the expansion of size capacity due to its small change-range and narrow applicability. Therefore, in practical production, the two strategies of increment in size number and capacity are recommended to be utilized simultaneously.

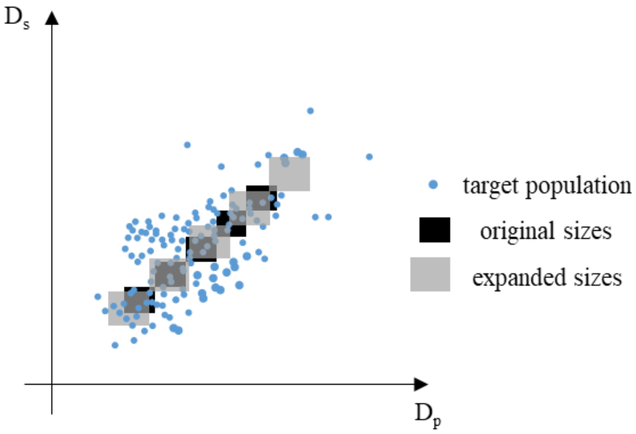

Figure 2.3 Mass customization strategies for custom-fit: Expansion of pattern size via expanded sizes.

2.1.1.2 Strategies for co-design

Apart from the increasing demand for garment fit, participation in design, including garment style, garment detail, fabric type, fabric color etc., called co-design (collaborative design), is highly desired by consumers in the garment industry (Teichmann, Scholl-Grissemann & Stokburger-Sauer, 2016). Pattern material and pattern shape are two points corresponding to the co-design in the manufacturing stage. Thus, we propose two mass customization strategies in terms of co-design, regarding pattern material and pattern shape respectively.

2.1.1.2.1 Fabric variation

"Rainbow spreading" is a typical strategy in garment production (Farley, 1988). It consists of lays with materials in different colors vertically. This strategy can be extended to endow the same kind of article with greater variability (e.g. color, composition, or texture). However, we need to be aware that not every garment production order needs a great diversity of fabrics, leading to a risk of overproduction. If we allow multiple fabrics to compose a ply horizontally during the spreading operation (rainbow ply), the variability can be applied to different articles. To explain more vividly, Figure 2.4 shows the feasibility of the strategy of combining the "rainbow spreading" with "rainbow ply". Patterns of the same article are grouped into one section on the marker, so that a single ply can be composed of different fabric pieces for cutting out. In this figure, it shows that the shaded area (full lay in mass production) is bigger than the area with lines which represent fabrics (step lay in mass customization). Therefore, we can conclude that overproduction can be effectively suppressed. Meanwhile, the personalized needs of pattern material can be well satisfied by using this strategy. In the future of mass customization, with the fast development of computerization and automation in industry, it is highly expectable that the horizontal strategy "rainbow ply" will be widely promoted, contributing to the updating towards mass customization.

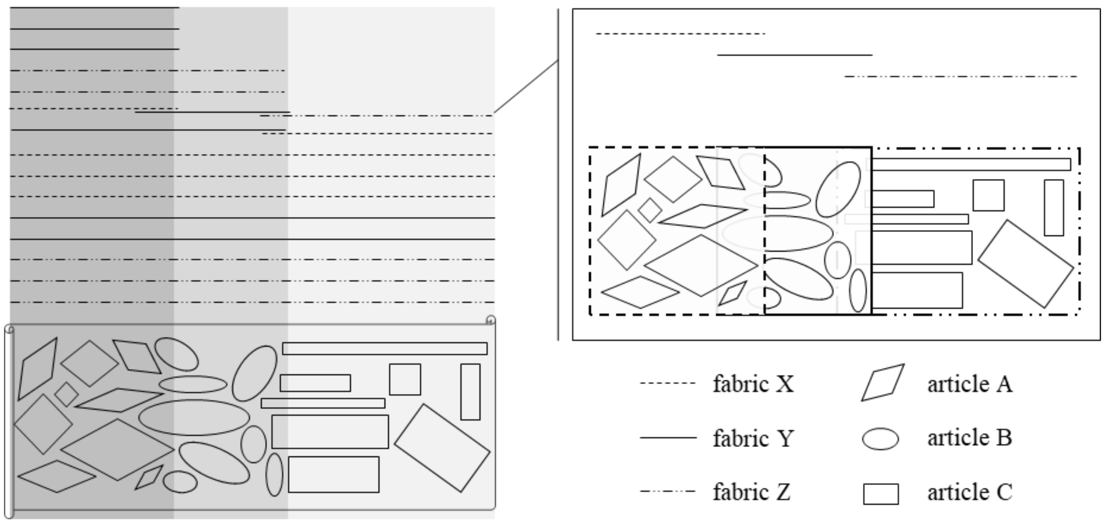

Figure 2.4 Mass customization strategies for co-design: Variation of pattern material via "rainbow-ply" spreading.

2.1.1.2.2 Module variation

In addition to fabric variation, the personalization in module variation is also feasible concerning the pattern shape. The variation of the garment module contains a slight modification of the main module (bodice) or a type alteration of specific moduli (e.g. collar, sleeve, pocket, waistband). It can be realized through conducting lean cutting with second cuts (first cut in terms of the common outline, then the second cut for cutting out all the variants) or even making extra markers for a wide module variety. When adopting a stepwise cutting, the key point is to generate the markers for stepwise cutting with the common outline of the related variants for the first cuts, shown in Figure 2.5.

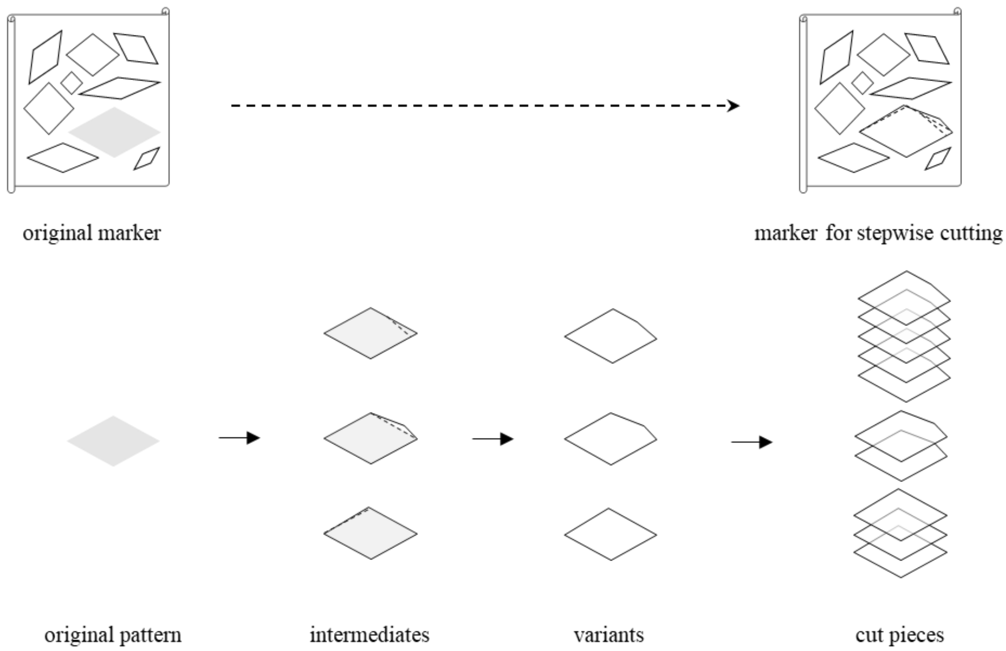

Figure 2.5 Mass customization strategies for co-design: Variation of pattern shape via stepwise cutting.

2.1.2 Definition of personalization level

The personalization level indicates the degree of customization for consumers. The fit is related to the distance between boy dimensions and the garment dimensions (Gupta & Zakaria, 2014). The design is related to the depth and width of the personalization (Tangchaiburana & Techametheekul, 2017). For the two categories of mass customization strategies that are mentioned above, we use custom-fit level and co-design level to specifically represent the personalization level, namely, the level of mass customization.

2.1.2.1 Custom-fit level

Fit is a complex concept having different definitions reported in the literature, and the most commonly used evaluation criterion is the aggregate loss (Ashdown, 2007; Gupta & Zakaria, 2014; Zakaria, 2016). The aggregate loss gives an objective assessment measuring the average distance between the body dimensions of samples and the dimensions of assigned sizes. However, this criterion may not have a precise or even proper presentation of fit. It is ascribed that it is very hard to normalize the effect of each key dimension on fit to consumers, and consumers' subjective feelings of fit are not in a simple linear correlation with distance. Therefore, we propose a new criterion of fit, namely, the custom-fit level, which contains a part of the objective assessment, measuring the average distance between the body dimensions and the dimensions of assigned garment sizes, combined with a subjective assessment.

Figure 2.6 demonstrates an example of custom-fit level definition with three sizes which are presented in different colors. Five custom-fit levels are weighting 0, 2, 5, 8, and 10. D (D_p and D_s) refers to the dimension (the primary dimension and the secondary dimension) of the size, and IntD (IntDp and IntDs) refers to the interval value (interval value of the primary dimension and that of the secondary dimension) (EN 13402-2, 2002). The two-dimensional space of the key dimensions is divided into sections by sizes differentiated with specific colors. Samples from the target population whose body dimensions fall into a certain section is assigned with the corresponding size. For each section, it is further divided into several subsections. Each subsection is marked with an exact weight, reflecting the objective difference between body dimensions of the sample and dimensions of the assigned size, simultaneously altered by consumers' subjective evaluation, which is related to their experience and feeling. The section with a weight of 10 is where the size locates, for any sample whose body dimensions are exactly in the intervals of this size dimensions, the fit is perfect. For the sample whose one body dimension is larger than the corresponding dimensions of all the sizes, its weight is 0, which means the sample cannot be accommodated. If one of the body dimensions is in the interval, and the other is just in a distance of the interval, its weight is 8; one of the body dimensions is in the interval, and the other is far from a distance of the interval, its weight is 5; for the rest situation, the weight is 2. The weights can be further set differently according to the consumer's subjective preference for any dimension. For instance, if they have a preference for the primary dimension, for the cases that one of the body dimensions is in the interval, and the other is just in a distance of the interval, its weight can be set to 8 when the body dimension is in the interval of the primary dimension, and to a smaller number like 7 when the body dimension is in the interval of the secondary dimension.

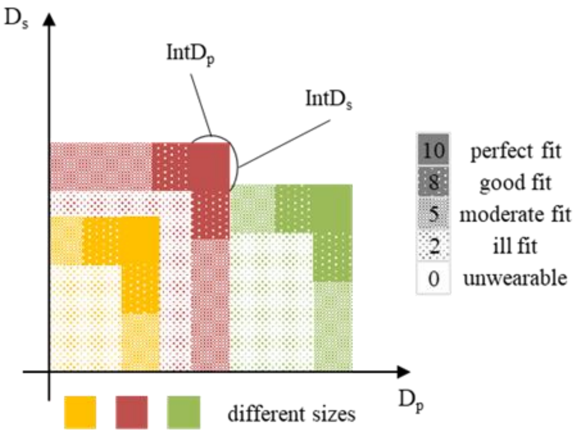

Figure 2.6 An example of custom-fit level definition.

2.1.2.2 Co-design level

Compared to the custom-fit level, there is hardly any literature concerning the definition of the co-design level. In detail, co-design is associated with the type and complexity of the requested design. Herein, the definition of the co-design level is based on the selected co-design points x, and related to the difficulty and cost of the individual co-design during manufacturing, which can be labeled as complexity coefficients $Cx \in [0, 1]$. As illustrated in Equation (2.1), the co-design level is evaluated by the sum value of the complexity coefficients of all the participating co-design points, as semi-quantitative characterization.

$$\text{co} - \text{design level} = \sum C_x \times E_x$$
$$E_X = \begin{cases} 1 & \text{if } X \text{ is selected} \\ 0 & \text{if } X \text{ is not selected} \end{cases}$$
(2.1)

For instance, for different co-design points, materials (complexity coefficient Cm=α) and pockets like patch pocket, slant pocket and welt pocket (complexity coefficient C_{PP}=β, C_{PS}=γ, and C_{PW}=δ), if the consumer selects a certain material and patch pockets, the co-design level is α+β, or if he selects a certain material and welt pockets, the co-design level is α+δ.

2.1.3 Estimation of cutting-related costs

Personalization levels and costs are tightly correlated, because the variety and depth of customizable options cause the manufacturing complexity thereby affect the costs. The majority of the garment manufacturing cost occurs in the garment cutting-related processes (Degraeve & Vandebroek, 1998; Vilumsone-Nemes, 2018). Costs relative to the garment cutting process can be divided into two groups, of which one group is caused by consumptions of materials (i.e., fabrics and markers) while the other is induced by operations (i.e., spreading, cutting as well as sorting and bundling). Labor cost and equipment costs are included in the calculation of operation costs, and it is worth noting that herein the power cost is classified into the equipment costs in order to simplify variables. The following equations provide each relationship of key factor(s) and the related cost. Instead of calculating the exact values of each cost, values of main factors can be used to represent the corresponding costs, in order to reveal the relative relationship briefly.

2.1.3.1 Fabric cost (C_f):

$$C_f = \sum P_f \times L_f$$
(2.2)

where P_f represents the price per unit length of fabric, L_f the used length.

The fabric cost depends on the length of fabrics required for the cutting only.

2.1.3.2 Marker cost (C_m):

$$C_m = \sum P_m \times L_m \times \alpha_m \tag{2.3}$$

where P_m represents the price per unit length of marker, L_m the used marker length, and α_m is the complexity of marker construction.

The marker cost depends on the used marker length and the complexity of marker making. The automation and paperless technologies will help to obtain the simplicity and low cost in marker making.

2.1.3.3 Spreading cost (C_s):

$$C_s = (P_o + P_{sm}) \times T_s$$
$$T_s = \sum L_f / V_s + N_p \times T_{sp} \tag{2.4}$$

where P_o represents the cost per unit time of operator, P_{sm} the cost per unit time of spreading machine, T_s the spreading time, V_s spreading speed, N_p ply number, and T_{sp} the time for per pause during spreading.

The spreading cost depends on several elements, i.e., the operator, the spreading machine, plies in the lays.

2.1.3.4 Cutting cost (C_c):

$$C_c = (P_o + P_{cm}) \times T_c$$
$$T_c = \sum L_c / V_c + T_{cp} \tag{2.5}$$

where P_{cm} represents the cost per unit time of cutting machine, T_c the cutting time, V_c the cutting speed, L_c the cutting length, and T_{cp} the time of pause during cutting.

The cutting cost depends on several elements, i.e., the operator, the cutting machine, markers of lays, lays.

2.1.3.5 Sorting and bundling cost (C_{sb}):

$$C_{sb} = P_o \times S_p \times T_g \times (1 + \alpha_{sb})$$
$$\alpha = N_{ps}/S_p \tag{2.6}$$

where S_p represents the production size (total garment number), T_g the time of sorting and bundling operations spent on each garment article, and $1+\alpha_{sb}$ the degree of difficulty, where α_{sb} means the sorting and bundling complexity, which is determined by N_{ps} the pattern set number and S_p.

The sorting and bundling cost depend on the production size, the sorting and bundling complexity. In general, it is comparatively much lower than the other cutting-related costs.

To comprehensively compare these cost changes, an in-depth analysis of the key factors for each cost is discussed through a case study in the next section.

2.2 Case study

To evaluate the performances (i.e., personalization and cost) of the above mass customization strategies, we present a case study containing 6 experiments for production of a women's basic straight skirt, updated from mass production to mass customization for a simulated order of 451 consumers.

2.2.1 Design of experiments

The details of the case study including the descriptions of objects, contents, and constraints are described in this subsection.

2.2.1.1 Study objects

The comparison of mass production and mass customization is carried out in the case study with a basic straight skirt for a target population of 451 consumers.

2.2.1.1.1 Product

Normally, women's skirts have relatively limited and simple patterns with fewer variants than other types of lower body garments, e.g. pants, certainly as well as the upper body garments. More specifically, the basic straight skirt is commonly used on official occasions, conventionally with the need of large output and further customization. Therefore, the basic straight skirt can be a typical and concise example. Herein, a women's basic straight skirt, which represents a commonly used clinging garment is selected in our study, whose sketch is shown in Figure 2.7. The corresponding primary and secondary dimensions are hip girth and waist girth.

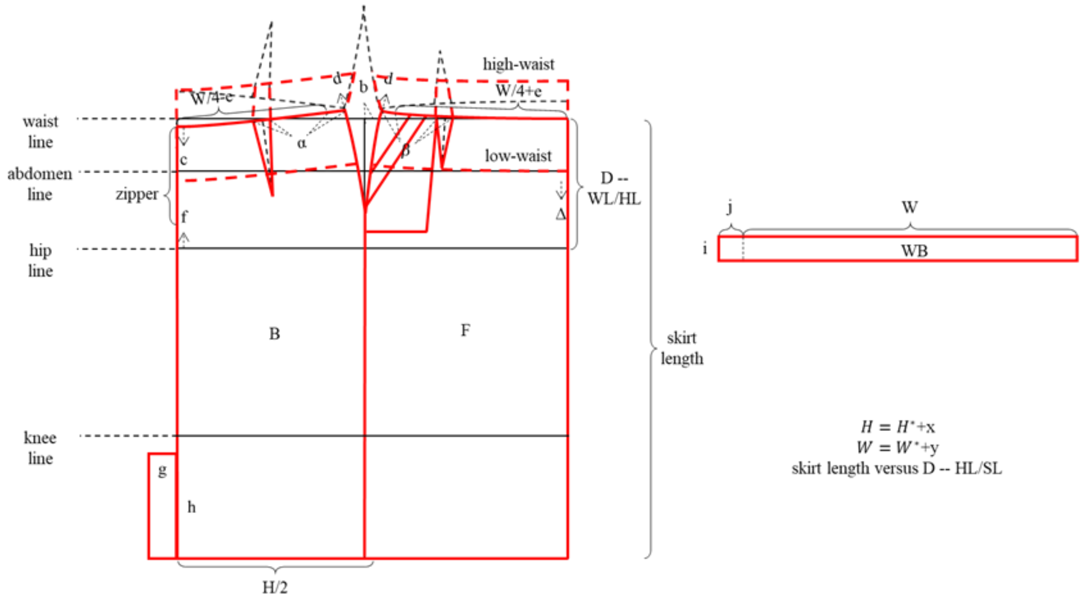

Figure 2.7 Prototype of a women's basic straight skirt.

2.2.1.1.2 Anthropometry data

A set of real body-dimension data measured from the target population of 451 French women, between the ages of 25 and 40, has been collected by using 3D scanning and prepared as data sources in the experiments.

2.2.1.2 Contents

We designed experiments for both mass production and mass customization with the previously proposed four strategies in order to evaluate the performances and to make comparisons as well. One of these experiments is conducted in the production mode of mass production, five other experiments demonstrate the corresponding production upgrade strategies towards mass customization, shown in Figure 2.8.

First, the experiment MP for mass production is conducted with an existing size chart of this skirt type from a garment company in the real market on s.Oliver website (https://www.soliver.eu/sizetables/size-table-women-GENERAL_SIZETABLE_WOMEN.html). Afterward, the other five experiments are made for each evolutionary process of mass customization, of which two for custom-fit and three for co-design. The related progressive relationship can be observed in Figure 2.8.

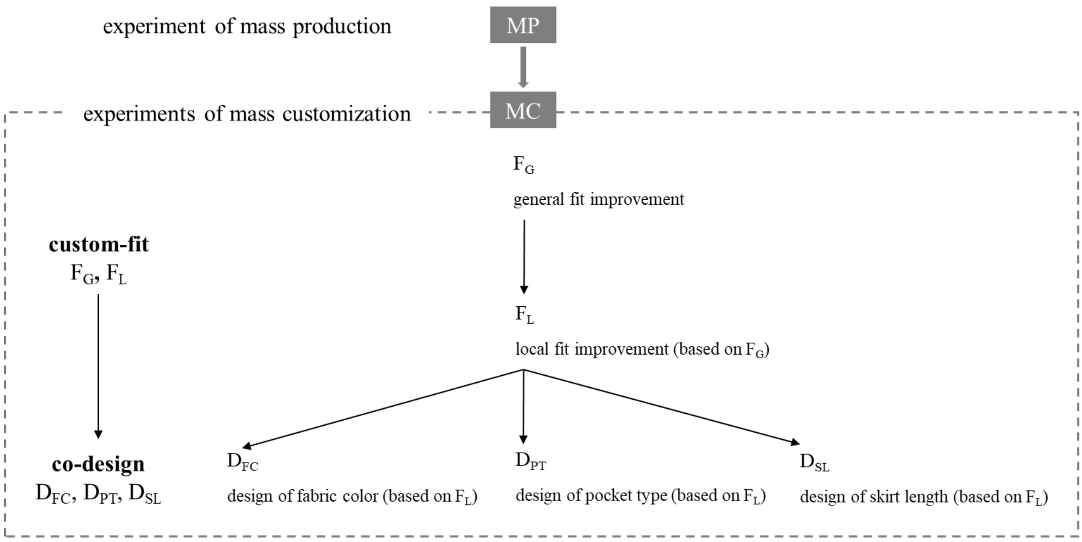

Figure 2.8 Flowchart of experiment implementation with mass customization strategies.

For custom-fit, the first mass customization experiment is defined as MC(F_G), and we generate a set of additional sizes by using a translation of the existing sizes, shown in Figure 2.10, with size number doubled from the existing mass production sizes. Compared with creating a novel set of sizes for mass customization, the strategy has the advantage of simplicity, reflected in a slight change in pattern development and product manufacturing. In addition, it exhibits the benefit of sustainability, namely, an increase of pattern utilization (dart variations are based on existing patterns, no new patterns are created), and flexibility in the switch between mass production and mass customization. The second experiment for custom-fit is an optimization of the experiment MC(F_G) by dart modification for mass customization, defined as MC(F_L). We apply darts with three sizes, namely, small, medium and large, to expand the capacity of the existing sizes, as illustrated in Figure 2.11.

As for the co-design part, customizations are conducted on the pattern material or the pattern shape. Pattern shape variation contains variations of the main module, i.e., the front and back patterns, and of specific small moduli, e.g. the waistband, the pocket, and the vent. In the study, three detailed experiments are designed, with the variations of fabric color, pocket type, and skirt length evolved from the experiment MC(F_L) and defined as MC(D_{FC}), MC(D_{PT}), and MC(D_{SL}) respectively.

In addition, all the details related to the experiments are summarized in Table 2.1.

Table 2.1 Details of experiments applied with mass customization strategies

Experiment		Description	Strategy
mass production	MP	no customization	use existing size chart from a real market
mass customization	MC(F_G)	general fit improvement	generate additional size, retaining sizes in experiment MP
	MC(F_L)	local fit improvement	apply multi-sized darts to sizes in experiment MC(F_G)
	MC(D_{FC})	design of fabric color	allow multi-fabric spreading with sizes in experiment MC(F_L)
	MC(D_{PT})	design of pocket type	distribute pocket patterns in markers with sizes in experiment MC(F_L)
	MC(D_{SL})	design of skirt length	use superimposed pattern outline for maker making with sizes in experiment MC(F_L)

To further conduct the experiments, we simulate one order of customized products for 451 people of the database. In the custom-fit experiments, we assign the most suitable size in the defined sizing chart according to the body dimensions of each consumer. In the co-design experiments, an equal division of design options is set. As shown in Figure 2.9, random distributions of single-point co-design selection in experiments MC(D_{FC}), MC(D_{PT}), and MC(D_{SL}) are made for the 451 samples. In this case, the assignment of samples to each co-design element is mostly uniform. In detail, for fabric, there are 3 fabric types, i.e. FB001, FB002, and FB003, 34% of the consumers for FB001, 31% for FB002, and 35% for FB003; for pocket type, 37%, 32%, and 31% of the consumers for patch pocket, slash pocket, and without pocket respectively. For skirt length, the percentages of the three skirt lengths are almost identical approaching 33%.

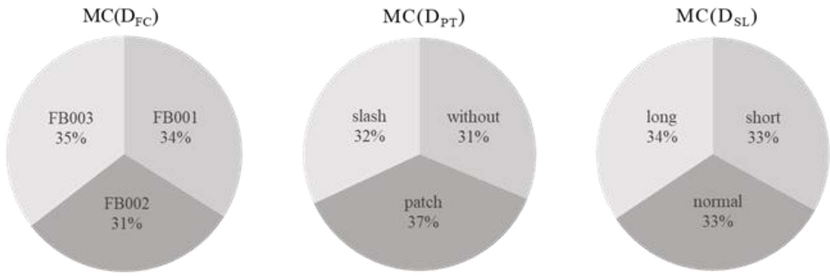

Figure 2.9 Random distributions of co-design selection in $MC(D_{FC})$, $MC(D_{PT})$ and $MC(D_{SL})$.

2.2.1.3 Constraints

The production constraints which have been considered in this case study are listed below.

a) To realize the concept of "manufacturing on demand", customized products are produced for individuals in mass customization, and excess products are valueless. To keep the constraint consistent, no excess production is considered in experiments, neither for the experiment MP.

b) In order to produce the exact quantities on demand, lay plans are made with step lays, where the layout of the articles on one marker is sequenced in ascending or descending order of ply number.

c) The cutting scope is set as follows:

Determined by specific cutting equipment in the industrial production, the maximum length of fabric is 3 m, and the maximum height of lay is 30 mm. The fabric thickness is set as 1 mm. Assuming that each layer of ply is tightly stacked, so the maximum ply number is set to be 30. Considering the maximum length of fabric

(3m), the maximal marker length with 3 articles is nearly this value. Thus, the maximum article number on each marker is set to be 3.

d) In industrial practice, allocating mixed combinations of small sizes and large sizes in the same lays is given high priority for a balance of multi-size distribution to markers, which would contribute to the marker efficiency and finally benefit the reduction of fabric cost (Vilumsone-Nemes, 2018). Herein, the size matching strategy is adopted.

2.2.2 Implementation of the experiments

The mass customization strategies, i.e., generating additional sizes, embedding various sizes of darts, spreading rainbow plies and operating second cuts are applied in the experiments MC(F_G), MC(F_L), MC(D_{FC}), MC(D_{PT}) and MC(D_{SL}) for production of a women's basic straight skirt to cater for consumers' personalized demands.

2.2.2.1 *General fit improvement (MC(F_G)*

As illustrated in Figure 2.8, it is serial of experiments in which the latter is updated from the former, herein the experiment MC(F_G) is based on the experiment MP and will be useful to generate the experiment MC(F_L). Therefore, in the experiment about size number increment MC(F_G), the new sizes are designed with enough interval to the original sizes instead of being bound, for the flexibility of dart variation of the following experiments. Afterward, in the experiment about the expansion of size capacity MC(F_L), multi-sized darts will fill up the reserved interval to make them interconnected.

The first step of fit customization is to generate a set of additional sizes through a translation of the existing mass production sizes in the mass customization experiment MC(F_G), as shown in Figure 2.10. For the existing mass production sizes, the minimum interval of the secondary dimension (Ds) is defined as Min (INT). According to the relative positions of the regression curve line (blue line) and original sizes (grey rectangles), additional sizes are determined by an upwards translation of original mass production sizes with the distance of 3 times of Min (INT), leaving the blank areas of 2Min(INT) for the dart setting of the next experiment. For instance, by translating the original medium size M (its primary dimension and secondary dimension are set to (MD_p, MD_s)), the corresponding additional size is generated as M* (MD_p, 3*Min(INT)+MD_s).

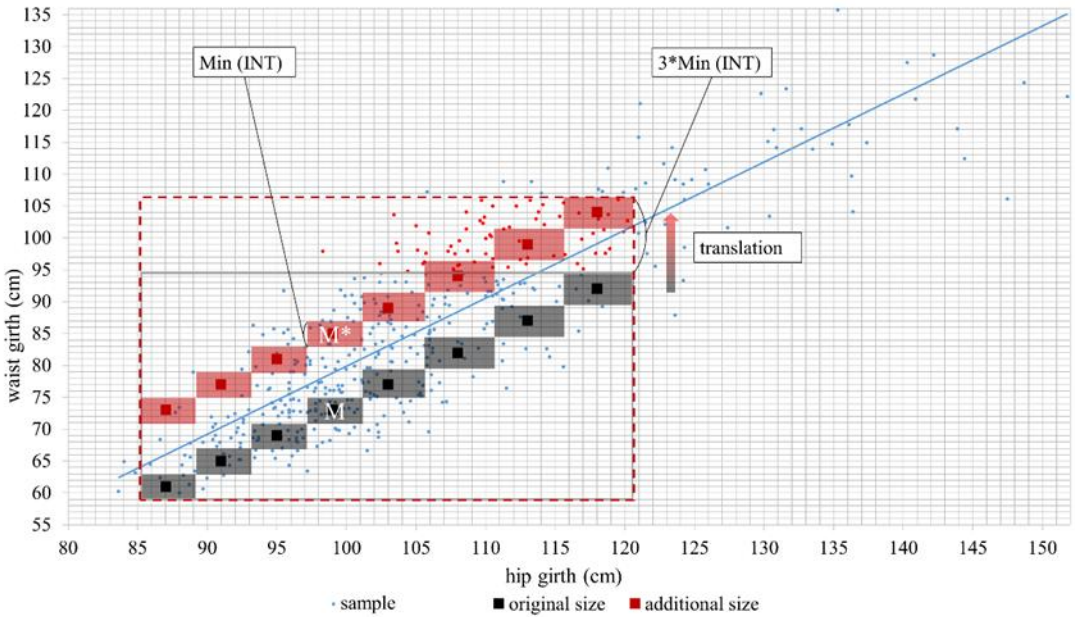

Figure 2.10 Size distribution in the mass customization by adding sizes (MC(F_G)).

From the area enclosed by a solid gray line to the area enclosed by a red dotted line, it is indicated that a larger portion of the target population is accommodated after the application of additional sizes (red rectangles). By adding size numbers to engulf more points (samples), we can conclude that the coverage range can be expanded and a global garment fit can be significantly improved.

2.2.2.2 *Local fit improvement (MC(F_L))*

Waist girth is the dimension that can be adjusted by darts (Figure 2.7). After realizing a general optimized coverage (a larger portion of the target population is accommodated in the previous experiment MC(F_G)) of the consumer body dimensions, the second step of fit customization is to extend the interval of waist girth via darts in multiple sizes in the experiment MC(F_L). We set the darts with the consideration of the shape stabilization of the garment and the maximal coverage range at the same time. Firstly, dart sizes should be appropriate and not produce a disturbing effect on the garment shape; secondly, we take full advantage of multi-sized dart in order to bring a maximal coverage range. Therefore, based on the experiment MC(F_G) shown in Figure 2.11, since the skirt has four darts, in this case, *Min (ITV)*/4 is set as the value of the interval of the dart. We set the new dart sizes as follows:

$$D_{size}+= D_{size} + Min(ITV)/4$$
$$D_{size}-= D_{size} - Min(ITV)/4$$

(2.7)

Where D_{size} refers to the original dart size, $D_{size}+$ refers to the large dart size, and $D_{size}-$ refers to the small dart size.

To visualize the upgrading of the system via the second experiment concerning the custom-fit, Figure 2.11 exhibits the size distribution of mass customization by multi-sized darts (MC(F_L)). In total, there are three dart sizes: small, medium (original), and large dart. Due to the dart size which is set in this specific case, the small dart is not a real dart but just a decorative thread. From the figure, it can be concluded that the application of multi-sized darts combined with the increment of size numbers results in further enhancement of the accommodation rate, and intuitively the higher proportion of the population with a perfect fit.

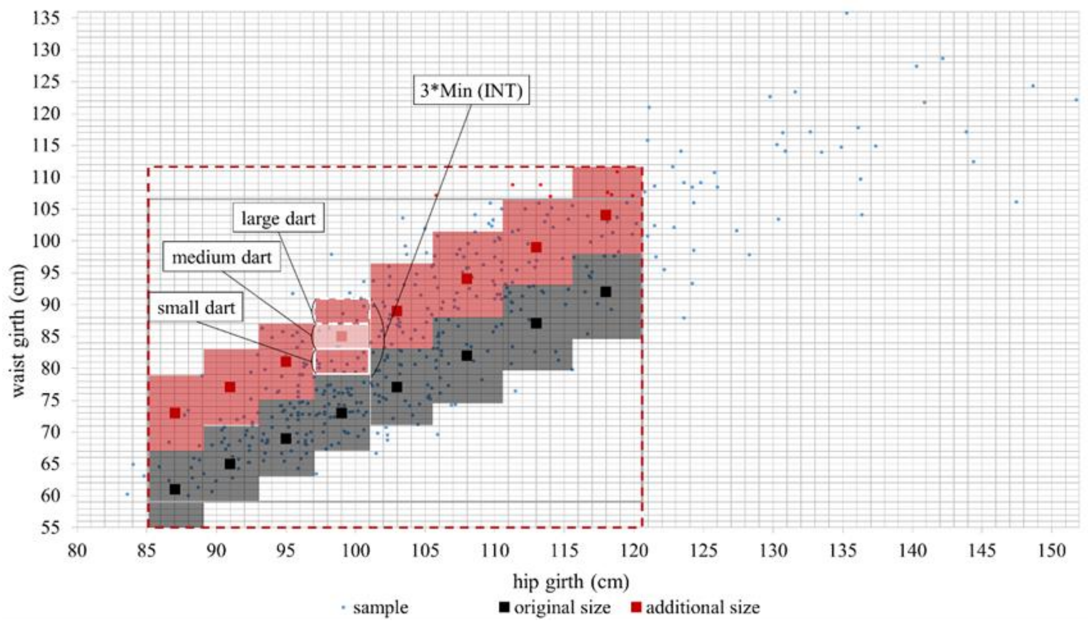

Figure 2.11 Size distribution of mass customization by multi-sized darts (MC(F_L)).

2.2.2.3 *Design of fabric color (MC(D_{FC}))*

To provide a customization of pattern material for the skirt, multi-fabric spreading is applied to support the fabric variation with rainbow plies. The principle of this strategy is trying to keep the same fabric in a ply, and otherwise permit rainbow plies containing multiple fabrics, which can be consulted in Figure 2.4.

Table 2.2 One spread contained in the cutting order planning result of MC(D_{FC})

Ply	Fabric	Size		
		XXS*	XXXL	XXL*
1 - 2	FB001	2	2	2
3 - 4	FB002	2	2	2
5	FB003	1	1	1
6 - 9	FB001	-	4	4
10 - 12	FB002	-	3	3
13 - 14	FB002	-	2	0
13 - 14	FB001	-	0	2
15 - 18	FB003	-	4	4
19 - 20	FB001	-	-	2
21 - 25	FB003	-	-	5
Ply number		5	18	25

Displayed in Table 2.2 is one of the spreads within the cutting order planning result of the experiment MC(D_{FC}), where the fabrics are named FB001, FB002, and FB003. It is noticed that the Ply 13 and 14 contain 2 different types of fabrics FB001 and FB002, which are different from other plies. The arrangement can be realized by the "rainbow ply" strategy.

2.2.2.4 Design of pocket type (MC(D_{PT}))

For the straight skirt used in this study, the main moduli are comprised of the front pattern and the back pattern, while specific moduli include the waistband, the pocket, the vent, and so forth. Experiments that regard co-designs of a main module (MC(D_{SL})) and a specific module (MC(D_{PT})) are carried out through the variation of skirt length and pocket type respectively in the following texts.

For the co-design of pocket type (MC(D_{PT})), attempts are made to occupy the spare room of lays with the small patterns of pockets first for a maximal cost-saving. Considering the material shade problem, the bundling problem, separate marker is seldom made for small pattern pieces, such as, collars, pockets, or cuffs (Vilumsone-Nemes, 2018). The advanced fabric dying technology (Yang & Huda, 2003, Yang & Naarani, 2004) improves the color consistency along the fabric so that patterns of the same article can be placed separately. With the development of item tracking technology (Preradovic *et al.*, 2009, Ngai *et al.*, 2012), small patterns can be well arranged during their transportation process. It can be inferred that it will no longer be a limiting condition for the garment production with a series of development. So far, there are few works of literature demonstrate the efficiency of marker making if a separate marker is permitted. Therefore, the following discussion is based on this assumption.

The main strategy is to make the groupage of the small patterns to form the close arrangement. It is worth noting that pattern set sequences should be considered based on pocket types for second cuts of the front pattern. Arrangement of the appropriate locations of pocket patterns on existing markers (areas which are highlighted with dotted lines in Figure 2.12 is a challenging job. If no sufficient place is left in the existing lays for the groupage of patterns, an extra marker should be adapted for the rest patterns.

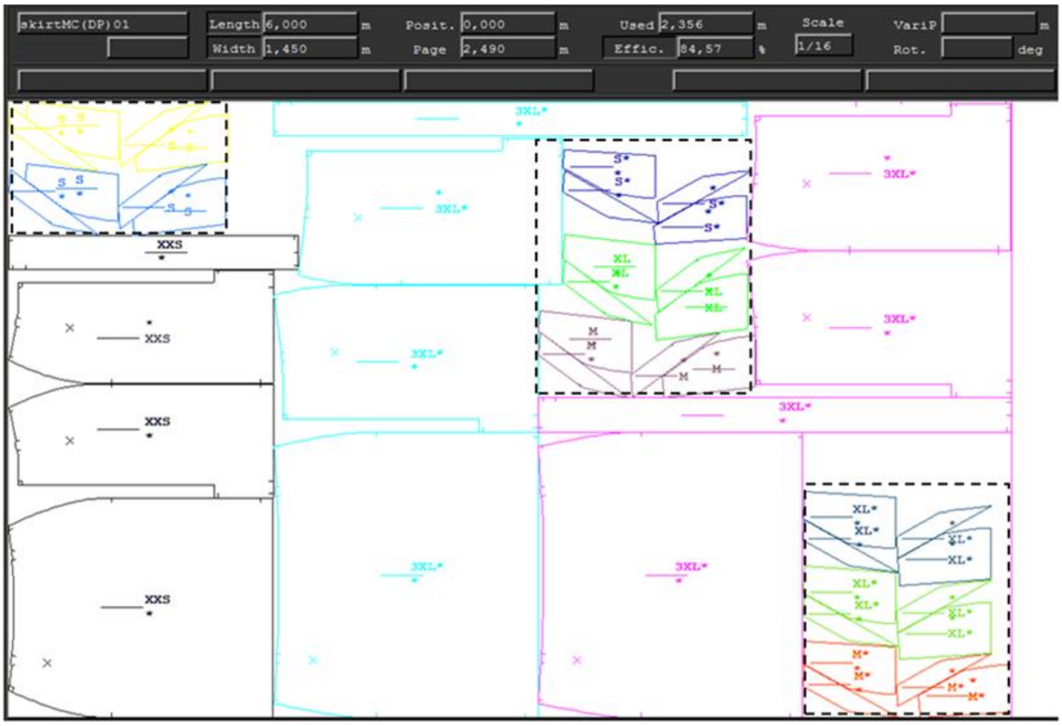

Figure 2.12 Different layouts of pocket patterns on an existing marker for MC(D_{PT}).

2.2.2.5 Design of skirt length (MC(D_{SL}))

For the co-design of skirt length, the purpose of the cutting order planning is to figure out the differentiated edge of various patterns for second cuts that are used in marker making, instantiated in Figure 2.5. As shown in Figure 2.13, a marker is made with a superimposed outline of patterns that are adapted for three different skirt lengths. For instance, the areas marked by a dotted line, a grey shadow, and a solid line represent patterns of the same size 3XL* with skirt lengths of 50 cm, 60 cm, and 65 cm, respectively. Similarly, pattern sequences based on skirt lengths are determined for more facile operations of second cuts.

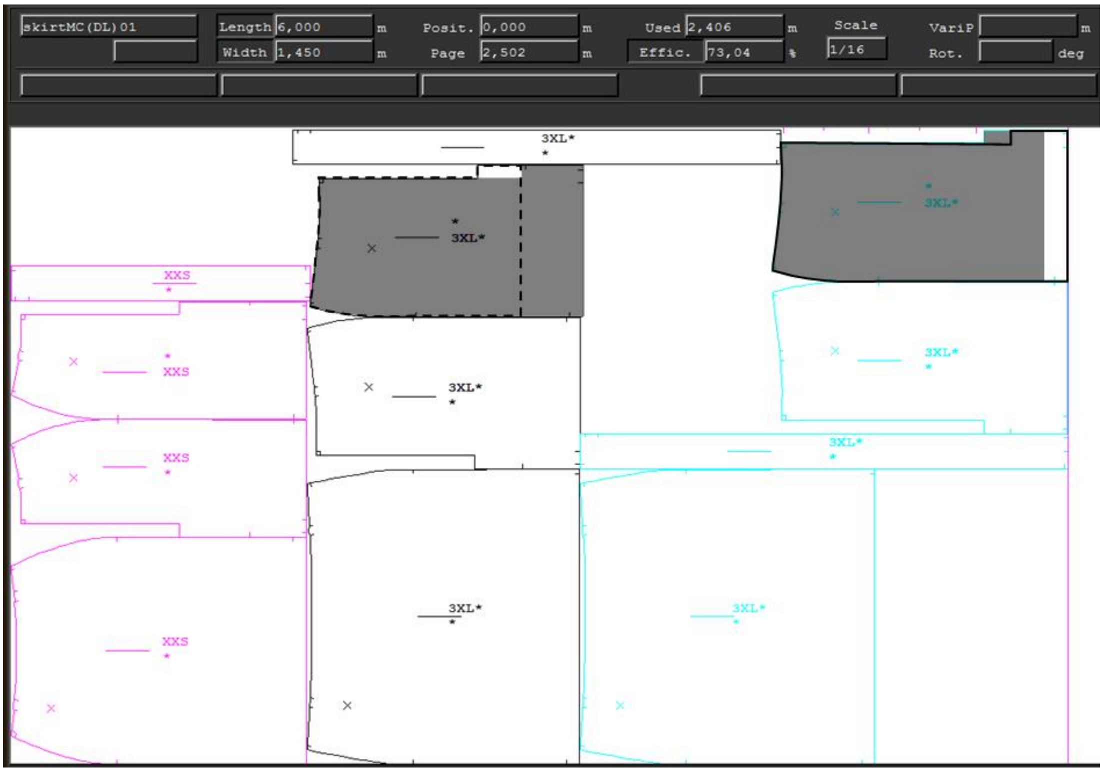

Figure 2.13 Marker with a superimposed outline of patterns for MC(D_{SL}).

2.2.3 Results and discussion

Based on the mass customization strategies presented in the experimental part, we discuss below the corresponding results regarding personalization levels and cutting-related costs.

2.2.3.1 Results on personalization level

The distributions of custom-fit levels and co-design levels of the experiments are displayed in the following texts in order to evaluate their performances.

2.2.3.1.1 Results of custom-fit

The distributions of custom-fit levels in the three experiments MP, MC(F_G), and MC(F_L) are displayed in Figure 2.14. It is shown in Figure 2.14 (a), and both of the experiments MC(F_G) and MC(F_L) have a good performance for improvement of garment fit. As a result, the proportion of low custom-fit levels (i.e., unwearable and moderate) is gradually reduced and almost eliminated, and higher custom-fit levels gradually dominate. In detail, the unwearable rate is evolved from 26% to 15% in the experiment MC(F_G) and from 15% to 10% in the experiment MC(F_L). In addition, the moderate rate is changed from 25% to 4% in the experiment MC(F_G) and from 4% to 1% in the experiment MC(F_L). Obviously, additional sizes in the experiment MC(F_G) mainly provide a good fit, multi-sized darts in the experiment MC(F_L) enhances the sizing system with a better custom-fit from good to perfect (Figure 2.14 (a)).

To be more specific, it can be observed in Figure 2.14 (b) that a significant increase from 48% to 81% is achieved in the experiment MC(F_G), and subsequently a further optimization is obtained via multi-sized darts in the experiment MC(F_L) towards 89%. The global fit improvement experiment MC(F_G) plays the role of dramatically decreasing the rate of low custom-fit levels, and the local fit improvement experiment MC(F_L) offers a further optimization to make sure that the target population has a dominant fraction in a perfect fit (83%). In summary, an integration of additional sizes and multi-sized darts efficiently contribute to a global and high custom-fit level.

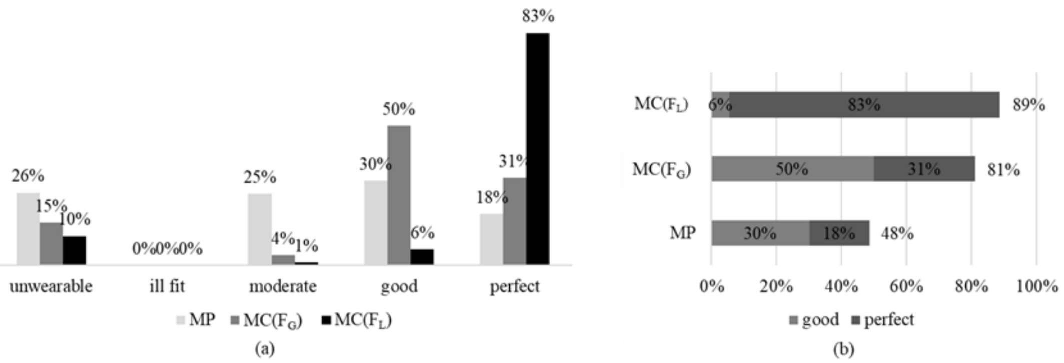

Figure 2.14 Custom-fit level distributions in experiments MP, MC(F_G), and MC(F_L).

2.2.3.1.2 Results of co-design

The following experiments are concerned about the co-design part, based on the completion of the aforementioned custom-fit experiments. Compared with the serial design of the two experiments of custom-fit, the co-design experiments are conducted in parallel. One co-design point is selected among the following three elements, i.e., fabric color, pocket type, and skirt length. The difficulties in realizing these designs in manufacturing are hard to be precisely normalized. Thus, the corresponding co-design levels of each co-design point for the whole population are assumed as the same in this study, not avoiding making the semi-quantitative comparison.

2.2.3.2 *Results on cutting-related cost*

The five cutting-related costs (regarding fabric, marker, operations of cutting, spreading, as well as sorting and bundling) are not directly calculated but represented by corresponding main factors. Based on Section 2.1.3, it can be concluded that the key factors have a strong positive correlation with the cutting-related costs. Therefore, the fabric length stands for the fabric cost (C_f), marker length for marker cost (C_m), spreading length and ply number for spreading operation cost (C_s), cutting length for cutting operation cost (C_c), degree of difficulty for sorting and bundling cost (C_{sb}).

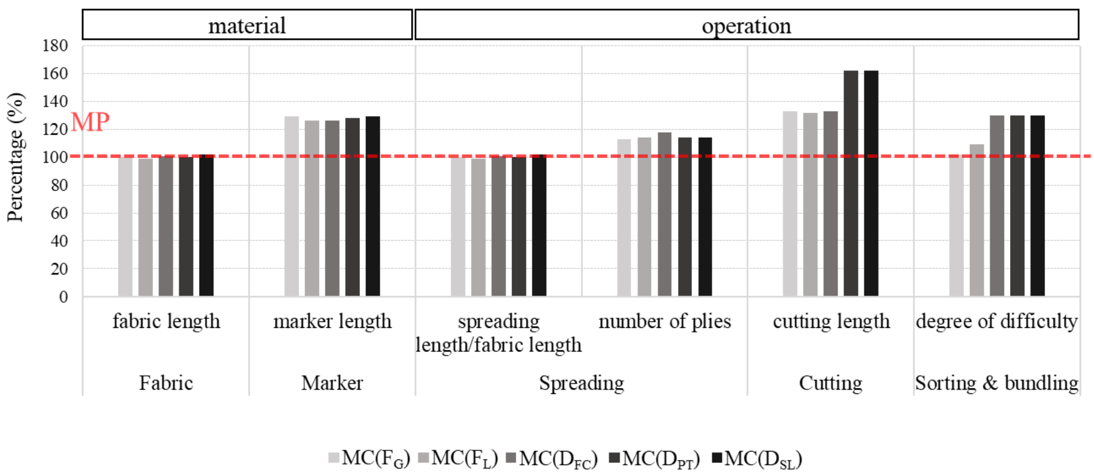

Figure 2.15 Cutting-related costs in different experiments.

Figure 2.15 shows the cutting-related costs in experiments under different mass customization circumstances where the costs in the experiment MP are set 100% for comparison. The material-related costs are composed of fabric cost and marker cost. There is almost no change in the fabric length, indicating that the fabric cost is not altered significantly. Compared with the fabric cost, the marker cost is significantly impacted due to the incorporation of the mass customization. The increase is mainly reflected in the lift in the marker length approaching over 120%. In addition, it is indicated that if the material cost is relatively stable once the first experiment of mass customization upgrade is carried out.

The operation-related costs include three parts, i.e., spreading cost, cutting cost, and sorting & bundling cost. The spreading cost is determined by the fabric length as well as the number of plies. There is almost no change in fabric length, while the number of plies is increased to some extent over 110%, mainly due to the application of "rainbow plies", leading to more time in the spreading pause. As a result, the benefit of the fabric variability will bring about a slight increase in the spreading cost. Similar to the material cost, the spreading cost retains the same standard once the first mass customization experiment is conducted. However, the cost of cutting and cost of sorting & bundling exhibit the different trends, of which the related cost is gradually enhanced. In detail, the two main steps, custom-fit and co-design have a distinct influence upon the related cost. As for the cutting-related process, the custom-fit experiment and co-design of fabric color have the same influence, and afterward, the co-design of pocket type and skirt length will bring more difficulty in the cutting-related processes, of which the cost is over 160%. As for the sorting & bundling cost, the custom-fit experiment has no significant impact on the degree of difficulty, while the co-design has a visible influence which elevates the related cost. Generally speaking, the spreading cost mainly originates from the material usage, while the other two operation costs dominantly rely on the complexity of the garment, which corresponds with the mass customization updating.

2.2.3.3 *Relationship between personalization levels and costs*

Based on Figure 2.15, the cost growth ratio (cost growth of each step divided by the cost of the previous step) in each step is summarized in Table 2.3. In order to clarify the important parameters determining the total cost, the growth ratio which is over 5% is listed in the flowchart of the upgrading process in Figure 2.16. In this section, the relationship between the personalization levels (regrading custom-fit and co-design) and the costs (regarding fabric, marker, spreading, cutting, and sorting and bundling) will be discussed.

Table 2.3 Comparison between production modes by costs

Cost	Corresponding factor		Growth ratio (%)				
			F_G-MP	F_L-F_G	D_{FC}-F_L	D_{PT}-F_L	D_{SL}- F_L
Fabric	fabric length	a	0	-1	2	1	3
Marker	marker length	b	29	-2	0	2	2
Spreading	spreading length	c	0	-1	2	1	3
	number of plies	d	13	1	4	0	0
Cutting	cutting length	e	33	0	1	22	22
Sorting & bundling	degree of difficulty	f	2	7	19	19	19

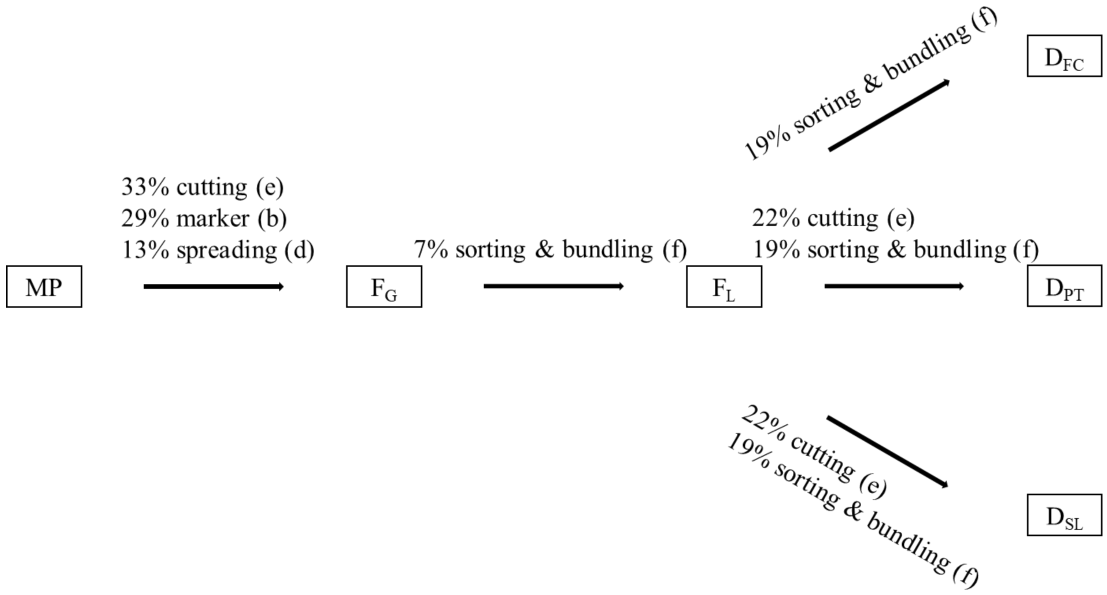

Figure 2.16 Flowchart of upgrading experiments with cost growth ratios.

As summarized in Figure 2.16, the cost growth ratios vary in upgrading experiments. In the aspect of custom-fit, additional sizes in the experiment MC(F_G) expand the coverage range and improve the global garment fit. Due to the doubling of size numbers, the cost increment lies in operation cost in cutting (33%) followed by spreading cost (13%), as well as material cost in marker (29%). In the following experiments, most of the cost growth occurred in the operation part instead of the material part. In the experiment MC(F_L), the multi-sized darts contribute to the outstanding local improvement. Using multi-sized darts in the experiment MC(F_L) is more powerful in local improvement of custom-fit level, reflected in a transition of custom-fit level from good to perfect. As for the cost in this experiment compared with the experiment MC(F_G), the cost is not altered significantly and the extra cost mainly exists in the sorting & bundling part with 7%. It proves that the two strategies concerning the custom-fit improvement will cause varied cost growth in different parts and extent. Briefly speaking, the strategy in the experiment MC(F_G) significantly ameliorate the custom-fit level of garments, but simultaneously bring about the issue of cost growth in material and operation. In contrast, the strategy in the experiment MC(F_L) provides a further improvement in custom-fit level without significant cost growth. Additional sizes with a support of multi-sized darts lead to a better performance for the balance of fit and cost.

In the aspect of co-design, all the co-design experiments cause a 19% cost growth in sorting & bundling. It can be ascribed to the increment of the complexity accompanied by the increase of the co-design level. In addition, for the experiments MC(D_{PT}) and MC(D_{SL}), there is a 22% of cost growth in the cutting operation. It originates from the second cuts for the complex objects. Furthermore, some extra markers in the experiment MC(D_{PT}) are also needed for holding the pocket patterns, which also raises the cost of the cutting operation. Compared with the two experiments, the experiment MC(D_{FC}) concerning the fabric color does not have an obvious effect on the cutting operation cost. Similarly, the increment of the co-design level also brings about some extent of cost growth mainly reflected in the operation part. Different strategies for the co-design improvement have different impacts on cost as well.

In summary, an increase of personalization (custom-fit and co-design) level can be achieved by a well-arranged multi-fabric spreading at a reasonable extra cost, of which each item is less than 33%. Based on the inference, the garment company can make a better decision to choose the targeted upgrading route, in order to control the cost to meet the demanded levels of custom-fit and co-design. The cost growths in mass customization experiments dominantly lie in the operation part. However, with the development of automation, the proportion of the operation cost to the material cost will be gradually decreased in the future, which is beneficial for the cost control of the mass customization.

It gives strong evidence that in the garment manufacturing domain, mass customization is a very promising tool for garment manufacturers to balance the contradiction between personalization and cost to stand in the fierce market competition facing the consumers' increasing demand for customized products.

2.3 Conclusion

In this chapter, we demonstrate practical mass customization strategies in terms of custom-fit and co-design for cutting-related processes (the sizing process and cutting process). A case study of women's basic straight skirt has been selected for validation in terms of personalization and cost using the proposed criteria. The results show that the proposed strategies can effectively help to make a tradeoff between personalization and cost.

The two custom-fit strategies, i.e., an increment of size number by generating additional sizes and an expansion of size capacity by setting multi-sized darts, have shown a good performance with controllable extra costs. The additional sizes and multi-sized darts improve the custom-fit level globally and locally, respectively. The related cost growth differs between the two strategies, which is feasible to be simultaneously utilized.

The two co-design strategies, pattern material (fabric) variation using "rainbow plies" has no obvious increase in the cutting-related costs, while pattern shape (including pocket type and skirt length) variation using second cuts or even extra markers brings about further lift. It is interesting that the cost growth does not lie in the fabric cost, but the marker and operation-related costs. It is expectable that with the aid of highly automated devices and intelligent computing technologies, the mass customization strategies especially the co-design part can take full economic advantages in the future.

This is a pioneering study of developing garment mass customization strategies particularly concerning the manufacturing process. The customization levels are demonstrated and the sources of the extra costs are calculated in detailed items. It helps enterprises to conduct the precise customization expectation and cost control, and finally make proper production strategy to accomplish the upgrading task of garment mass customization.

For a better application of the proposed strategies in practical production, it is necessary to make the formulation and optimization of each specific cutting-related process (e.g. sizing, cutting order planning, and marker making). Since the fit is a fundamental need of users, and considering the good performance in the global fit improvement and an acceptable extra cost, we will continue to introduce additional sizes (increment of size number) in the next **Chapters 3 to 5**. However, the generation of new sizes will be achieved via a genetic algorithm, rather than a simple upwards translation of original mass production sizes in this chapter, in order to achieve a higher generality and flexibility. In addition, a mathematical modeling of the relationship between personalization and cost will be carried out. It is fundamental for developing the pricing strategy for mass customization to help the company to gain an advantage in the fierce market competition.

Chapter III:

Optimization of Garment Sizing in the Context of Mass Customization

Chapter 3 Optimization of Garment Sizing in the Context of Mass Customization

The previous chapter proposes four practical mass customization strategies for the cutting-related processes and evaluates the personalization and economic performances. Since the garment fit is the basic need for consumers, and In Chapter 2, we already validated that the introduction of additional sizes can bring a global improvement of garment fit for the target population with a controllable extra cutting cost. In this chapter, we present a fit-oriented garment sizing system for garment mass customization (Figure 3.1 Topic of **Chapter 3**), which adopts a Genetic Algorithm (GA) to optimize the generation of additional sizes. The system is validated with a good performance of personalization (fit) through a case study of women's basic straight skirt as well. As shown in Figure 1.12, the optimization of the sizing process is discussed in detail in this chapter. In **Chapter 4** and **Chapter 5**, the optimization of the other two cutting-related processes, i.e., cutting order planning and marker making will be discussed.

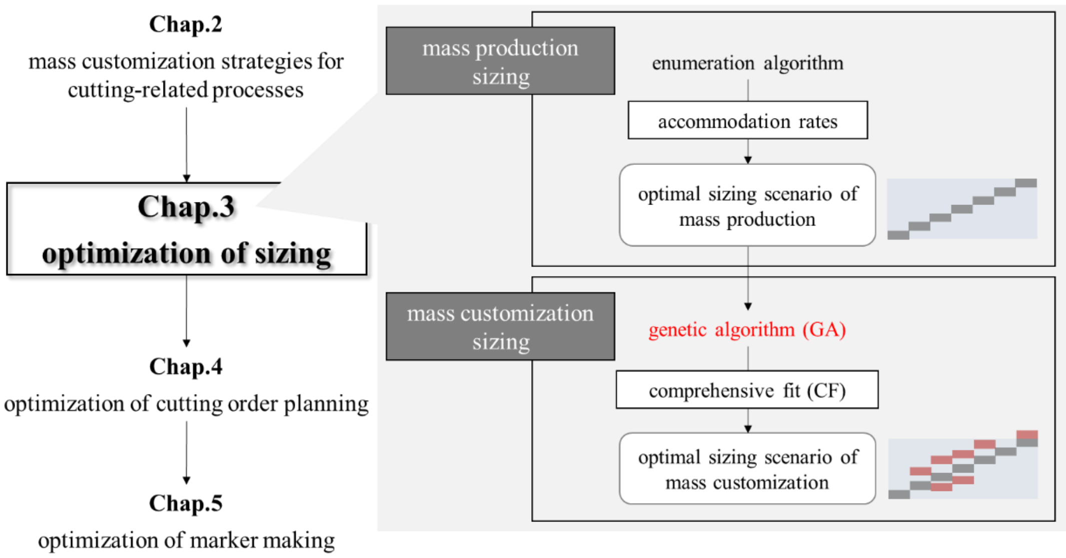

Figure 3.1 Topic of **Chapter 3**.

This chapter is presented as follows. In Section 3.1, we first introduce the concept and structure of the GA-based fit-oriented sizing system with additional sizes by adaptation from a traditional mass production sizing system. In section 3.2, a case study of a basic straight skirt is given to validate the effectiveness of the proposed system. Finally, we give some concluding remarks and overall insight in section 3.3.

3.1 Fit-oriented sizing system for garment mass customization

As mentioned earlier, to develop a cost-efficient mass customization strategy, it is recommended to adopt a classical mass production process (Duray, 2002). Accordingly, the proposed fit-oriented sizing system for mass customization, illustrated in Figure 3.2, is established by developing a series of additional sizes based on a mass production sizing system with standard sizes. The upper portion of this figure shows the flowchart of establishing a garment sizing system in mass production (Gupta & Zakaria, 2014), and the lower portion gives the adaptation procedure to generate mass customization sizes, in which the classical mass production sizes are also retained.

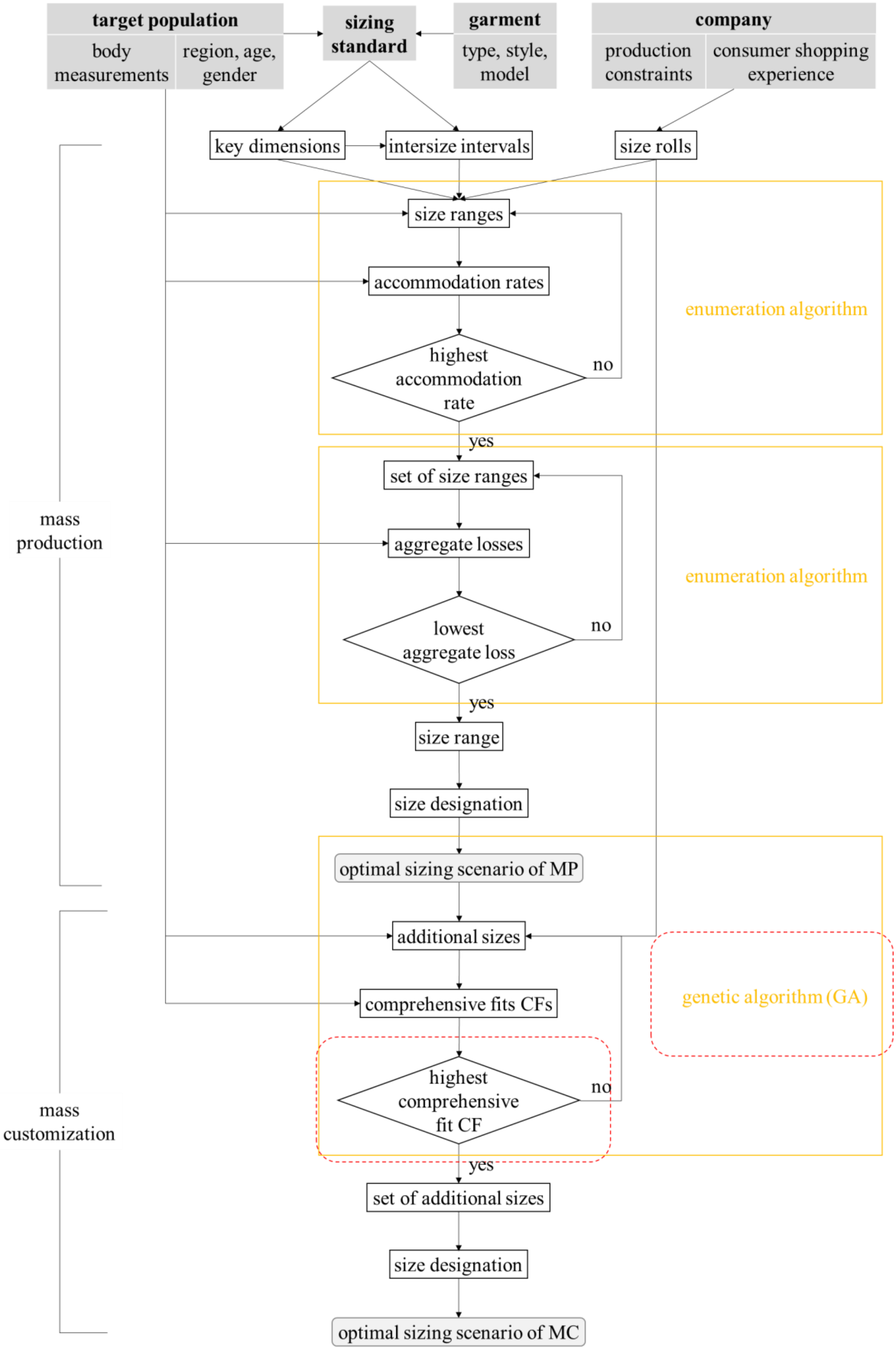

Figure 3.2 Flowchart of the proposed fit-oriented sizing system.

The inputs of this sizing system are taken from the following main sources, i.e., the target population, the garment, the company, as well as the sizing standard as references. Initially, the 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 the 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 consumers 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 mass production size scenarios for all defined size rolls. On the basis of the produced classical sizes from the mass production sizing system, the proposed mass customization 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 that has the highest CF is selected for the next step (size designation). At this point, the optimal mass customization size scenario is generated.

Section 3.1.1 and Section 3.1.2 present the steps and algorithms adopted for standardizing garment sizing (considering the portion of the mass production sizing system and the portion of the mass customization sizing system respectively).

3.1.1 Sizing system development

In this section, we give the procedures of building a mass production sizing system as well as building a mass customization sizing system which is based on the former procedure.

3.1.1.1 *Sizing system development for mass production*

A mass production 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 the primary dimension (D_p) and the 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, 2002; International Organization for Standardization, 1991).

- 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 (Figure 3.3). Based on experience and the concept of "interval of indifference" (Koblyakova, 1980), for each key dimension, we can first get the value range of its intersize interval, usually composed of a set of specific integer numbers (Gill, 2008).

Then, the interval values ($IntD_i$, i=s or p) are evaluated with a linear regression (O'brien & Shelton, 1941) of the two key dimensions ($D_s=\alpha+D_p*\beta$) by this equation, namely,

$$V_{int} = min\left[\left|\left(\beta - \int D_s \Big/ \int D_p\right)\right|\right] \tag{3.1}$$

when V_{int} reaches its minimum, 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.

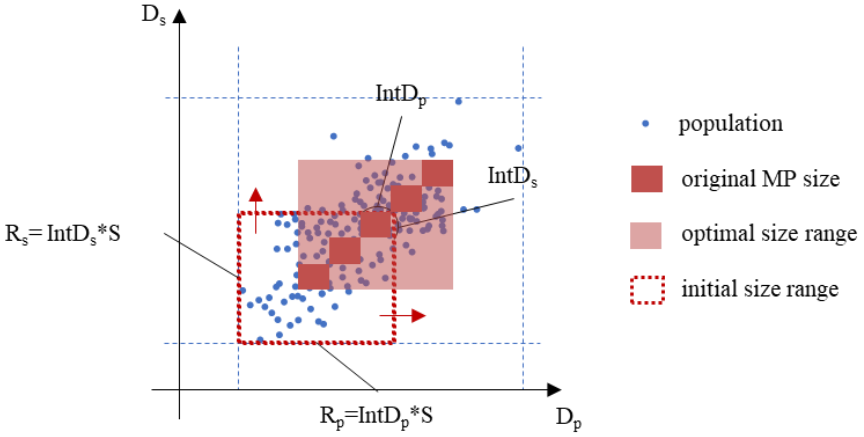

Figure 3.3 Sketch of size range determination.

- Size roll (S) determination

A suitable number of sizes, namely, size roll, is responsible for a good compromise between the company and consumer in terms of personalization and cost (Zakaria, 2016). More precisely, the size roll in mass production should be neither too small nor too large in order to control the production and the distribution costs, meanwhile enhancing the 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 Figure 3.3, a standard size range linearly varies from very small to very large (Ibanez *et al.*, 2012), and is determined when the maximum portion of the target population is accommodated by a fixed size roll S and the intersize interval $IntD_i$, namely,

$$maxR_i - minR_i = \int IntD_i \times S \quad (3.2)$$

- Coverage range/accommodation rate calculation

The 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% (Gill, 2008).

- Aggregate loss calculation

As the general criterion evaluating sizing systems (Gupta & Gangadhar, 2004), 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),

$$d = \sqrt{\sum (D_i - A_i)^2} \tag{3.3}$$

Gupta & Zakaria (2014) defines 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 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 that provide the best selection of the garment fit to the consumers. Arabic numerals or alphabet are common codes used in the 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, 2003; International Organization for Standardization, 1977).

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

$$(A_p, A_s) = \left(minR_p + (2N_s - 1) \times \int \mathrm{D_p}/2, minR_s + (2N_s - 1) \times \int D_s/2\right) \tag{3.4}$$

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 is minimized, namely,

$$EDmin = min \sum \left[\left(minR_i + (2N_s - 1) \times \int D_i/2 \right) - D_i(medium) \right]^2 \tag{3.5}$$

3.1.1.2 *Sizing system development for mass customization*

A newly proposed mass customization sizing system is realized with a series of additional sizes generated on the basis of the classical mass production 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 mass customization equals the size roll in mass production. Thus, in our case study, the size rolls vary from 7 (in the mass production environment) to 14 (in the mass customization environment with 7 additional sizes) respectively in the two 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 mass production sizes. Concretely, the additional sizes are created through a translation of classical mass production sizes along the secondary dimension (Figure 3.4 (a)). The mass customization strategy of setting additional sizes enables the size system 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 (Fan, Yu & Hunter, 2004). In contrast, a mass production sizing system based on proportional sizing cannot reflect the variety of body shapes within a single garment size in a target market (Ashdown *et al.*, 2001).

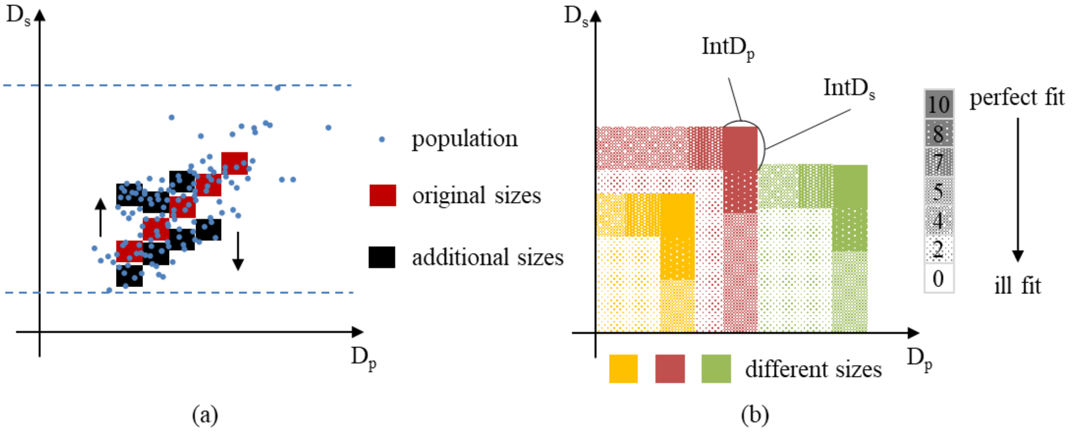

Figure 3.4 (a) Sketch of additional-size generation; (b) Example of fit definition.

- Comprehensive fit (CF) calculation

The comprehensive garment fit is the criterion that is used for the optimization and the evaluation of the mass customization sizing system in this chapter. The garment fit is generally defined by the relation between garment size dimensions and body dimensions (Ashdown, 2007). The aggregate loss that is used for the sizing system evaluation in mass production (as mentioned above), is the most commonly used criterion to represent the garment fit in the literature (Ashdown, 2007; Gupta & Zakaria, 2014; Zakaria, 2016). However, consumers' 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. Therefore, we define the criterion CF to assess the overall fit impact of the mass customization sizing system on the target population. The graph (b) in Figure 3.4 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 that is related to a specific garment size. CF is defined as the weighted average of the whole target population's satisfaction on garment fit:

$$CF = \sum P_z \times W_z \tag{3.6}$$

where z is a specific custom-fit level with the corresponding weight W_z, P_z refers to the percentage of the target population that is accommodated in the area with the custom-fit level z, $z \in [1, N_{fl}]$, N_{fl} is the number of various custom-fit levels, as shown in Figure 3.4 (b), N_{fl} =7.

- Size designation

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

3.1.2 Algorithm applications in sizing systems

In this study, we apply two enumeration algorithms and a genetic algorithm for solving the sizing problems in mass production and mass customization respectively, as shown in Figure 3.2.

3.1.2.1 Enumeration algorithm for mass production

The enumeration algorithms are used in the development of a mass production 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 (Gupta & Zakaria, 2014).

3.1.2.2 Genetic algorithm for mass customization

The enumeration algorithms have good performances for mass production due to its light computational load. However, when applying them to build mass customization sizing systems, it becomes more complicated because finding the best set of additional garment sizes is a combinatorial optimization problem, and the computational load grows exponentially with the number of additional garment sizes. In this case, GA developed by (Holland, 1973) 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 (Lee, 2018). In our study, the procedure of the GA used to generate the optimal additional size combination for mass customization is demonstrated in Figure 3.5 and the specific steps are described as follows:

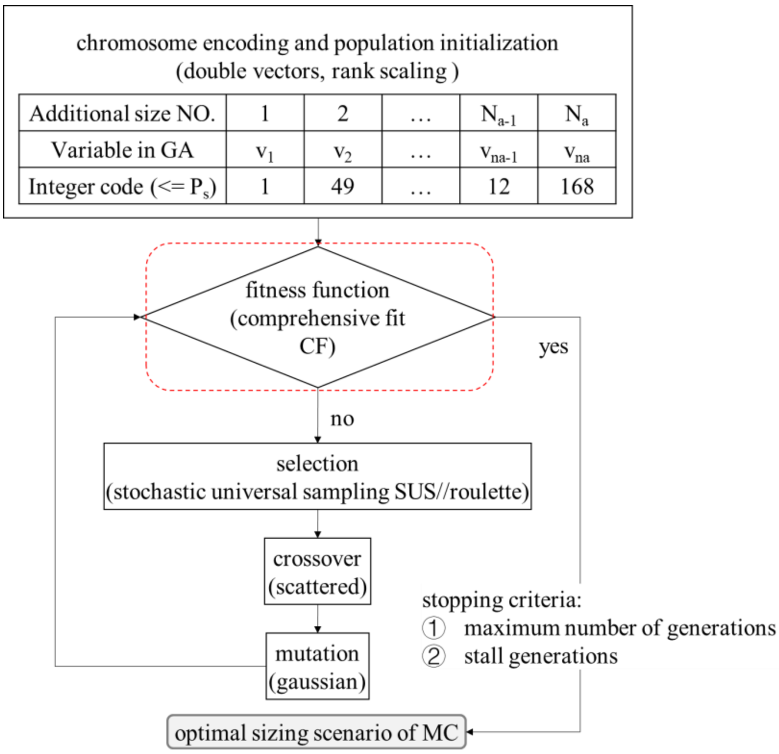

Figure 3.5 Flowchart of the applied genetic algorithm.

In Figure 3.5, 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. A further demonstration of the applied GA is bellowed.

- Encoding

In general, the real-encoding method is adopted for solving constrained optimization problems, while the integer-encoding method for combinatorial optimization problems. For this combinatorial optimization problem, a problem of searching for the best set of additional garment sizes, each denoted by a design variable (V_{na}), representing a possible additional garment size in its specific location (Figure 3.6), is coded on a specific integer number. The GA decodes the chromosome of individuals in order to obtain its phenotypic values (i.e., the exact set of additional garment sizes) corresponding to the decision variable values (referred to Figure 3.5). 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.

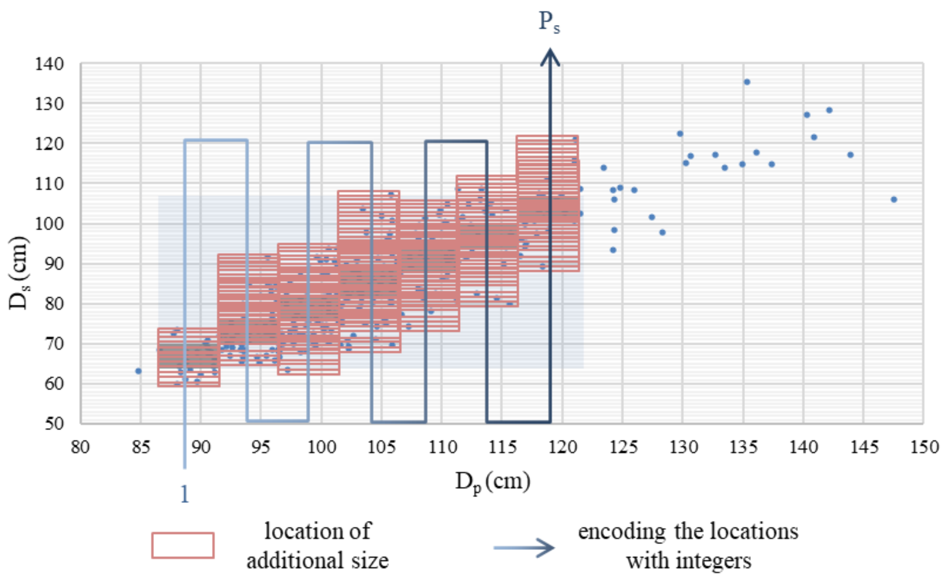

Figure 3.6 Possible additional sizes encoded in the genetic algorithm.

- Initial population

An initial population composed of a fixed number of individuals (e.g. max (min ($10\times N_a$, 100), 40) where N_a is the additional size number) 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 determine the upper and lower bounds of the predicted number of possible additional garment sizes. Each variable is in the range of 1 to P_s, P_s is the total possible locations of additional sizes (Figure 3.6).

- 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. The SUS strategy 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 (Baker, 1987, July). Crossover and mutation are likely to produce illegal solutions. As an initial attempt, we use scattered and gaussian respectively in the crossover function and mutation function with this integer problem. The obtained results prove the good performance of the GA. The population generation with this proposed GA is shown in Figure 3.7.

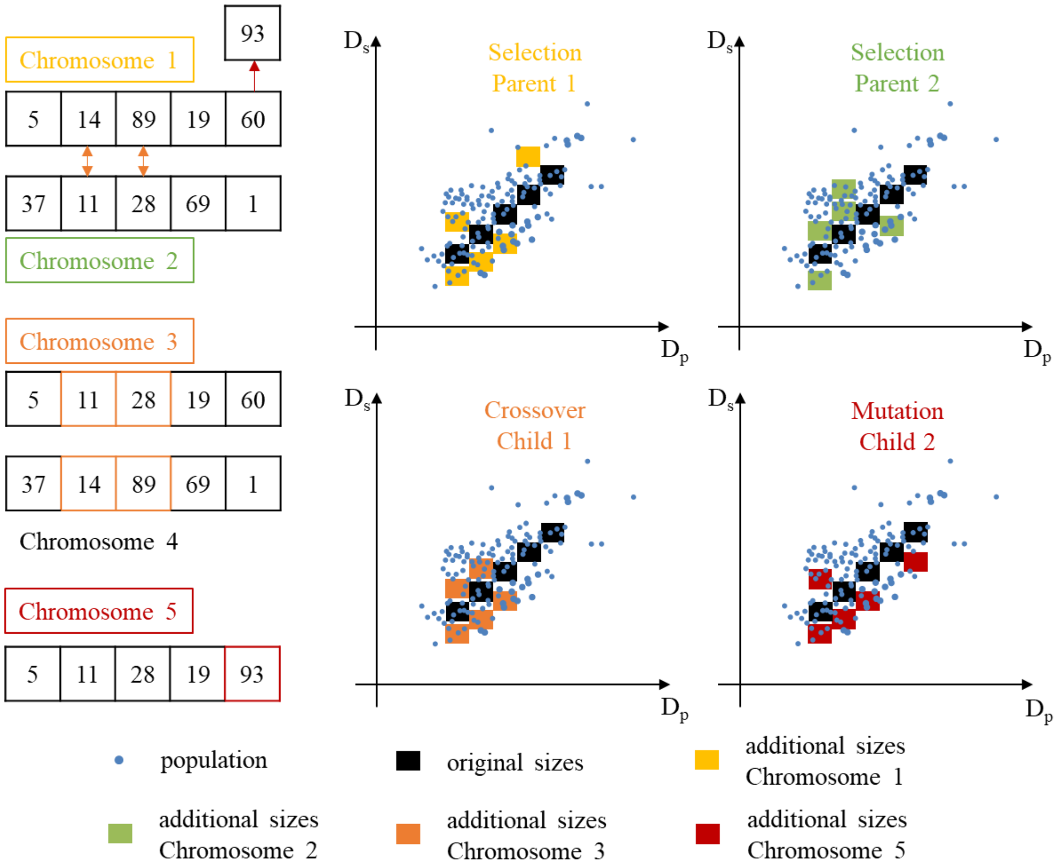

Figure 3.7 Population generation with operators in the genetic algorithm.

- 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 a certain number of generations (e.g. 50) is less than a pre-defined threshold (tolerance), the algorithm stops.

A comparison of the proposed GA and enumeration algorithm for generating the number of 1 to 3 additional garment sizes shows that the GA has better performances in terms of solution quality and computation time.

3.2 Case study

Consumer satisfaction with the overall fit at the lower body (e.g., a skirt) is generally lower than that at the upper body and the total body (LaBat & DeLong, 1990). The basic straight skirt is a clinging skirt type commonly used in formal occasions, 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 is composed of several simple patterns, it is relatively more feasible and more realistic in the product development and manufacturing processes. In this section, a case study of women's basic skirt production is used to validate the proposed system and to analyze the relationship between personalization and cost. The key body dimensions are the waist girth (WG) and the hip girth (HG), where the latter is taken as the primary dimension. We perform a sizing treatment for different production modes (i.e., mass production, craft production, and mass customization). Then, the corresponding cutting costs are calculated, and an analysis of fit and cutting cost is made to evaluate the performance of mass customization that is supported by the proposed optimization techniques under the concept of "design to cost".

3.2.1 *Experiment design*

The size charts are designed for mass production and mass customization, while craft production uses personalized patterns that each individual is served with a specific size. The experiment design, the data collection, the parameter setting, and the used analytical methods are described as follows.

3.2.1.1 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 that is composed of 301 instances is randomly selected from the population. Both the sizing systems for mass production and mass customization are built with this dataset.

- A testing dataset, composed of the remaining 150 instances, serves as the real consumer demand in the mass customization and craft production sizing scenarios. In mass production, the consumer demand is set to be an integral multiple of 150 ranging from 0 to 15000 (100 times 150).

In addition, the real patterns for all garment sizes are developed using the 3D garment software, i.e., Lectra Modaris.

3.2.1.2 *Parameter setting*

Parameter setting in sizing is mainly based on industrial practice. The intersize interval can be the same magnitude across all the sizes or vary across the size range (Winks & Winks, 1997). Based on the intersize intervals in the European standard (EN 13402-3, 2003) and the binary linear regression analysis of the relationship between the two key body dimensions (viz. HG and WG), where β equals to 1.13, to simplify the operation, in the case study, interval of hip girth (IntHG) is set to be 5, interval of waist girth (IntWG) be 6.

3.2.1.3 *Analytical method*

The comparisons of fit are made among the three different production modes, i.e., craft production, mass production, and mass customization. The variation tendencies of the comprehensive fit with the additional size number are described using modal values. A related analysis has been conducted to unveil the relation between the comprehensive fit and the additional size number.

3.2.2 Results and discussion

For mass production and mass customization, we produce sets of sizes and calculate the Comprehensive Fits (CFs) by using the proposed fit-oriented sizing system. Next, in **Chapter 4**, we use an extended IP model to figure out the corresponding unit cutting costs using measured personal body dimensions of the instances. For craft production, as specific garment patterns are generated for each personalized individual, the value of CF is regarded as 10.

The following section illustrates the sizing results and the CFs under different production modes (viz. mass production, mass customization, and craft production) of garment manufacturing.

3.2.2.1 Sizing results

In the mass production 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, we introduce a number of additional sizes to the previous mass production sizing system in order to obtain the highest value of CF and establish the mass customization sizing system.

For mass production, the reasonable accommodation rate between 65% and 85% is obtained with size rolls, i.e., 5, 6, or 7. The sizing system with a size roll of 7 corresponds to the highest accommodation rate, and thus it is used to represent the performance of mass production in our analysis and for the comparison. With the exact size ranges and intervals, the size dimensions of each size are calculated by using Equation 3.4. We define the size whose dimensions are the closest to the median dimension values as size M, referring to Equation 3.5. Table 3.1 shows the mass production size chart with a size roll of 7.

Table 3.1 Size chart with size roll of 7 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]	

As aforementioned, the additional sizes for mass customization can be made by varying the secondary dimensions (WG) of the classical mass production sizes while keeping invariant for their primary dimensions (HG). The body dimensions of the instances on the left and bottom decide the limitations of WG for a given HG range. By setting the maximal additional size number to be 7, we make experiments adapted from the original mass production sizing system (the black rectangles in Figure 3.8 (a)). Figure 3.8 (b)-(h) give 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.

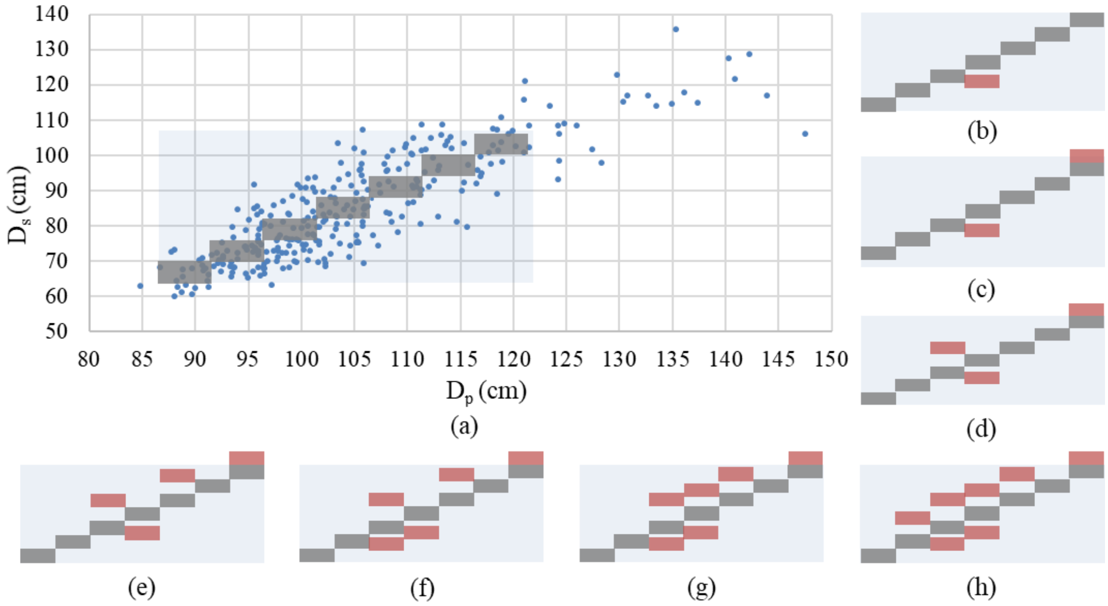

Figure 3.8 Size distributions with the additional size number ranging from 0 to 7.

Table 3.2 Size chart with size roll of 14 in mass customization

HG (cm)	WG					
	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*	-	-

Table 3.2 shows the mass customization size chart with a size roll of 14. The size codes of the additional sizes are marked with *.

3.2.2.2 Comprehensive fits (CFs)

The same custom-fit level definition as demonstrated in Figure 2.6 (b) and CF calculation by Equation 3.6 are used in mass production as well as in mass customization. In this case, a total of 7 custom-fit levels named unfit, ill-fit, minus medium-fit, medium-fit, minus good-fit, good-fit, perfect-fit are assigned with the weights of 0, 2, 4, 5, 7, 8, and 10 respectively (see Figure 2.6 (b)). Then, the CFs are calculated by Equation 3.6. The CF of mass production is 6.88. The CF of mass customization increases from 7.10 to 8.20 when adding new sizes. 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. The increasing rate progressively decreases with the number of additional sizes (as shown in Figure 3.9).

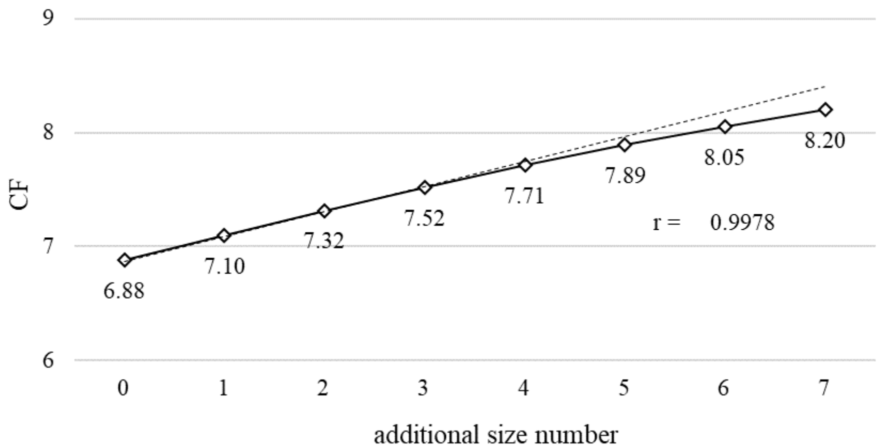

Figure 3.9 The comprehensive-fit trend with the additional size number ranging from 0 to 7.

Table 3.3 gives the evaluation results of the mass customization sizing systems with various size rolls. It shows that adding more sizes brings not only an increase in the CF but also a decrease in the aggregate loss. However, the accommodation rate can be further improved when maintaining the size roll to be a stable value. For instance, the sizing system can improve the accommodation rate when the size roll is always higher than 9.

According to the changing values of the three indices for the sizing system evaluation (CF, aggregate loss, and accommodation rate), it is demonstrated that, as expected, 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 personalization (fit) correctly and accurately.

Table 3.3 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	RWG		
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

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.

3.3 Conclusion

In this chapter, optimization has been made for the sizing of the garment manufacturing processes in mass customization. To be more specific, we have proposed a fit-oriented sizing system and a new criterion called Comprehensive Fit (CF) for evaluating the fit. The sizing strategy for mass customization is to create additional garment sizes based on the mass production sizing system, because the procedure is easier and can reduce the extra cost in new pattern development and manufacturing processes as well. A Genetic Algorithm (GA) has been applied to locate the appropriate additional garment sizes, with the CF defined as the objective function. To demonstrate the efficiency of the proposed mass customization sizing system (the custom-fit strategy by using additional sizes), we present a case study of women’s straight skirt. The results show that the system can effectively improve the garment fit for a target population.

The proposed system provides an effective way for garment manufacturers to provide custom-fit products. For further improvement and extension, a fit-related pricing strategy for the sizing system can be developed to provide consumers with accurate prices for each specific personalization.

It is worth noting that the variation of patterns induced by the enlarged size quantity in mass customization has a great impact on the cutting process. To specify, the increased size number in mass customization leads to the enhanced variety in marker, which influences the marker length and marker cutting length. A more precise cutting order plan can be realized, by using the actual values of the two marker parameters to consider their differences. The corresponding optimization of cutting order planning in garment mass customization will be addressed in the next chapter, aiming to evaluate the economic performance of this mass customization strategy, and reveal the relation between personalization and cost.

Chapter IV:

Optimization of Garment Cutting Order Planning in the Context of Mass Customization

Chapter 4 Optimization of Garment Cutting Order Planning in the Context of Mass Customization

In this chapter, as markers vary greatly (regarding the marker length and the cutting length) with various size combinations especially when using additional sizes, we present a cost-oriented garment Cutting Order Planning (COP) system for garment mass customization, in which marker variations are considered (Figure 4.1). An expanded Integer Programming (IP) model is developed to generate the optimal cutting order plan with the lowest overall cutting cost (including the costs of fabric, spreading operation, and cutting operation) for evaluating the economic performance (the overall cutting cost) of the proposed mass customization sizing system in the previous chapter. Furthermore, the balance between fit and cost is addressed.

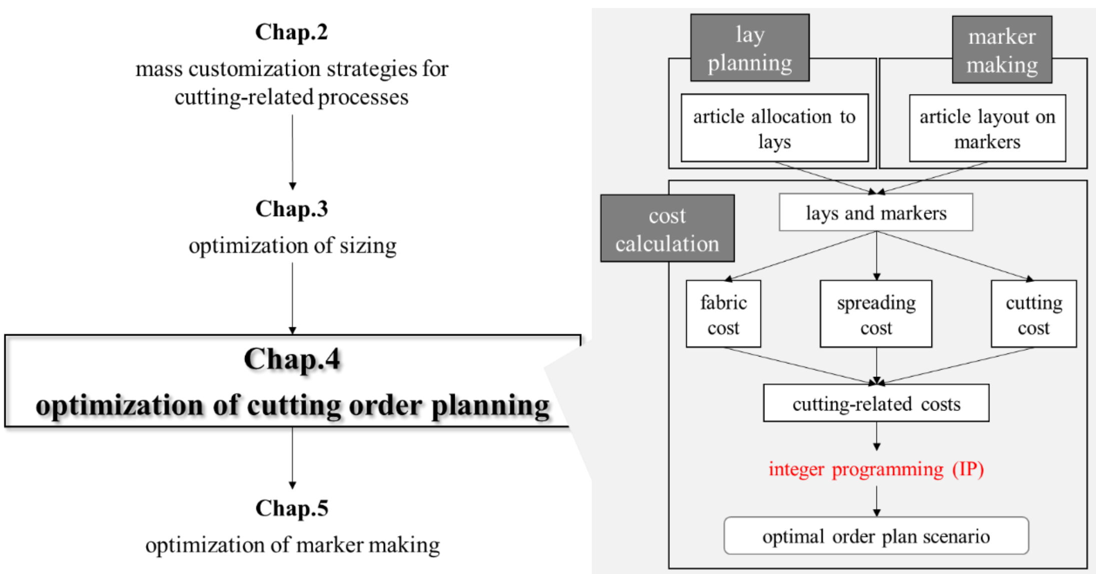

Figure 4.1 Topic of **Chapter 4**.

This chapter is presented as follows. In Section 4.1, the COP problem is defined and the related optimized IP mathematical model with marker variations is formulated. A further extension of the case study in **0** is given in Section 4.2 as an implementation of the COP system. The relations between the fit and the cutting cost for various sizes have been analyzed to reveal the underlying relationship between personalization and cost. The paper is finally concluded with a summary and overall insights detailed in Section 4.3.

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

The garment production planning in the cutting room, usually considered as an NP (non-deterministic polynomial-time)-hard problem (Fowler, Paterson & Tanimoto, 1981; Nascimento *et al.*, 2010; M'Hallah & Bouziri, 2016), 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 mass production domain, each ply of lays is complete that residual products (i.e., the cut-pieces of garment 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 mass production are not available in mass customization, 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, so that step lays are implemented to reach an explicit low cutting cost. As shown in Figure 4.2, 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.

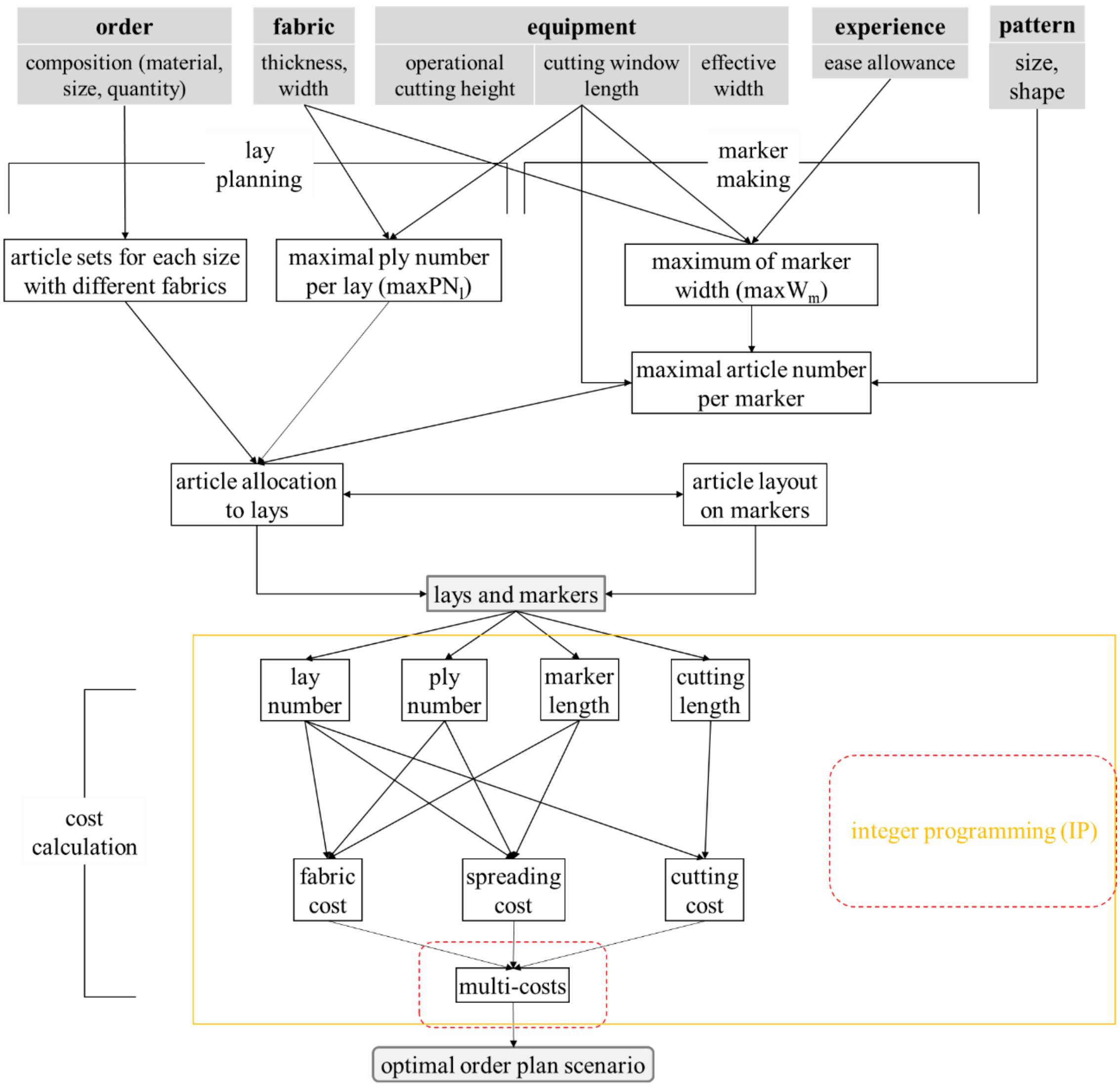

Figure 4.2 Flowchart of the proposed cost-oriented cutting-order-planning model.

Section 4.1.1 and Section 4.1.2 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 IP model to work out the optimal cutting order plan for mass customization, respectively.

4.1.1 Modules of the proposed cutting-order-planning model

The three modules (lay planning, marker making, and calculation of cutting-related costs) in the COP model are detailed in this section.

4.1.1.1 *Module of lay planning*

Lay planning determines parameters (i.e., the contained garment articles, the ply number) of lays for an order. The order is produced either by forecast or by demand, indicating the required quantity of garment articles to produce for each garment size with different fabrics. One of the constraints in lay planning is that the order demand should be adequately met. The ply number is limited by the operational cutting height (H_c) and fabric thickness (T_f). This constraint is shown in Equation (4.1),

$$maxPN_l = \lfloor H_c/T_f \rfloor \tag{4.1}$$

where $maxPN_l$ represents the maximum ply number per lay.

Lay planning and marker making are both interrelated (illustrated in Figure 4.2 and Figure 4.3 (a)). The spreading surface is in line with the marker surface. Their widths and lengths are subject to fabric width, ease allowance, cutting window length, and pattern attributes. Size combinations in the 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 for each garment article their marker lengths are set to a fixed constant, and the same situation with the cutting lengths, while in fact, these parameter values differ considerably between markers. The marker variation and the industrial application are explained in detail in the following marker making module.

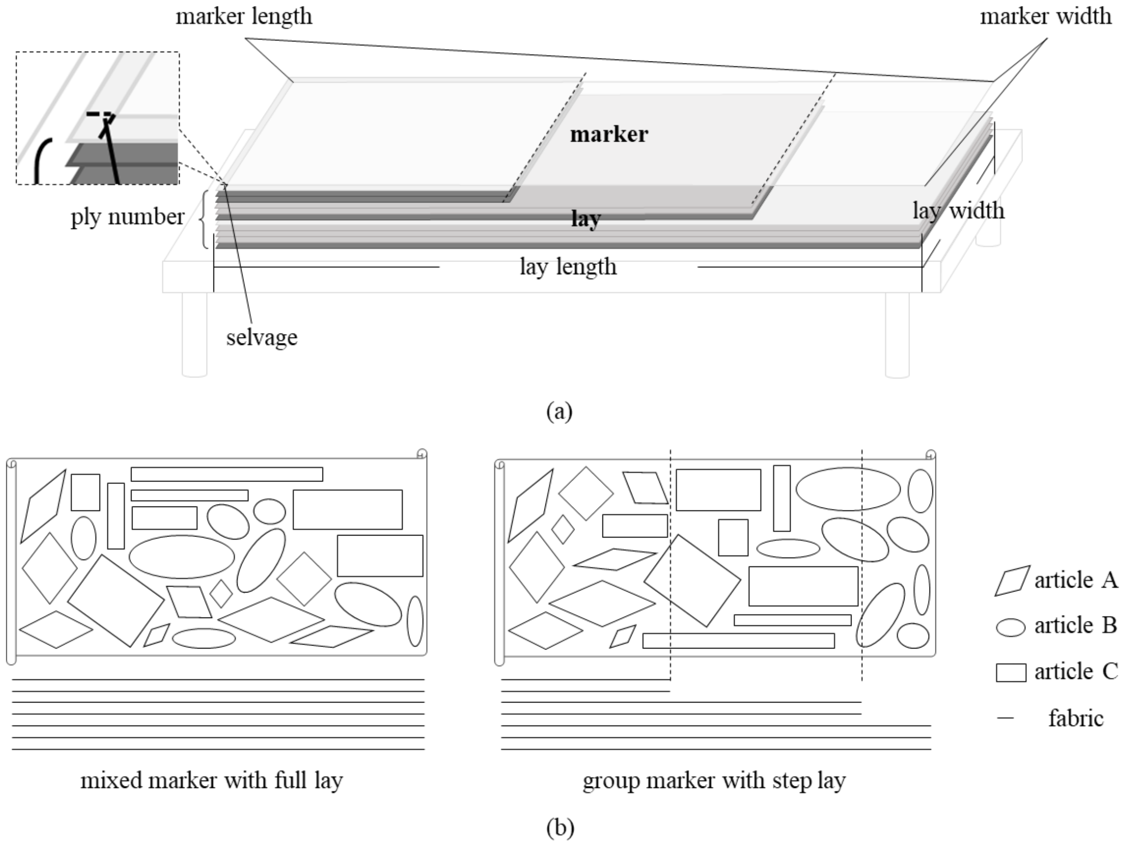

Figure 4.3 (a) Sketch of a set of lay and marker; (b) Sketch of different lays and markers.

For large order sizes in a mass production 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 (Farley, 1988) is preferred when it comes to quite small order sizes like in a mass customization situation, in which excess garment products are not expected.

4.1.1.2 *Module of 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 garment articles. The marker size mainly depends 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 (Vilumsone-Nemes, 2018), where usually enough fabric allowance is made among patterns and slice sections. Indeed, the 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:

$$maxW_m = W_f - E_a \tag{4.2}$$

There are various marker types in garment production (Haque, 2016). Each type of marker has its 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 garment article are arranged in an individual section of the marker. Mixed markers are commonly applied in mass production 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 Figure 4.3 (b).

4.1.1.3 *Module of 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 the conduction of operations. Of all the five costs arising from the cutting process, the marker cost will become significantly lower with the automation of production, and the sorting and bundling cost is considerably lower than the others. Thus, 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 Figure 4.2. 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):

$$C_f = \sum P_f \times L_f \tag{4.3}$$

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

2) Spreading cost (C_s):

$$C_s = (P_o + P_{sm}) \times T_s$$
$$T_s = \sum L_f / V_s + N_p \times T_{sp} \tag{4.4}$$

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):

$$C_c = (P_o + P_{cm}) \times T_c$$
$$T_c = \sum L_c / V_c + T_{cp} \tag{4.5}$$

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.

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

Lay planning is one part of the cutting stock problem (Farley, 1988), and can be solved by mathematical methods (Farley, 1988; Degraeve & Vandebroek, 1998; Degraeve, Gochet & Jans, 2002) with the aid of soft computing technologies (Martens, 2004; Fister, Mernik & Filipic, 2010; Yang, Huang & Huang, 2011), which is introduced in detail in Section 1.1.5. Integer Programming (IP) is proved to be an effective tool for the COP (Degraeve &

Vandebroek, 1998), the basis of other researches (Degraeve, Gochet & Jans, 2002; Martens, 2004). Considering the previously described differences of the COP in mass production and mass customization, we propose an expanded IP model on the basis of the Zeger Degraeve's mixed integer programming model (MIP) (Degraeve & Vandebroek, 1998) in order to tackle the lay planning problem with both step lays and full lays. Compared to the existing IP in the literature, 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 the mass customization environment:

Given:

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 (Gersak, 2013)
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
V_m	existence of marker m, $m \in M$, = 0, $TPN_m = 0$, $PN_{m1} = 0$, = 1, otherwise
PN_l	ply number of lay l, $l \in L$, $\leq maxPN_l$, $= TPN_m/U_m$, PN_{m1}/U_m, $m \in M$
P_f	fabric price per unit length
P_o	operator cost per hour
V_s	spreading speed
V_c	cutting speed
T_{sp}	number of hours for each pause during spreading
T_{cp}	number of hours for the pause during cutting

Assumption:

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

Variables:

TPN_m	total ply number of lays with marker m, m∈M
PN_{sm}	ply number of subsections with marker m, m∈M, on a downward trend
U_m	copies of lays with marker m, m∈M, $U_m - 1 \leq TPN_m / maxPN_l \leq U_m$, $U_m - 1 \leq PN_{m1} / maxPN_l \leq U_m$

Constraints:

1) satisfaction of demands for each size, garments arranged in full lays and in step lays should meet the order demand

$$\sum_{m \in M} SN_{sm} TPN_m + \sum_{m \in M} \sum_{1}^{maxSN_m} SN_{ssm} PN_{sm} \geq OD_s \tag{4.6}$$

2) lay number determined by ply number

$$U_m - 1 \leq TPN_m / maxPN_l \leq U_m \tag{4.7}$$

$$U_m - 1 \leq PN_{m1} / maxPN_l \leq U_m \tag{4.8}$$

3) diminishing subsection heights in step lays

$$PN_1 \geq PN_2 \geq \ldots \geq PN_{maxSN_m} \tag{4.9}$$

Objective function:

$$Min \sum_{m \in M} \left(w_u \times U_m + W_{tpn} \times TPN_m + W_{pn} \times \sum_{1}^{maxSN_m} PN_{sm} \right)$$

$$W_e(W_u, W_{tpn}, W_{pn}) = f\left(SN_{sm}, L_m, CL_m, SN_{ssm}, L_{sm}, L_s, P_f, P_o, V_s, V_c, T_{sp}, T_{cp}\right) \tag{4.10}$$

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

4.2 Case study

We made an extension of the case study in **Chapter 2**, that the proposed COP system is applied to calculate the overall cutting costs when applying sizes generated in **Chapter 2**. Moreover, the relationship between the overall cutting cost and the number of additional garment sizes is studied through this case study.

4.2.1 Experiment design

The batch cutting is applied in the cutting processes of mass production and mass customization, while the single-piece cutting is applied in the cutting process of craft production. Correspondingly, the unit cutting costs for mass production and mass customization are figured out by using the proposed cost-orient Cutting-Order-Planning (COP) model, while for craft production, the cost is estimated in the single-piece manufacturing environment. In regard to the experiment design, the data collection, the parameter setting, and the used analytical methods are described as follows.

4.2.1.1 *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.

-As mentioned in **Chapter 2**, a training dataset is composed of 301 instances that are randomly selected from the population. Both the sizing systems for mass production and mass customization 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 mass production scenario.

-The same testing dataset, composed of the remaining 150 instances used in **Chapter 2**, also serves as the real consumer demand in the COP of the mass customization and the CF scenarios.

Patterns for all garment sizes created in **Chapter 2** are used in this section. Markers for all the size combinations are drawn using the software Lectra Diamino Fashion. The data extracted (including the marker length and the cutting length) from these markers are used in COP.

4.2.1.2 Parameter setting

Parameter setting in the COP is based on the related literature and the production experience. In our experiment, we take a Vector 2500 Techtex produced by Lectra as the cutting equipment. The parameters associated with the cutting operation are set as follows. 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 are set in our experiment are given in Table 4.1.

Table 4.1 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

In order to propose different scenarios, we consider 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 the selvage is 0.02 m for each fabric lay. We also set three levels of operator cost, i.e., 5 €/h, 10 €/h, and 20 €/h, to simulate different production situations. The spreading operation is automatic with the speed of 2400 m/h, and the time for each spreading pause is 1/60 h. Two cutting process modes are considered, i.e., 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. In total, 30 different scenarios are considered.

4.2.1.3 Analytical method

Comparisons of the cutting costs are made among the three different production modes, i.e., craft production, mass production, and mass customization. The variation tendencies of unit cutting cost with additional size numbers in mass customization and craft production, the unit cutting cost in mass production with the order size are described. Additionally, the related analysis has been conducted to unveil the relation between the unit cutting cost and the additional size number, and the relation between the unit cutting cost and the comprehensive fit.

4.2.2 Results and discussion

For craft production, we take the average values of marker related parameters (i.e., the marker length and the cutting length) in mass customization as the estimated values in the single-piece cutting. For mass production and mass customization, the variance of markers is considered in the COP to calculate the corresponding unit cutting costs in the batch cutting.

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

4.2.2.1 *Cutting order planning and cutting costs*

The production mode differs, the COP varies in details. 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 mass production and mass customization scenarios. With the order size of mass production ranging from 0 to 13400, in which the maximal value 13400 is determined by 100 times 134 (the basic forecasted order size for the consumer demand of 150, according to the size distribution in mass production with a roll size of 7), the COP results (Figure 4.4) show that the larger the order size is, the lower the cutting cost will be. However, when the order size is large enough (above 6000 in our experiments), the cutting cost tends to be stable at a specific value. We use the cutting-cost values of the order size 10000 as the stable values to represent the cutting costs in mass production. In mass customization, the order size is the exact number of 134 for the consumer demand of 150, the cutting costs are calculated with the increase of additional sizes from 1 to 7. For craft production, we regard the cutting operation as a simple-ply cutting and use the average marker length of a single garment article for the cutting cost calculation.

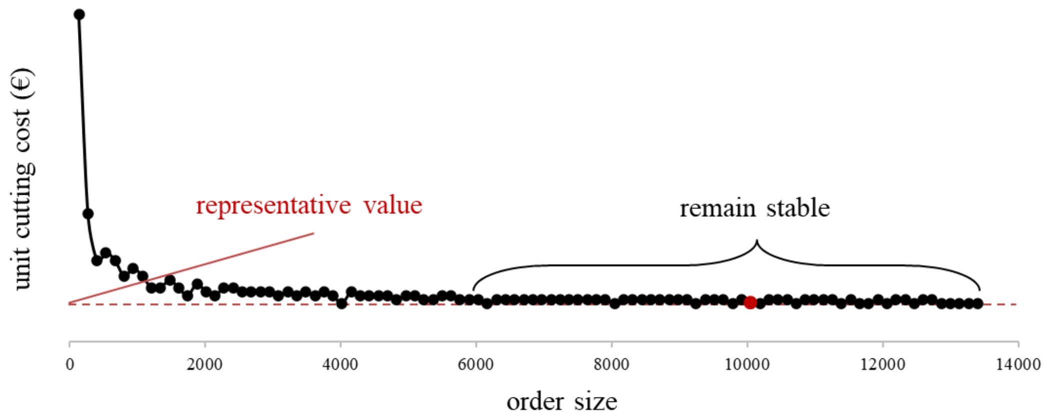

Figure 4.4 Cutting cost trend in mass production.

Table 4.2 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	0.66	3.15	6.25	12.46
	10	0.21	0.71	3.19	6.30	12.51
	20	0.30	0.79	3.28	6.38	12.59
400	5	0.17	0.67	3.15	6.26	12.47
	10	0.22	0.71	3.20	6.30	12.51
	20	0.31	0.80	3.29	6.39	12.60

Table 4.2 indicates the cutting costs in mass production. The manual cutting and a higher operator cost result in increases in 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 4.3 gives the estimated unit cutting costs of craft production. As expected, the cutting costs in craft production are much higher than those in mass production (Table 4.2) due to the manual operation and short markers. It is shown that fabric price also plays an absolutely important role on the unit cutting cost like that in mass production.

Table 4.3 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

In mass customization, the correlation coefficients show a strong linear relationship between the unit cutting cost and the additional size number. However, the unit cutting cost slightly fluctuates that there exist some turns of trends (Figure 4.5) 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 (Figure 4.6).

The trend of the unit cutting cost varies when the cutting speed differs or the fabric price varies. When the number of additional sizes increases, the unit cutting cost decreases if the cutting operation is automatic (Figure 4.5 (a)) or the fabric is expensive (Figure 4.5 (d)). Otherwise, when the cutting operation is manual and the fabric is at a quite low price, the unit cutting cost increases (Figure 4.5 (b)). 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 can bring more possible size combinations with shorter markers and finally reduce the fabric usage.

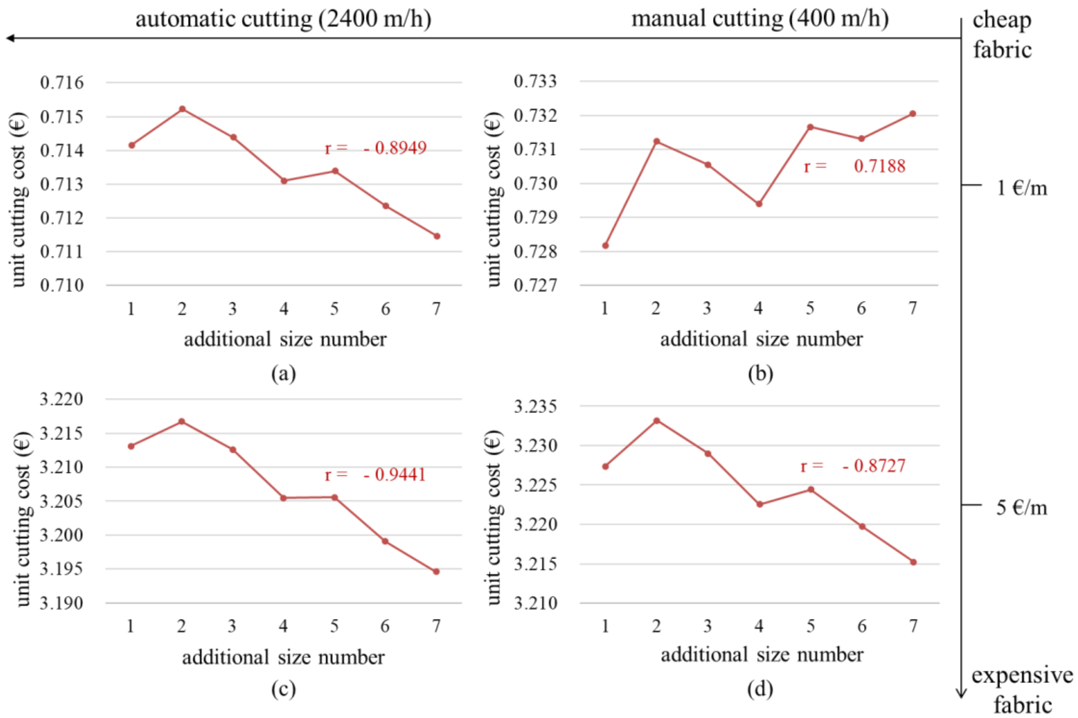

Figure 4.5 Partial cutting costs in mass customization (operator cost=10 €/h).

It is seen that a higher operator cost also causes a small increase in unit cutting cost, but does not affect its variation trend (Figure 4.6). This is because the operator cost accounts for a small weight in the objective function of the overall cutting cost.

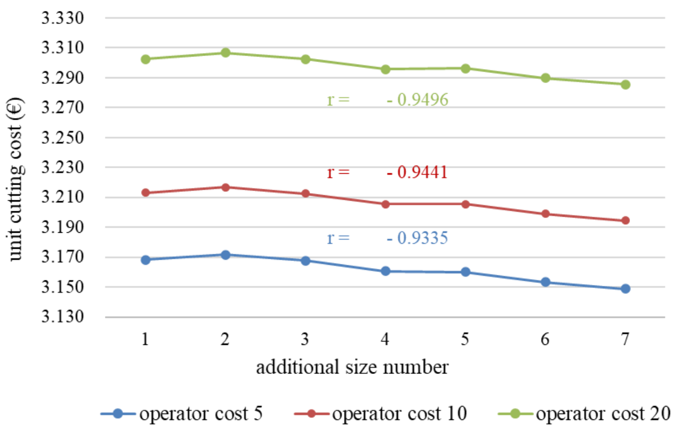

Figure 4.6 Partial cutting costs in mass customization (cutting speed=2400 m/h, fabric price=5 €/m).

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 operation is 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 decreases because of a strong positive correlation with the fabric cost. In addition, the cutting cost varies slightly with different sizing scenarios, where the details in the cost trends would depend on the garment type. Especially for mass customization, 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 mass customization. Additionally, mass customization can enlarge the user population to some extent.

4.2.2.2 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 the garment manufacturing to control the cost, especially the cutting cost, during the design stage. An analysis of the unit cutting cost variation trend with the CF in mass customization is described in this section.

The correlation coefficients indicate that the CF has a strong linear relationship with the unit cutting cost in mass customization. Similar to 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 the CF increases (Figure 4.7). Figure 4.7 (a) is with an automatic cutting and Figure 4.7 (b) with a manual cutting. The appropriate sizing scenarios (red points) which are lower in the unit cutting cost but higher in the CF can be found in these curves. In Figure 4.7 (a), there is only one good solution when the CF = 8.2 with the best personalization level and the cheapest cost, while in Figure 4.7 (b), there are several good solutions, the first, fourth and sixth points, with better tradeoffs of personalization and cost. The results enable the decision-maker to find the best scenario according to the personalization or cost required in garment mass customization. It is also worth noting that the details in this cost/fit trend would differ among various garment types.

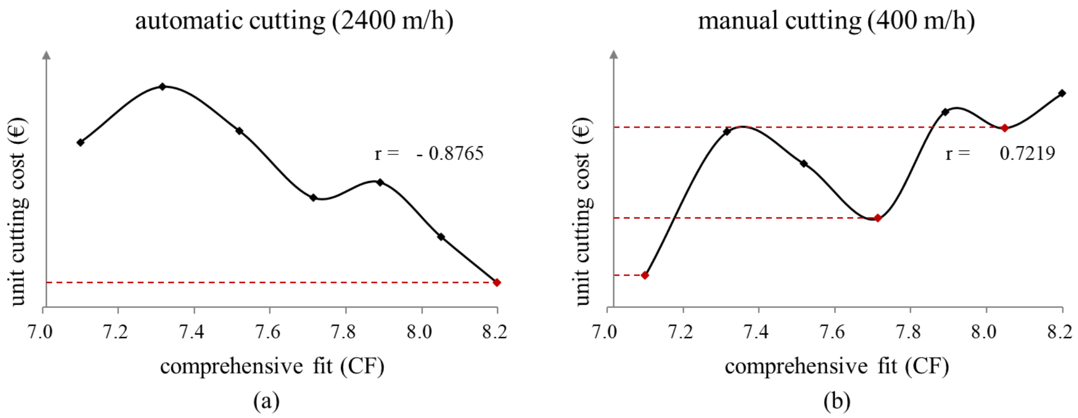

Figure 4.7 Cutting cost trends in mass customization according to comprehensive fit for two different cutting speeds (fabric price=1 €/m, operator cost=10 €/h).

With a comparison of mass production, mass customization, and craft production on the CF and the unit cutting cost (Figure 4.8), we find that the mass customization strategy can efficiently improve the CF with a slight increase in unit cutting cost compared to a significant cost increase in craft production. In the current industrial and business situation, automation in production has been widely accepted by companies and luxury fabrics are largely preferred by more consumers, so the proposed system providing the local optimums (Figure 4.5 (a)(c)(d), Figure 4.7 (a)) is extremely significant to the garment mass customization tendency.

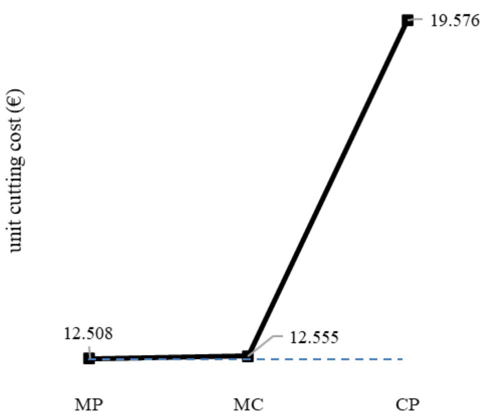

Figure 4.8 Cutting costs for various production modes (automatic cutting, fabric price=20 €/m, operator cost=10 €/h).

Having mastered how the cutting cost varies with the CF, 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, according to the specific production situation (in terms of the fabric cost and cutting speed). In practice, compared with the significant-high unit cutting cost in craft production, a slight increase of the unit cutting cost brought by mass customization can be much more acceptable for garment manufacturers. And, more remarkable in mass customization, there are also local optimums that provide the best tradeoffs between personalization and cost, from which both the company and consumers can get benefits in the end.

4.3 Conclusion

In this chapter, optimization has been made for the Cutting Order Planning (COP) of the garment manufacturing process with consideration of the greater marker variance brought by mass customization. As a result, a cost-benefit analysis has been available for decision-makers in the garment industry towards mass customization. To be more specific, we propose a COP system, in which the expanded Integer Programming (IP) model has been built to determine the COP solution yielding the least costly cutting process with precise data of marker parameters (i.e., the marker length and the marker cutting length). With the accurate cutting costs form the COP system and the garment fits from the sizing system, we evaluate the cost/personalization ratios in various production situations.

To demonstrate the efficiency of the proposed sizing system in **Chapter 3**, we present a specific case study of women's straight skirts, in which the underlying relationship between personalization and cost was explored. It is found that the relationship between the cutting cost and the number of additional garment sizes is nonlinear and fluctuating, strongly influenced by a combination of different factors such as the fabric price, labor cost, and cutting speed. Local optima can arise, of which the identification is crucial for developing mass customization by obtaining a better compromise between the personalization (e.g., the Comprehensive Fit (CF)) and the cost (e.g., the cutting cost).

Thereupon, with the concept of "design-to-cost", the proposed system provides a reference for the garment industry to handle the tradeoff between personalization and cost in mass customization, in order to meet consumers' growing demand of personalization at an acceptable cost. It provides garment manufacturers with guidance on developing effective manufacturing strategies for the production mode transformation from mass production to mass customization. Additionally, as an attempt of the automation and intellectualization in garment manufacturing, it is in the spectrum of Industry 4.0.

The efficiency of the proposed COP system relies on obtaining the accurate marker-related data, i.e., the marker length and the marker cutting length. The wider garment size roll, especially in mass customization, leads to a greater marker variance. However, the semi-automatic work of making all the markers in the current practical production is of low efficiency in time and accuracy.

Consequently, we consider using the marker prediction to solve this issue in the next chapter.

Chapter V:

Optimization of Garment Marker Making in the Context of Mass Customization

Chapter 5 Optimization of Garment Marker Making in the Context of Mass Customization

The large number of sizes in garment mass customization leads to an exponential increase of size combinations (markers), which induces a larger workload of marker making. In the current production, creating all the markers using a commercialized marker making software in a semi-automatic way for all the size combinations is a tedious and heavy work. In contrast, the application of machine learning technologies to marker prediction is expected to be beneficial in both time and accuracy. In this chapter, the marker making optimization (Figure 5.1) is performed by using the marker length estimation with machine learning methods, i.e., Multiple Linear Regression (MLR) and Radial Basis Function Neural Network (RBF NN). Finally, the cutting costs, as in the experiments of the previous chapter, are estimated using the predicted marker lengths in order to evaluate the prediction performance.

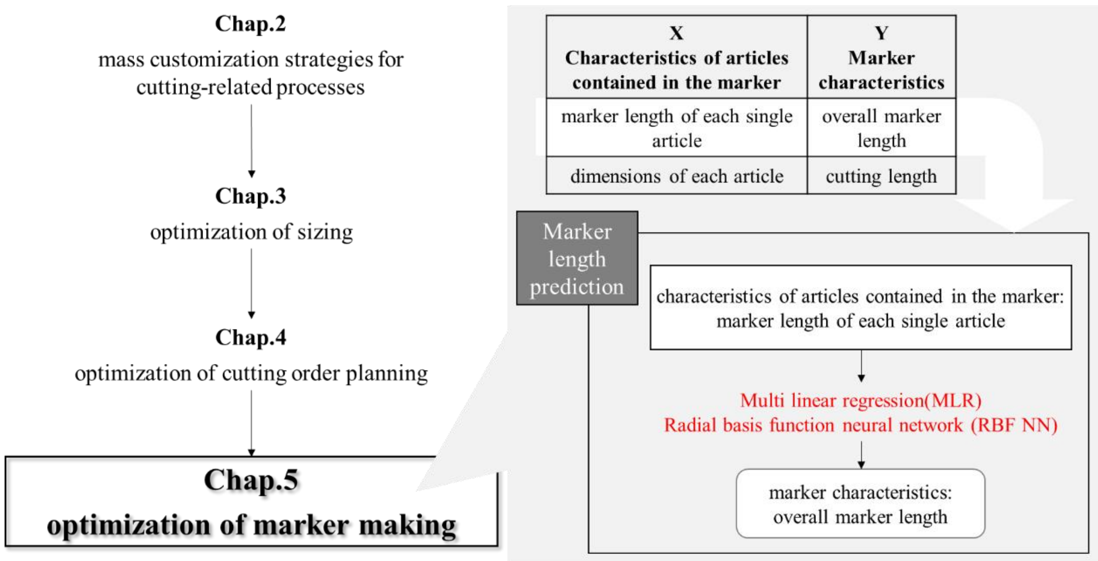

Figure 5.1 Topic of **Chapter 5**.

This chapter is presented as follows. Firstly, section 5.1 describes the problem and the model of marker length estimation. The prediction methods for marker length estimation and the related performance measurement are introduced. Afterward, in Section 5.2, a comparison of prediction performance between the two different machine learning methods is made through a case study of a basic straight skirt. Finally, a conclusion is given in Section 5.3.

5.1 Marker length estimation for garment mass customization

Marker making is a subprocess inside the garment cutting process. It aims to layout garment patterns within a rectangular surface with a fixed width in high efficiency. The identification of the accurate marker parameters is needed (e.g. the marker length, the cutting length, and the cutting route) for making the best plan of the cutting process. When the number of garment sizes increases in the mass customization environment, the marker quantity rises sharply due to the much larger number of size combinations. Therefore, the acquisition of these marker parameters for a precise cutting plan by creating all the markers in the traditional semi-automatic way leads to a heavy workload. The marker length estimation problem can be regarded as a regression problem, where the marker lengths of the contained garment article sizes are taken as inputs and the overall marker length for their combinations as output. In this context, we originally apply machine learning-based methods to predict accurate marker lengths.

Section 5.1.1 presents the marker length estimation problem and the corresponding prediction model, while Section 5.1.2 demonstrates the two algorithms applied in the prediction model.

5.1.1 Marker length estimation problem

In the marker making, several sets of patterns (each set belongs to one specific size of garment article), are placed within a rectangular surface called a marker.

Regardless of the impact of marker type, different size combinations of garment articles result in differences between markers. A simple equation for intuitive judgment can be given in Equation (5.1). The marker quantity m can be expressed below,

$$m = \sum_{s=1}^{maxSN} a^s \tag{5.1}$$

where *s* represents the number of garment sizes that are contained in the marker, *maxSN* represents the maximal size number in the marker depending on the cutting equipment, *a* represents the total optional size number.

It can be found that the marker quantity *m* is conspicuous with exponential growth if the total size number sharply rises. If these total optional sizes are of a larger number (in the mass customization environment), the creation of all the markers by the semi-automatic method (creating markers manually with CAD software) will be time-consuming with limited accuracy.

Marker parameters (i.e., characteristics of garment articles contained in the marker and those of the marker itself) are adopted for marker prediction, as shown in Figure 5.2. In the marker prediction problem, the independent variables are characteristics of garment articles that are contained in the marker, such as marker length of each single article and the dimensions of each article, while the dependent variables are characteristics of the marker itself, i.e., the overall marker length and marker cutting length. Combined with the real production, the marker lengths of each single garment article that is contained in the marker are accessible and facile to be considered, and consequently, are taken as the independent variables for predicting the overall marker lengths, i.e., the corresponding dependent variables.

X Characteristics of articles contained in the marker	Y Marker characteristics
marker length of each single article	marker length
dimensions of each article	cutting length

	Marker NO.	Marker lengths of each single article contained in the marker					Marker length
		X					Y
		x1	x2	x3	x4	…	y
training	1	1.12	1.20	1.22	1.54	…	4.56
	2	1.56	1.77	-	-	…	3.15
	3	1.01	1.43	1.71	-	…	3.89
	…	…	…	…	…	…	…
	105	1.19	1.26	1.32	1.67	…	4.89
testing	106	1.51	1.67	-	-	…	3.01
	107	1.50	1.87	-	-	…	3.19
	…	…	…	…	…	…	…

Figure 5.2 Marker parameters adopted for marker prediction.

5.1.2 Algorithm applications in marker length estimation model

The techniques of Multiple Linear Regression (MLR) and Radial Basis Function Neural Network (RBF NN) have been applied to the marker length estimation model, where the marker length of each contained article is taken as input (X) and the overall marker length as output (Y). The stratified 10-fold cross-validation is used to find the proper hyperparameters of the two models, degree of X or number of neurons. Then the prediction performances are compared by using the mean square error.

5.1.2.1 Prediction method

For the marker making problem, the underlying regularity is complex to be built. Some machine learning techniques will Radial Basis Function Neural Network (RBF NN). The marker length estimation problem can be regarded as a regression problem, where the marker length of each contained garment article is taken as input (X) and the overall marker length as output (Y), as shown in Figure 5.2. For this specific problem, it is not dependent on time, and there is no available analytical model. Multiple Linear Regression (MLR) is a statistical technique that uses several explanatory variables to predict the outcome of a response variable. Polynomial regression is applied in the experiment as a special case of MLR, in which the relationship between the independent variable vector (X) and the dependent variable (Y) is modeled as an nth (n=1-10) degree polynomial in X, from linear to non-linear. Compared with a simple linear regression, polynomial regression basically fits a wide range of curvature with the inferential framework of multiple regression, and a broad range of function can be fit under it, so as to provide the best approximation of the relationship between dependent and independent variables. Furthermore, RBF NN is an artificial neural network using radial basis functions as activation functions, where the output of the network is a linear combination of radial basis functions of the inputs and neuron parameters (Murray, 1995, Mujtaba, 2001, Cheng & Lee, 2001). The advantage of RBF NN is its superiority compared with the Back-Propagation (BP) neural network in approximation ability, classification ability, as well as learning speed. In general, the structure and training are simple, and the learning convergence speed is fast. It is a universal approximator for any linear and nonlinear functions, and overcome the problem of local minimum. Taking into account the above points, the two machine learning techniques are selected as the applied methods for solving the marker length estimation problem in our study (Figure 5.3).

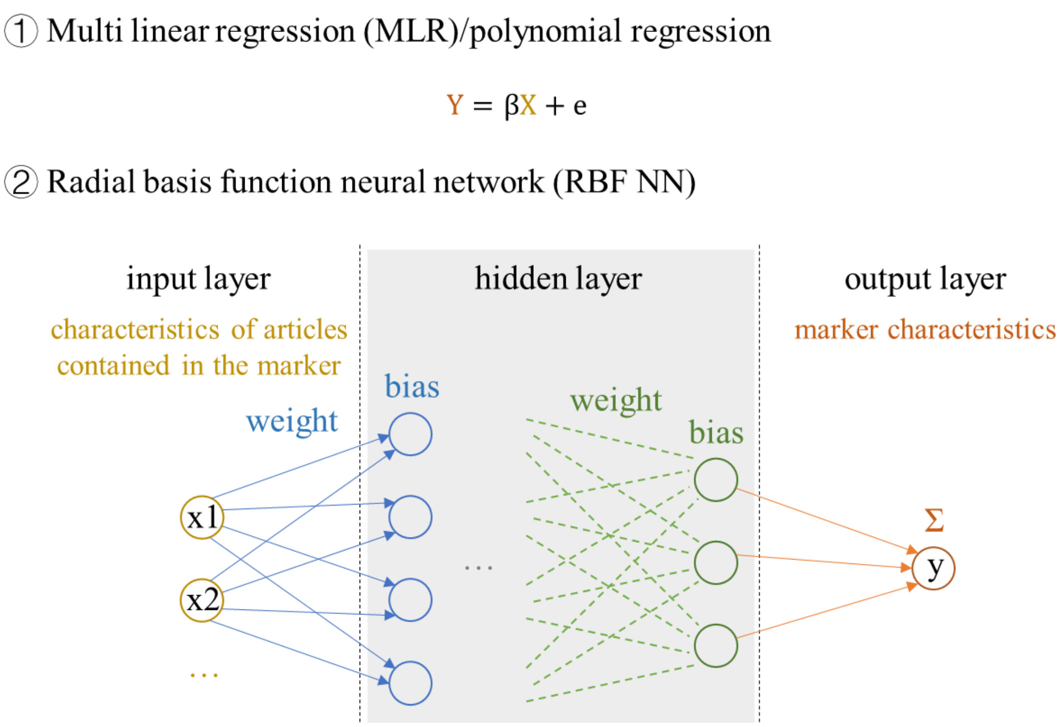

Figure 5.3 Applied prediction methods.

5.1.2.2 Performance validation

The stratified 10-fold cross-validation process is used in this study to learn the models. The stratified K-fold cross-validation is a variation of K-fold that returns stratified folds that are made by preserving roughly the same percentage of samples for each class (Diamantidis, Karlis & Giakoumakis, 2000). K is set to 10 for evaluating the prediction error rate of the models in order to find the best selection of appropriate parameters (regression degree and neuron number).

To measure the performances of marker length estimation by the applied methods (MLR and RBF NN), we use the Mean Square Error (MSE) to measure the deviation. The MSE, as a measure of the quality of an estimator, reflects the squares of the distance between the predicted value and the original data. The calculation of MSE is illustrated in Equation (5.2).

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(x(k) - \hat{x}(k))^2 \tag{5.2}$$

where $x(k)$ presents the k original data, $\hat{x}(k)$ the k presents the predicted value, n presents the total number of testing data. The values are always non-negative, and it means a better performance in estimation when it is closer to zero.

5.2 Case study

Three garment size sets aimed at shifting from mass production to mass customization are adopted for constructing the experimental markers. The markers are of two types, i.e., mixed marker and group marker, generated via Lectra CAD software. Thus, the experimental marker lengths can be measured. Due to the semi-automatic operation, the same marker making experiments based on the commercialized software are conducted at least three times to ensure accuracy. The prediction models with methods of multiple linear regression (MLR) with the degree of X from 1 to 10, and radial basis function neural network (RBF NN) with the neuron number varying from 1 to 40 are tested. By varying the regression degree and neuron number, we can observe the effects of underfitting and overfitting and find the appropriate degree of X for MLR and neuron number for RBF NN.

Considering the effects of the three size sets and of the two marker types, we realize a comparison of prediction performances between the models using these two machine learning methods.

5.2.1 Experiment design

In this study, we adopted three size sets of the basic straight skirt, namely, 7 original sizes (MP sizes), 7 additional sizes (MC sizes), and the combination of all the 14 sizes (MP+MC sizes). The experimental marker lengths of the mixed markers and the group markers containing two of these sizes are collected for measuring the prediction performances, which maintains the continuity of our previous study. The MLR method and RBF NN method are applied to the prediction models separately. The hyperparameters of the two models, namely the degree of X and number of neurons, are optimized with a stratified 10-fold cross-validation process.

5.2.1.1 Data collection

There are 7 basic sizes for mass production (MP sizes), 7 additional sizes which are newly introduced for mass customization (MC sizes), and in total 14 sizes for mass customization (MP+MC sizes), produced in Chapter 3. In order to maintain the continuity of our previous study, the initial attempt in this study is to estimate the marker lengths of markers that contain two garment articles. Thus, two types of markers, i.e., mixed marker and group marker, are made by using the commercialized software Lectra Diamino for all the pair-wise garment articles with the garment sizes taken from these size sets.

As mentioned above, the marker quantity increases exponentially with the total size number (5.1). The total size numbers are 7 for mass production and 14 for mass customization, and the garment article number placed on one marker is set to 2 in this study. Consequently, there are 49 (7^2) and 196 (14^2) combinations of two garment articles for mass production and mass customization, respectively. They (49 and 196) are exactly the total marker numbers, which also reflects the heavy marker making workload. In addition, marker type is considered so that the mixed marker and the group marker are both applied in the marker making for all the combinations of garment article sizes.

As introduced in Section 5.1.2.1, input X represents the marker length of each single garment article that o is contained in the marker (X_1: size of garment article 1, X_2: size of garment article 2), and output Y represents the overall marker length with the same size combination. Through the aforementioned experimental work of marker making, the related information (marker parameters) can be extracted and summarized. Afterward, the relationship between X (X_1 and X_2) and Y is correlated via three-dimensional (3D) surface plots (Figure 5.4), where X are differentiated by different size sets, i.e., MP sizes, MC sizes and MP+MC sizes, while Y are altered by different combination modes, i.e., mixed marker and group marker.

Figure 5.4 shows marker length distributions of two-article markers (both mixed marker and group marker) with different size sets (MP sizes, MC sizes, and MP+MC sizes). The size numbers of the three size sets are 7, 7, and 14 respectively, so that the corresponding numbers of size combinations are 7^2, 7^2, and 14^2. Therefore, the 3D surface plots are composed of 49, 49, and 196 dots, respectively.

As shown in Figure 5.4, all the dots approximately distribute on a plane in each 3D plot, signifying a certain degree of regularity and predictability. Meanwhile, the dot distributions also show different degrees of irregularity, which will examine the prediction ability of the two machine learning techniques, i.e., MLR and RBF NN.

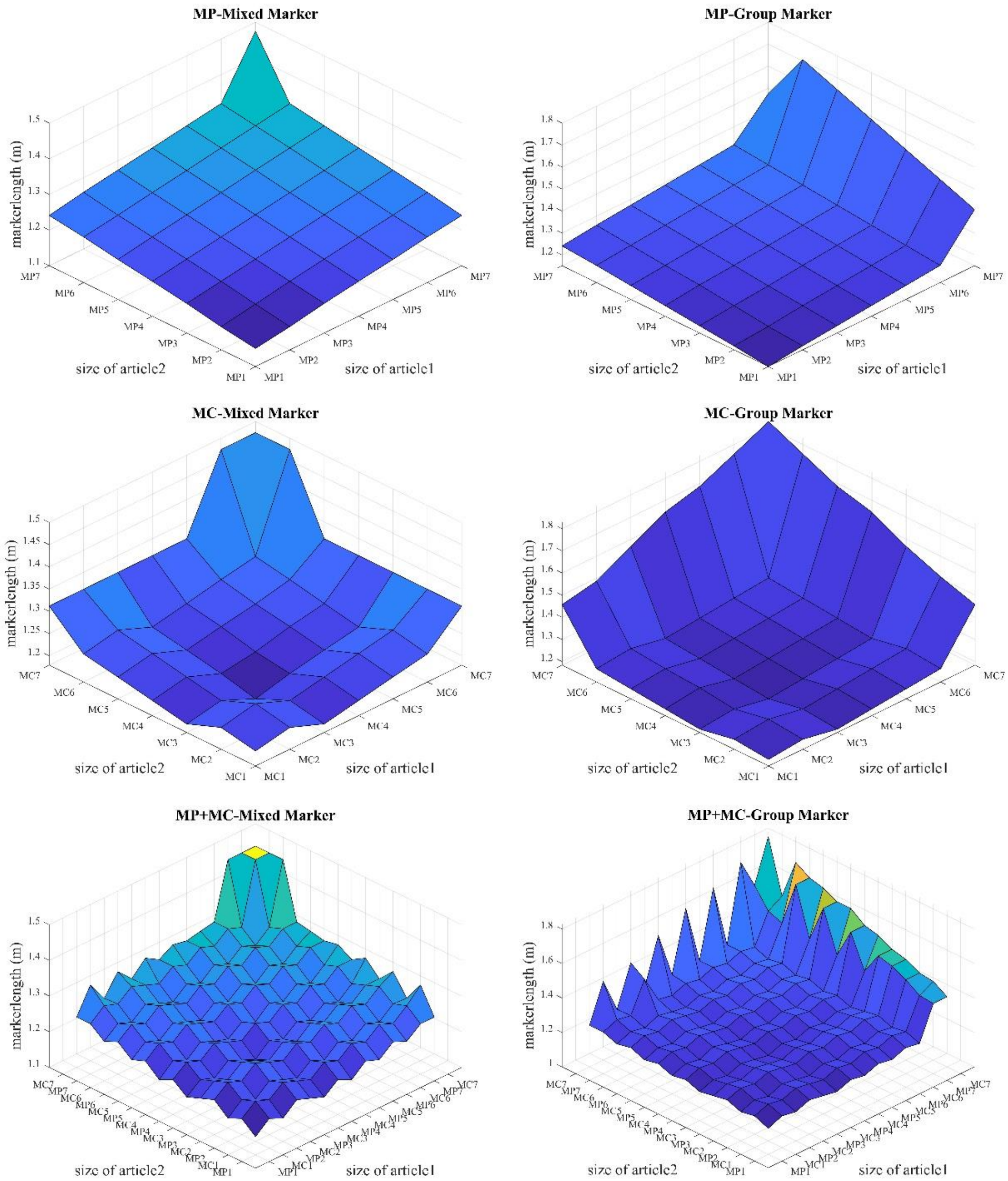

Figure 5.4 Marker length distributions of two-article markers with different size sets (MP sizes, MC sizes, and MP+MC szies).

For the mixed markers, as shown in Figure 5.4, the distributions of mixed marker lengths are axisymmetric (the axis of symmetry is: size of article1=size of article2) due to the interchangeable input elements. This is because all patterns are mixed on mixed markers. Namely, mixed markers that contain the same garment articles have the same overall marker lengths. In contrast, for the group markers, as illustrated in Figure 5.4, the distributions of group marker lengths exhibit asymmetries. That is because patterns of each garment article are concentrated in one specific section of group markers, so that the exchange of the garment articles leads to some extent of the variation of the overall marker length. Namely, the placement sequence of garment articles in group markers slightly affects the overall marker lengths. Figure 5.5 gives an example, where one garment article of the size MP3 and another of the size MC6 are arranged into two group markers with different sequences and a mixed marker. It can be found that the sequence of garment articles leads to the difference of marker length, 1.302 and 1.527 m. In contrast, the mixed marker can realize a tighter arrangement of patterns with a minimum marker length of 1.273 m.

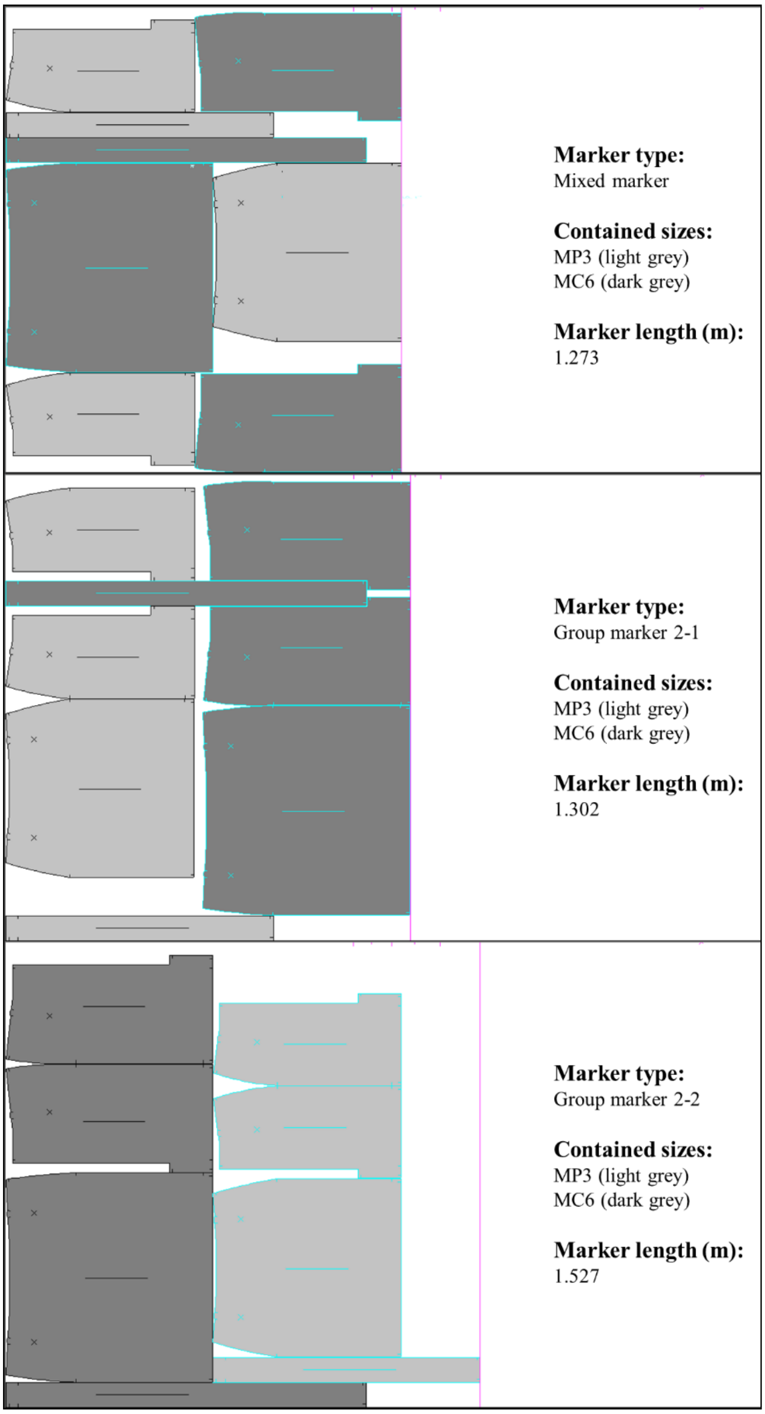

Figure 5.5 Marker lengths of different-typed markers with the same garment size combination (MP3 and MC6)

5.2.1.2 Parameter setting

Two prediction models are used to carry out the prediction using the MLR method and RBF NN method separately. The hyperparameters of the two models, the degree of X or number of neurons, are optimized with a stratified 10-fold cross-validation process.

The obtained deviations for the MLR model, evaluated with the Mean Square Error (MSE) test (5.2), are summarized in Figure 5.6. In detail, it includes the MSE of marker length estimation using the MLR method, the X degree ranges from 1 to 10, for the two types of markers, i.e., mixed marker and group marker, with three size sets, i.e., MP sizes, MC sizes and MP+MC sizes. It can be observed that with the X degree of MLR varies, the MSE is accordingly changed with fluctuating curves, where underfitting and overfitting occur. The lower X degree indicates a comparatively better performance in the prediction.

For both mixed marker and group marker, when the X degree of MLR model equals 1 (linear), the MSE is relatively high, especially for group markers. It indicates that the relationship between X and Y is nonlinear. Specifically, for mixed marker, the MSEs can reach a very low value when the X degree is set to 2-4. It is worth noting that MSEs with MC sizes are more sensitive to those with other size sets, proving that a suitable X degree of MLR model can lead to a much better prediction accuracy. Compared with mix marker, all the MSEs of MLR models for group marker exhibit some extent of fluctuation, indicating a higher difficulty in prediction. Similar to mixed marker, X degrees of 3-5 with relatively low MSEs are recommended to be utilized. The reason for the increment of MSE with a high X degree can be ascribed to overfitting, trapped into local optimum. Therefore, it is not recommended to set the X degree of MLR model to a very high value, but to determine in accordance with the inflection point. In summary, for the MRL model, a relatively lower value for X degree, which can lead to a satisfactory MSE value, is recommended. It ensures a higher accuracy, and prevents overfitting at the same time.

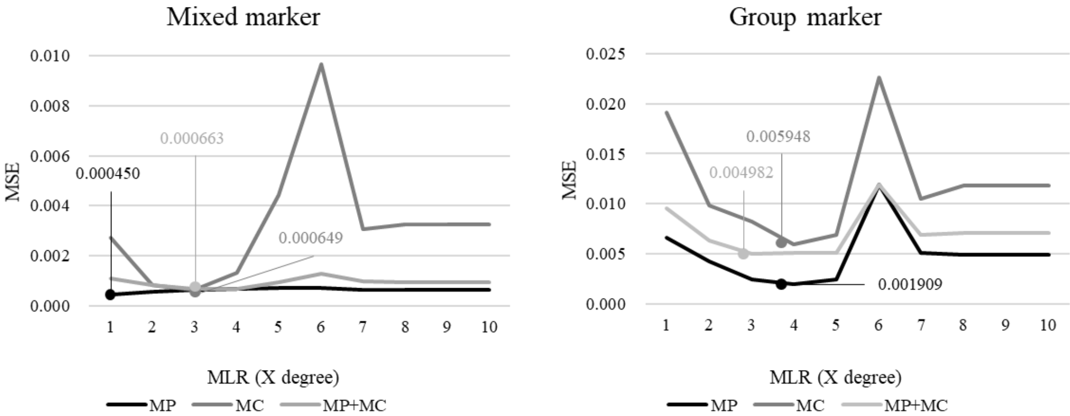

Figure 5.6 MSE of marker length estimation with MLR (X degree 1-10).

The obtained deviations for the RBF NN model, evaluated with Mean Square Error (MSE) test (5.2), are summarized in Figure 5.7. In detail, it includes the MSE of marker length estimation using the RBF NN method, the neuron number ranges from 1 to 40, for the two types of markers, i.e., mixed marker and group marker, with three size sets, i.e., MP sizes, MC sizes and MP+MC sizes. In comparison of the two different marker types, the prediction for group marker using the BRF NN method requires a larger neuron number, so it can be concluded that the difficulty in prediction is still higher for group marker than mixed marker. In addition, an appropriate neuron number should be found for prediction with MC sizes, for the corresponding MSE is more sensitive to neuron number. Similar to the MLR model, for the RBF NN model, a large neuron number will tend to occur overfitting, while on the contrary, a small neuron number cannot lead to a satisfactory accuracy. This is exactly the significance of adopting the related parameters (i.e., X degree and neuron number) of MLR as well as RBF NN models with different values.

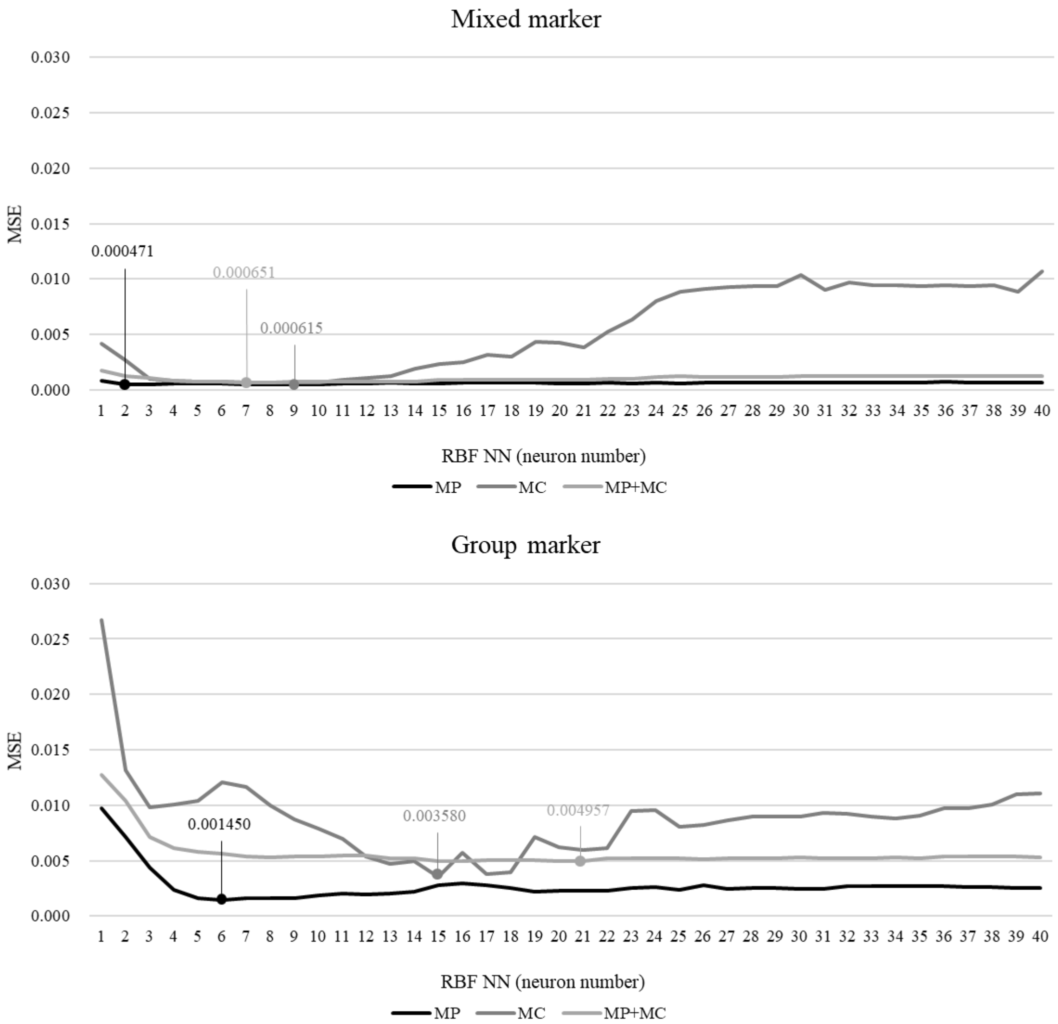

Figure 5.7 MSE of marker length estimation with RBF NN (neuron number 1-40).

In order to compare the prediction performances of the models using the MLR and RBF NN methods, the lowest MSE value of each prediction model is listed in Figure 5.8. Taken as a whole, after the selection of appropriate parameter value (X degree and neuron number), the MSE can reach a very low value, which indicates that both methods have good performances in marker length estimation. The performances by using the two methods are similar (MSEs are small and mainly concentrated between 0.0005 and 0.005), of which the prediction performance of the RBF NN model is slightly better than that of the MLR model (mostly a smaller MSE value for RBF NN compared to that for MLR). For different size sets, using RBF NN can conventionally achieve a more universal satisfactory estimation, as well for MC sizes only. For the two marker types, MSEs with mixed markers are all less than 10^{-3}, while those with group markers are all more than 10^{-3}. It shows that the prediction accuracy of mixed marker has an obvious superiority than that of group marker by using the two machine learning methods.

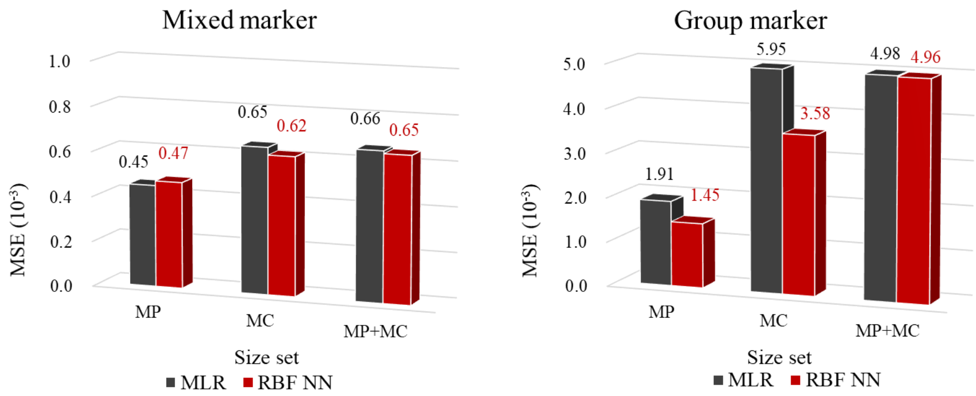

Figure 5.8 Comparison of prediction performances using MLR and RBF NN methods for different types of markers with different size sets.

Another interesting finding is, for the same marker type and prediction method, the prediction performance of marker that contains MP sizes (in a linear distribution) is the best compared with the other two conditions (MC sizes and MP+MC sizes). It can be deduced that the prediction performance is related to the regularity of garment sizes. Specifically, the higher regularity degree the garment sizes have, the better prediction performance the model has. It provides the suggestion that the sizing system can take the regularity into consideration, for example, introducing additional sizes that exhibit a linear relationship. The regular garment sizes will bring the convenience in product development and production. Also, the productivity can be enhanced as a result.

In general, the X degree of MLR and the neuron number of RBF NN should be set to higher values for group marker than for mix marker, and with MC sizes or MP+MC sizes than with MP sizes. It indicates that a more complex relationship exists underneath for MC sizes, as well as for group marker. Besides, it is also positively correlated to the prediction difficulty and deviation, that even though a higher X degree and a larger neuron number are adopted, there are still obvious errors and deviations in prediction with the introduction of MC sizes. And, the same situation occurs with the utilization of a group marker instead of a mixed maker.

5.2.2 Results and discussion

In this section, in order to further evaluate the performance and validate the prediction of two machine learning-based models, the distances between the predicted values and the corresponding experimental values are demonstrated and the cutting costs that calculated with the two sets of data are compared.

5.2.2.1 Prediction performances

A testing data set is adopted and a comparison between the predicted marker lengths and the experimental ones is made. Figure 5.9 shows the prediction performances of the MLR (black dots) and RBF NN (red dots) models using MLR and RBF NN for mixed marker and group marker with MP sizes, MC sizes, and MP+MC sizes. The performance for a certain size combination is indicated by the distance between the dot and the standard line y=x (in blue), where the predicted value equals the real value (experimental value). That is, the closer to the standard line the dots are, the better prediction performance we can obtain.

As mentioned before, the MLR and RBF NN parameters have been optimized for the minimum MSEs (enclosed in parentheses in Figure 5.9), which can be consulted in Figure 5.8.

For both MP sizes and MC sizes, the dots that are located near the standard lines when each of the two size sets is used alone for prediction, showing a relatively good prediction accuracy for both mixed marker and group marker. However, when utilized simultaneously (MP+MC sizes), which are adapted for mass customization, the prediction difficulty is fiercely increased, especially with group marker.

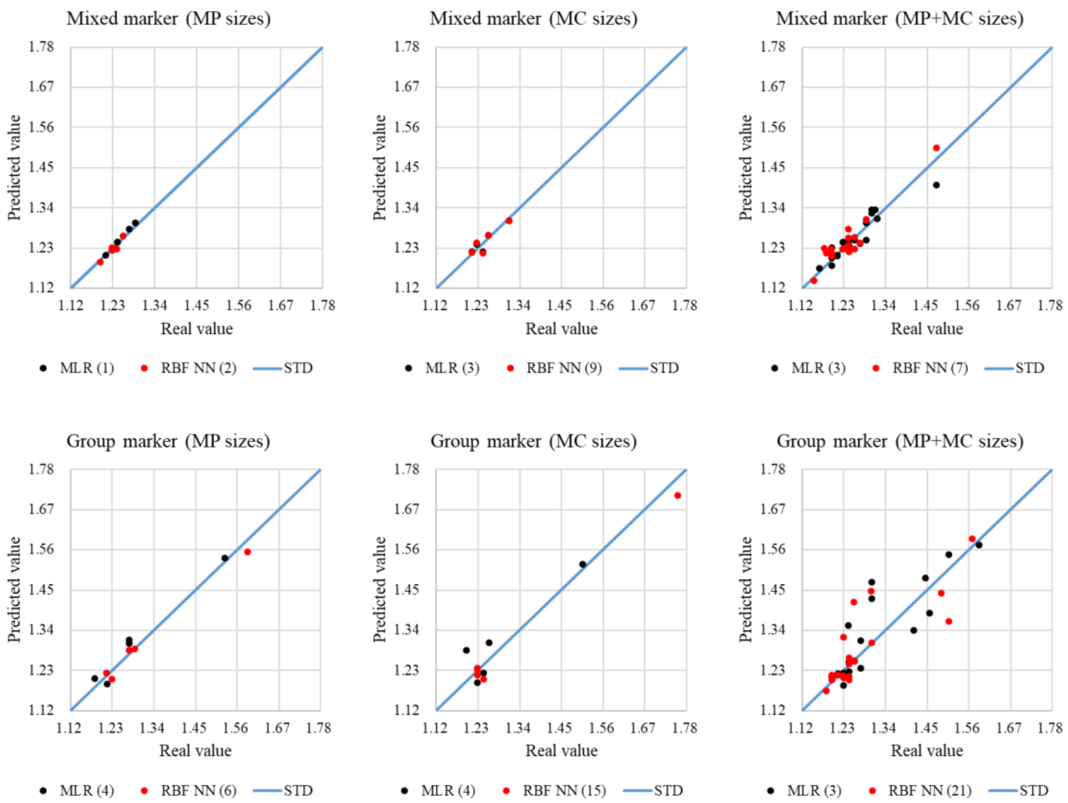

Figure 5.9 Comparison of predictions between MLR and RBF NN models for different types of markers with different size sets.

5.2.2.2 *Cutting costs with estimated marker lengths*

The prediction performance is also evaluated by calculating the cutting costs as in the experiments of the previous chapter with the predicted marker lengths by using the two machine learning-based methods. The impact of the error in marker length estimation brings to that in cutting cost estimation is assessed, in order to check whether the marker prediction enables the COP to help achieve accurate cutting costs and make proper decisions in garment production.

The predicted marker lengths are of two-article markers. However, for craft production, the cutting operation is performed with a simple-ply cutting in the COP. Consequently, the calculation of cutting costs in craft production does not require predicted marker lengths.

The cutting costs in mass production and mass customization are calculated as the same as in **Chapter 4** but with the predicted values of marker lengths. For the scenarios with different parameters in Table 4.1, The rangeabilities and MSEs of the estimated unit cutting costs using the predicted marker lengths by using MLR and RBF NN are listed in Table 5.1 and Table 5.2.

As shown in Table 5.1, even though the estimated marker length has a wide rangeability between 10% to 20%, the corresponding predicted unit cutting cost has just a narrow rangeability between 0 % to 2%. This means that the cutting cost is not that sensitive when applying predicted marker lengths. It is also shown in Table 5.2, for the cutting cost estimation using predicted marker lengths, both methods have satisfied performances with MSEs all below 0.001.

Moreover, both MLR and RBF NN have good performances of marker length estimation and cutting cost prediction with no significant differences, nevertheless, the prediction performance is better when using MP sizes than using MP+MC sizes, where the former size set has a higher regularity (in linear).

Table 5.1 Comparisons of marker length and cutting cost by rangeability

Production mode (Size set)	Marker length		Unit cutting cost	
	MLR (%)	RBF NN (%)	MLR (%)	RBF NN (%)
mass production (MP sizes)	[-8.45, 7.95]	[4.01, -7.90]	[0.07, 0.26]	[-0.03, 0.06]
mass customization (MP+MC sizes)	[-16.74, 13.57]	[-16.32, 13.02]	[-1.47, 0.96]	[-1.63, 0.88]

Table 5.2 Comparisons of marker length and unit cutting cost by MSE

Production mode (Size set)	Marker length		Unit cutting cost	
	MLR	RBF NN	MLR	RBF NN
mass production (MP sizes)	0.0004	0.0006	0.0003	0.0000
mass customization (MP+MC sizes)	0.0025	0.0023	0.0065	0.0080

In mass customization, the unit cutting cost varies slightly when the number of additional sizes increases as previously mentioned in **Chapter 4**. Figure 5.10 demonstrated the trends of the unit cutting cost with additional MC sizes. It is seen that when using the predicted marker lengths for the cutting cost calculation in mass customization, the results enable the COP to indicate the accurate trends of unit cutting cost changing with the increasing number of additional sizes, however, there exist negative bias.

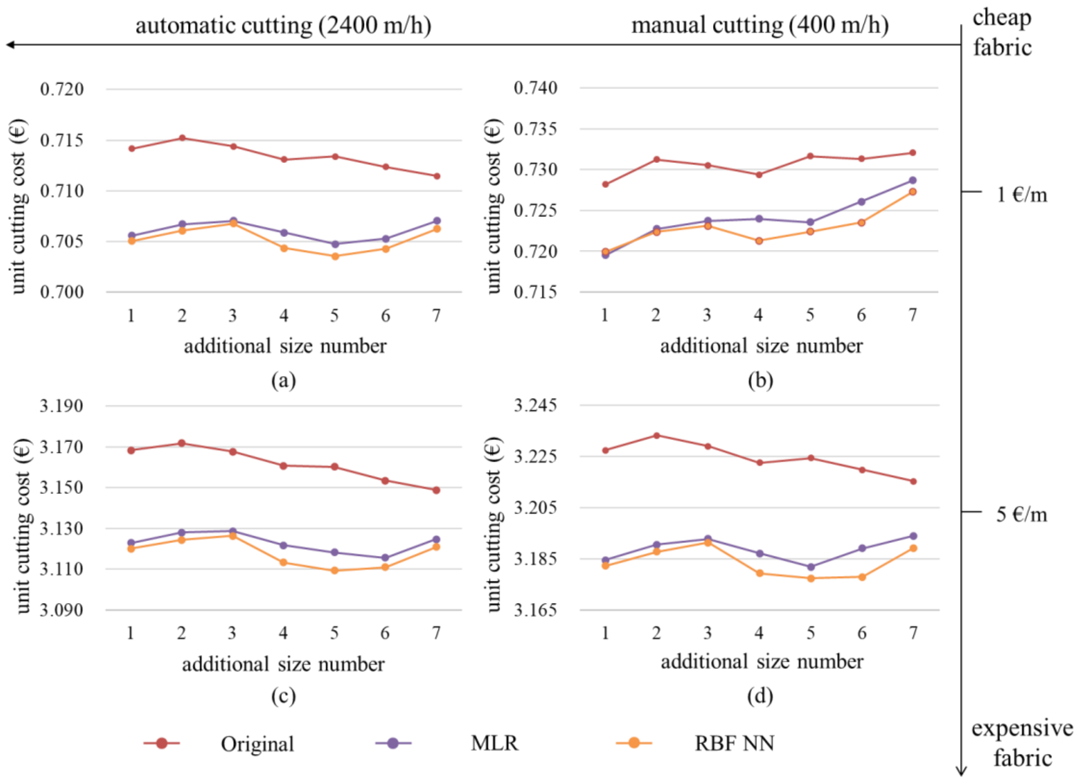

Figure 5.10 Partial cutting costs in mass customization with experimental and predicted marker lengths (operator cost=10 €/h)

It indicates that, though there are impacts of negative bias, the marker length estimation results with machine learning methods enable the COP to predict the precise trends of unit cutting cost with the additional sizes in mass customization and work well with the more regular sizes in mass productions.

Figure 5.11 gives trends of the marker length prediction error with the additional sizes in mass customization (Figure 5.11 (a)), the cutting cost prediction error with the additional sizes (Figure 5.11 (b)), and the ratio of cutting cost prediction error to marker length prediction error with the additional sizes (Figure 5.11 (c)). The trend of marker length prediction error is comparatively smooth and lightly decreases in the final phase. The cutting cost prediction error has a gradual downward trend with the additional size, and further declines seem likely. Similarly, the ratio of cutting cost prediction error to marker length prediction error is mostly less than 1 and becomes smaller with the additional mass customization sizes.

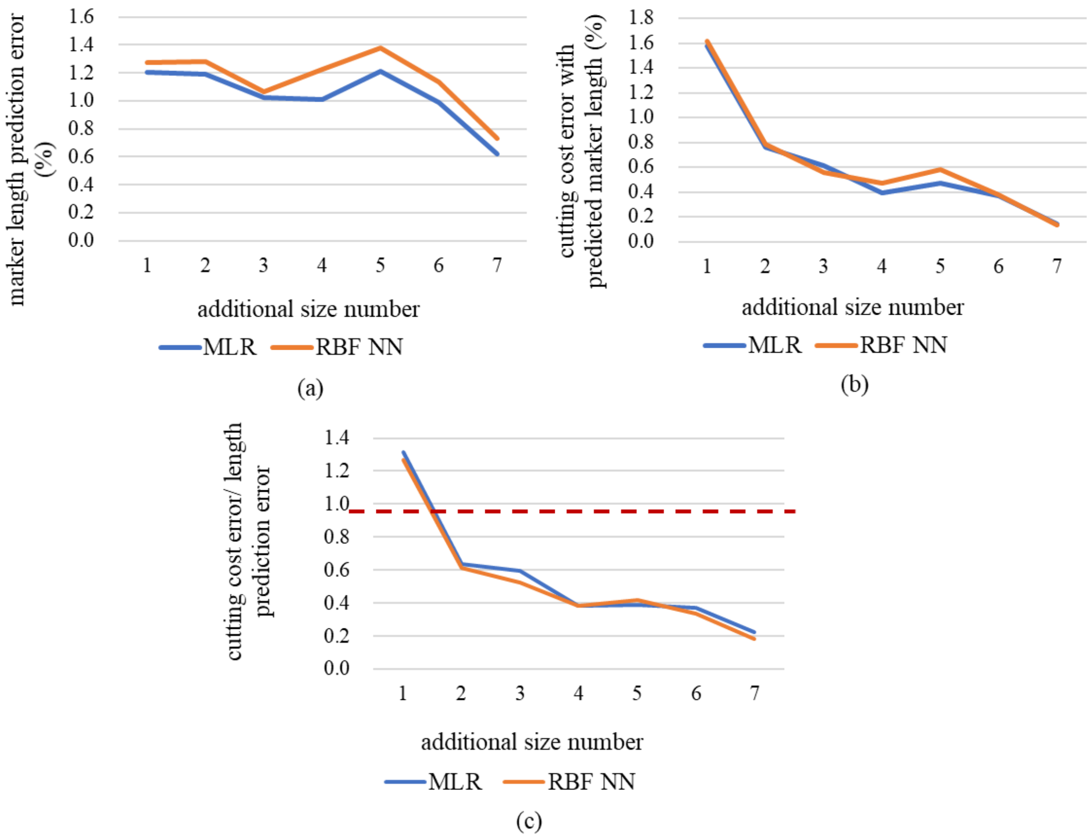

Figure 5.11 Partial cutting cost prediction errors, marker length prediction errors, ratios of cutting cost prediction error/marker length prediction error in mass customization (cutting speed=2400 m/h, fabric price=1 €/m, operator cost=10 €/h))

It is found that the cutting cost prediction error is mostly smaller than marker length prediction error, and the more accurate prediction result can be achieved when using more additional sizes. This is because a larger amount of data with more additional sizes can train the prediction model more efficiently and lead to more accurate prediction results.

5.3 Conclusion

In this chapter, we originally carried out the marker length estimation with the aid of machine learning technologies. In the upgrading of garment production from mass production to mass customization, which results in a sharp increase of size combinations (marker variance), so it is of great importance to release the heavy labor workload of the tedious and inaccurate marker making work. Two machine learning techniques, i.e., Multiple Linear Regression (MLR) and Radial Basis Function Neural Network (RBF NN) are applied to predict the overall marker lengths. Two marker types are addressed, i.e., mixed marker and group marker. Three garment size sets are adopted, for mass production (MP sizes) and mass customization (MC sizes, and MP+MC sizes). These different conditions are beneficial for investigating the performance of marker length estimation when facing the challenge of mass customization upgrading.

In general, RBF NN slightly outperforms MLR in marker length prediction, which is well capable of dealing with more universal marker prediction work. The higher irregularity of the MC sizes results in the poorer marker prediction performance, which indicates that a higher size regularity, like linear sizes, tends to a better prediction performance. The marker prediction of group marker is more complex compared to that of mixed marker, which indicates that marker length estimation of group marker is harder. For estimating accurate unit cutting costs, the marker length estimation with machine learning methods can help in both mass production and mass customization, and work more efficiently with relatively regular sizes. Additionally, it is capable of providing the accurate trends of unit cutting cost with the additional sizes in mass customization but is with bias.

In summary, both methods are generally performant in marker length estimation, of which RBF NN can be slightly more powerful, especially for predictions of markers with more complex size combinations (sizes in mass customization). The estimated marker lengths can be basically used for making an accurate prediction of unit cutting costs in both mass production and mass customization.

Meanwhile, we need to explore more possibilities to improve the performance. For instance, the dimensions of each article could be taken into the input, or the higher size regularity can be considered in sizing, which enables to improve the predictability and even better serve the down streaming process, like cutting and sewing.

Chapter VI:

General Conclusion and Future Work

Chapter 6 General Conclusion and Future Work

Mass customization features an integration of wide product variety and high production efficiency, which meets the increasing demand of consumers on product personalization with reduced product cost. The upgrading of the production processes for promoting the revolution from mass production to mass customization is a complex issue, but also an opportunity as well as a challenge for the apparel industry. In this thesis, focusing on the garment cutting-related processes, we have proposed a series of practical mass customization strategies that are concerned with the garment cutting process, and realized production optimizations of three specific cutting-related processes, namely, sizing, cutting order planning, and marker making (see Figure 6.1).

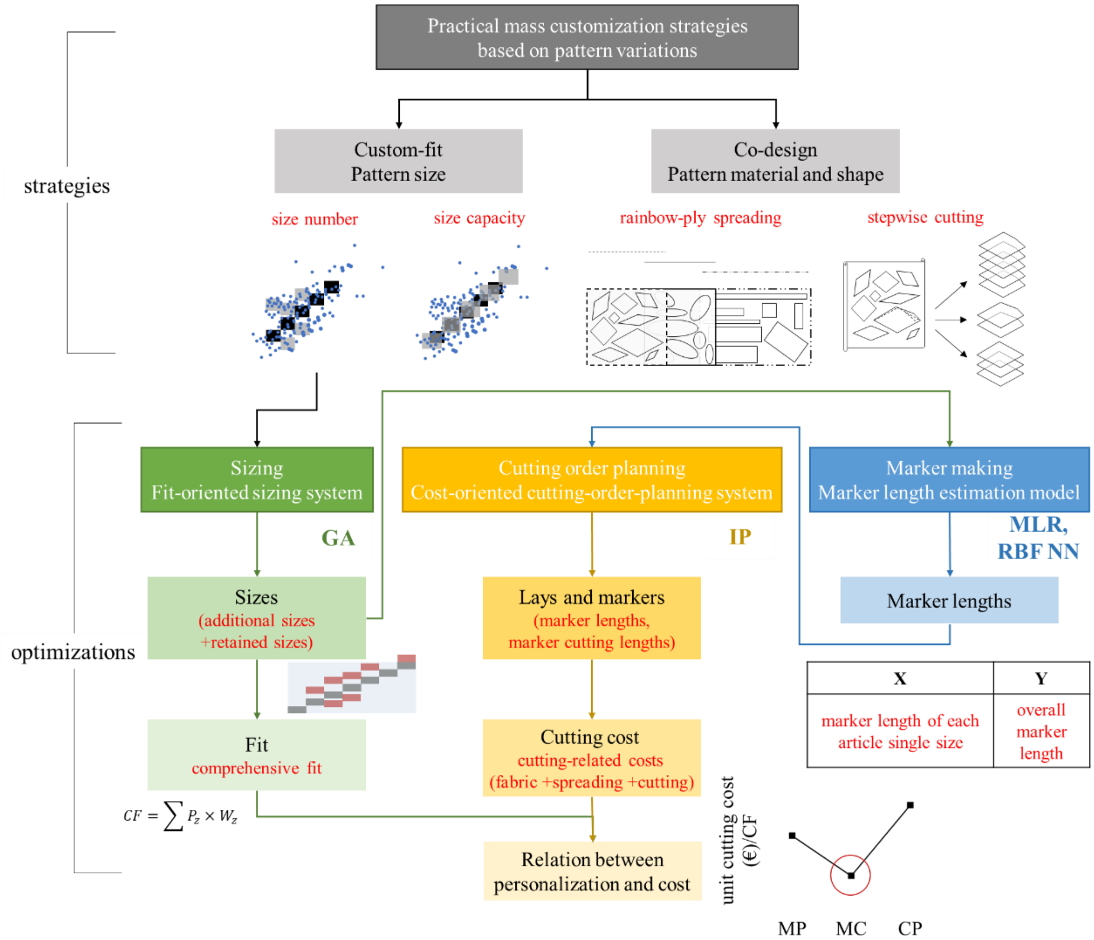

Figure 6.1 General scheme of this thesis.

The practical mass customization strategies have been developed regarding two categories, i.e., custom-fit (pattern size) and co-design (pattern material and shape). The increment of size number with additional sizes and expansion of size capacity with multi-sized darts are the mass customization strategies regarding the custom-fit, while the fabric variation with a “rainbow plies” spreading and module variation with a stepwise cutting are those regarding the co-design. The effectiveness of the strategies is evaluated on both personalization and cost. The two custom-fit strategies improve the custom-fit level globally and locally, respectively, and both behave well with controllable extra costs. The cost growth differs between the two strategies, which are recommended to be simultaneously utilized. The co-design of material (fabric) with “rainbow plies” brings about no obvious increase in the cutting-related cost, while that of shape (pocket type and skirt length) brings about further lift of cost due to second cuts or even extra markers. Due to the necessity (the fit is the basic need of consumers) and potential (good personalization and economic performances), the custom-fit strategy by using additional sizes is adopted in the subsequent optimizations of the three cutting-related processes. i.e., sizing, cutting order planning, and maker making.

A fit-oriented sizing system has been built with the introduction of additional garment sizes and retaining original mass production sizes. The additional sizes are adapted from the original mass production sizes due to a reduction of difficulty and a limitation of extra cost in new pattern development and garment manufacturing. In the sizing system, a Genetic Algorithm (GA) is applied to locate the appropriate additional garment sizes, with the Comprehensive Fit (CF), a new criterion for evaluating the garment fit, defined as the objective function. The system is proved to effectively improve the garment fit for a target population.

A cost-oriented Cutting Order Planning (COP) system has been established with consideration of marker variance brought by a marked increase of size number in mass customization. An expanded Integer Programming (IP) is used for the COP to determine the optimal solution yielding the least costly cutting process with precise data of marker parameters (i.e., the marker length and the marker cutting length).

By analyzing the results generated from the proposed systems (sizing and COP), the underlying relationship between the CF (personalization) and the unit cutting cost (cost) has been explored. It is found that the relationship between the cutting cost and the number of additional garment sizes is nonlinear and fluctuating, strongly influenced by a combination of different factors such as the fabric price, labor cost, and cutting speed. Local optima can arise, of which the identification is crucial for developing mass customization by obtaining a better compromise between personalization (the fit) and cost (the cost).

Due to the more complex size combinations in the mass customization environment, it is of great importance to release the heavy labor about tedious and inaccurate marker making work. As a result, marker length estimations for both mixed marker and group marker containing sizes from different size sets, i.e., mass production (MP sizes), mass customization (MC sizes and MP+MC sizes), have been conducted with the aid of machine learning techniques, i.e., Multiple Linear Regression (MLR) and Radial Basis Function Neural Network (RBF NN). Both machine learning methods are proved to be generally efficient in marker length estimation, of which RBF NN is slightly more powerful especially for the prediction of more complex size combinations.

1. Contributions

The main contributions of my thesis are summarized below.

- Based on the industrial practice, we have developed the mass customization strategies to meet consumers' growing demand for personalization at an acceptable cost. This is a pioneering work in garment manufacturing. The realization of a semi-quantitative analysis of the relation between personalization and cost is also original. It can help enterprises to conduct the precise customization expectation and cost control, and finally work out a proper production strategy to accomplish the upgrading task towards garment mass customization.
- We have built the fit-oriented sizing system which is optimized by a genetic algorithm. It is an effective way by using a practical and flexible sizing process for garment manufacturers to provide custom-fit products.
- We have also built the cost-oriented Cutting Order Planning (COP) system solved by an extended integer programming. It takes into account the marker variance that is greater in mass customization, providing a precise calculation of cutting-related costs for mapping out the efficient production plan.
- With the results obtained from the proposed sizing and COP systems, the relation of cutting cost and garment fit in various garment production modes, i.e., mass production, craft production, and mass customization, have been analyzed in a case study of a basic straight skirt. It is shown that the trend of cost changes with an increasing fit is fluctuating (not linear as expected), strongly influenced by the machine speed and material price, where local optima may occur. This provides support for manufacturers to make

decisions to achieve better compromises between personalization and cost in real production.

- We have applied two machine learning techniques, i.e., Multiple Linear Regression (MLR) and Radial Basis Function Neural Network (RBF NN) to estimate the overall marker lengths of markers in various garment production modes with various sets of garment sizes and different marker types. The experimental results show that both proposed approaches are performant in estimating the overall marker lengths, and work better with mixed markers and comparatively regular sizes. In addition, although some extent of bias exists, the estimated marker lengths are feasible to be used instead of real experimental data for making a relatively accurate prediction of cutting costs in production planning.

2. Limitations and perspectives

Limitations and perspectives of this research are pointed out as follows.

- In the case study of this research, the selected garment type is a basic straight skirt, which is comparatively simpler in design and production. And a few options of customization (three for fabric type, three for pocket type, three for skirt length) are discussed in the preliminary design of mass customization. In further research, we will select more types of garments as the object of the study. Apart from other types of skirts, it could be a shirt, pants, or a suit, and provide a wider range of customization options to study the diversity in a real market.
- In the case study of this research, a small database containing 451 French women between the ages of 25 and 40, collected by using 3D scanning, is applied. The body dimensions differ significantly in different ethnic groups and regions in practice. For a more general application in future work, we will adopt a much bigger anthropometric database of information about various populations in different regions.
- Increasing the size number with additional sizes, one of the proposed four mass customization strategies, is implemented automatically in the proposed

sizing system by using a GA. In future research, the implementations of the other three strategies will also be conducted automatically with the aid of computer algorithms.

- The future in-depth study can be carried out in improving the production optimizations of cutting-related processes. To be specific, an additional heuristic algorithm will be developed to improve the performance of GA with a shorter computation time. Apart from the cost, the time is also a key criterion in mass customization, which will be formulated in the IP for estimating the cutting-related production time. Apart from the marker length of each garment article, their dimensions will be taken as an additional input x in the marker length estimation model using MLR and RBF NN for a higher accuracy.
- This research mainly focuses on cutting, and the closely related upstream process sizing. The future work will be extended to the downstream processes, i.e., sewing, ironing, finishing, and packing, to make the research completer and more applicable to the actual garment production. In addition, a pricing strategy based on personalization can be developed to provide consumers with accurate prices for each specific personalization. Finally, we will link all the studied processes to establish an advanced optimization and decision-making system for the whole garment manufacturing process towards the upgrading to mass customization.

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Appendix: Publications and Conferences

Book chapters:

[1] **Xu, Y.**, Thomassey, S., & Zeng, X. (2018). AI for Apparel Manufacturing in Big Data Era: A Focus on Cutting and Sewing. In Artificial Intelligence for Fashion Industry in the Big Data Era (pp. 125-151). Springer, Singapore.

Journal papers:

[1] **Xu, Y.**, Thomassey, S., & Zeng, X. (2020). Optimization of garment sizing and cutting order planning in the context of mass customization. *The International Journal of Advanced Manufacturing Technology, 1-19*.

[2] **Xu, Y.**, Thomassey, S., & Zeng, X. (2020). Upgrading solutions of cutting-related processes facing the challenge of garment mass customization. *Textile Research Journal*, (major revision).

[3] **Xu, Y.**, Thomassey, S., & Zeng, X. (2020). Machine Learning-Based Marker Length Estimation for Garment Mass Customization, (under preparing).

Conferences with proceedings:

[1] AUTEX, World Textile Conference, 2017, Corfu, Greece.

Xu, Y., Thomassey, S., Chen, Y., & Zeng, X. (2017, October). Comprehensive evaluation of garment assembly line with simulation. *In IOP Conference Series: Materials Science and Engineering (Vol. 254, No. 16, p. 162013)*. IOP Publishing.

[2] APPIS 2020, the 3rd International Conference on Applications of Intelligent Systems, Las Palmas de Gran Canaria, Spain.Jo

Xu, Y., Thomassey, S., & Zeng, X. (2020, January). An Application of Machine Learning to Marker Prediction in Garment Industry: Marker Length Estimation by Neural Network for the Exponentially Increasing Magnitude of Possible Size Combinations. *In Proceedings of the 3rd International Conference on Applications of Intelligent Systems (pp. 1-5)*.

Conferences without proceedings:

[1] JRDA, 6ème Journées Régionales des Doctorants de l'Automatique, 2019, Lille, France.

[2] JRDA, 5ème Journées Régionales des Doctorants de l'Automatique, 2018, Amien, France.

Abstract

The work aims to make optimizations of garment production and resolve the dilemma between personalization and cost in the context of mass customization. Firstly, practical mass customization methods regarding cutting-related processes (including sizing) are proposed adapted from the industrial practice of traditional mass production. Due to the good performances of personalization and cost, additional sizes are adopted in the further optimizations of specific cutting-related processes, i.e., sizing, cutting order planning, and marker making with exact methods and artificial intelligence techniques. A genetic algorithm is used for the best set of additional sizes, an integer programming is employed for the best cutting order plan (i.e., the lay planning with the corresponding markers), a multi-linear regression, and a neural network are applied to estimating marker lengths. The proposed mass customization methods are proved to be efficient. The underneath indirect relationship between personalization and cost is established. With the help of the optimized cutting-related processes, the balance of personalization and cost is demonstrated. The estimation of marker length reduces the marker making workload and provides marker lengths for cutting cost estimation with a high efficiency and an acceptable accuracy. All the above enable the garment production to shift from mass production to mass customization.

Keywords: Mass customization; Cutting-related processes; Integer programming, genetic algorithm, machine learning; Garment production.

Résumé

Ce travail vise à optimiser la production de vêtements et à résoudre le dilemme entre le personnalisation et le coût dans le contexte de la personnalisation de masse. Tout d'abord, des méthodes pratiques de coupe (incluant la définition des tailles) pour la personnalisation de masse issues des pratiques industrielles de production sont proposées. Des tailles additionnelles, sélectionnées pour leurs bonnes performances de personnalisation et de coût, sont utlisées pour optimiser les processus de coupe, à savoir le taillant, le matellassage et placement, par des méthodes exactes et d'intelligence artificielle. Un algorithme génétique est utilisé pour construire l'ensemble de tailles optimisant le bien aller, une optimisation linéaire en nombres entiers est utilisée pour définir la planification de la coupe la moins coûteuse, une régression multi-linéaire et un réseau neuronal sont appliqués pour estimer la longueur des placements. Ces différentes méthodes proposées pour améliorer la personnalisation de masse se sont avérées efficaces. La relation indirecte entre le degré de personnalisation et le coût de la coupe est établie. Ces methodes ont également permis de définir les meileures compromis entre la satisfaction consommateur et les coûts de production. Le modèle de prévision de la longueur de placement permet de réduire la charge de travail pour le calcul de placement et fournit ainsi les longueurs de placements utiles pour estimer les coûts avec une efficacité élevée et une précision acceptable. L'ensemble de ces travaux contribue à la transition de la production de masse de vêtements vers personnalisation de masse.

Mots clés: Personnalisation de masse; Processus de coupe de vêtements; Optimisation linéaire en nombres entiers, algorithme génétique, apprentissage automatique; Production de vêtements.