ปัญหาการวางแผนในการวางแบบตัดที่คำนึงถึงข้อจำกัดเรื่องกำหนดการในการเย็บประกอบ ในบริบทของการผลิตเฉพาะลูกค้าเชิงมวล

นายกฤษดา พัวสกุล

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรดุษฎีบัณฑิต
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Marker planning for fabric cutting with sewing schedule constraint in mass customization context

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กฤษดา พัวสกุล : ปัญหาการวางแผนในการวางแบบตัดที่คำนึงถึงข้อจำกัดเรื่องกำหนดการในการเย็บประกอบ ในบริบทของการผลิตเฉพาะลูกค้าเชิงมวล (Marker planning for fabric cutting with sewing schedule constraint in mass customization context) อ.ที่ปรึกษาวิทยานิพนธ์หลัก: รศ. ดร. ปวีณา เชาวลิตวงศ์, 129 หน้า.

งานวิจัยฉบับนี้มีวัตถุประสงค์เพื่อสร้างฮิวริสติกสำหรับปัญหาการวางแผนในการวางแบบตัดภายใต้ข้อจำกัดของกำหนดการเย็บประกอบ ในบริบทของการผลิตเฉพาะลูกค้าเชิงมวล ภายใต้บริบทการผลิตเช่นนี้คำสั่งซื้อจะมีความหลากหลายมากขึ้นทั้งจำนวนไซส์ และปริมาณสั่งซื้อในแต่ละไซส์ โดยมีคุณลักษณะจำเพาะอีกประการคือขนาดสั่งซื้อจะน้อยกว่ากรณีการผลิตแบบเชิงมวล

งานวิจัยนี้ได้แบ่งปัญหาการวางแผนแบบตัดออกเป็น 2 ส่วน โดยที่งานส่วนแรกมีวัตถุประสงค์เพื่อตอบสนองการวางแผนแบบตัดด้านค่าใช้จ่าย ดังนั้นงานในส่วนนี้เป็นการพิจารณาปัญหาการวางแผนแบบตัดที่มีฟังก์ชั่นวัตถุประสงค์ในการลดค่าใช้จ่ายที่เกิดจากจำนวนแบบตัดที่ใช้และจำนวนตัวเกินที่เกิดขึ้น จากนั้นงานในส่วนที่สองจะมีวัตถุประสงค์เพื่อให้การวางแผนมีความสอดคล้องกับกำหนดการเย็บประกอบ ดังนั้นงานในส่วนที่สองจะเป็นการวางแผนแบบตัดที่มีฟังก์ชั่นวัตถุประสงค์ในการลดภาระการจัดเก็บชิ้นส่วนระหว่างผลิตลง

ฮิวริสติกสำหรับปัญหาแรกจะใช้ Linearized marker planning model ในการหาคำตอบเบื้องต้น จากนั้นคำตอบที่ได้จะถูกปรับปรุงโดยหลักการ Greedy ที่มุ่งเน้นไปที่การลดจำนวนชั้นผ้าที่เกินกว่าความจำเป็นลง และการปรับเปลี่ยนแบบตัดให้เหมาะสมด้วยวิธีการย้ายสแต็ค อีกทั้งยังมีการ randomize คำตอบตั้งต้นเพื่อหลีกเลี่ยงการติดอยู่กับ local optimum อีกด้วย ส่วนฮิวริสติกสำหรับปัญหาที่สองจะนำคำตอบจากวิธีการแรกมาปรับปรุงโดยมุ่งเน้นไปที่การปรับเปลี่ยนแบบตัดให้สอดคล้องกับกำหนดการเย็บประกอบ ด้วยวิธีการจัดเรียงแบบตัดให้เหมาะสมและการย้ายสแต็คเป็นหลัก

ในการวัดสมรรถนะของวิธีการที่พัฒนาขึ้น ฮิวริสติกที่หนึ่งได้ถูกนำไปทดลองกับปัญหาหลากหลายขนาด สำหรับปัญหาขนาดเล็กและกลาง ฮิวริสติกสามารถให้คำตอบที่ดีที่สุดในทุกปัญหา และผลการทดสอบกับปัญหาขนาดใหญ่ ฮิวริสติกก็สามารถให้คำตอบที่ดีกว่าวิธีการแบบ GA ที่สามารถให้คำตอบที่ดีที่สุดกับปัญหาขนาดเล็กและกลางเช่นกัน ในขณะที่ฮิวริสติกที่สองได้ถูกทดลองกับปัญหาขนาดใหญ่ ซึ่งผลลัพธ์ที่ได้เมื่อเปรียบเทียบกับวิธีการแบบ GA เช่นกัน ก็สามารถให้คำตอบที่ดีกว่าอย่างชัดเจน

ภาควิชา วิศวกรรมอุตสาหการ ลายมือชื่อนิสิต ....

สาขาวิชา วิศวกรรมอุตสาหการ ลายมือชื่อ อ.ที่ปรึกษาหลัก ....

ปีการศึกษา 2559

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The objective of this research is to develop heuristics for marker planning problem within a sewing schedule under mass customization production context. In this context, a number of sizes and an amount of demand in each size are varied in a wider range than a mass production system but with lesser total demand.

The proposed problem is divided into two subproblems. The first subproblem corresponds with the cost dimension of a marker planning. Hence, the objective is to minimize the total cost related to a number of markers and excessive units. The second subproblem aims to integrate a sewing schedule into marker planning. Therefore, the objective is to minimize a work-in-process inventory workload.

The initial solution from the first heuristic is determined by an LP relaxation of marker planning. Then, it is improved by a greedy-based algorithm. This algorithm focuses on reducing an unnecessary plies and adjusting marker patterns. Furthermore, initial solutions are randomized to avoid getting stuck with a local optimum. The second heuristic further improve a first heuristic’s solution by focusing on rearranging marker patterns in order to correspond with a sewing schedule.

To measure performance of the proposed heuristics, the first heuristic is tested with many problems. For small-and medium-sized problems, the heuristic can reach to the optimal solutions in all problems while with large-sized problems, heuristic solutions are better than solutions from GA which can reach to optimal solutions as well. The second heuristic is tested with large-sized problems. The second heuristic can perform better than GA method.

Department:	Industrial Engineering	Student's Signature	....
Field of Study:	Industrial Engineering	Advisor's Signature	....
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Chapter 1

Introduction

1.1 General background.

1.1.1 The nature of garment production system.

The nature of garment production system is relatively close to a pull system which a sub-assembly and assembly process is seen as backbone of a production system whereas the other upstream processes only supply required parts to this process. The reason why this pull system is applied is strongly related to a variety of parts that will be kept in an inventory. Generally, each part composes of five dimensions, i.e., color, size, type of fabric, type of part, and due date. Obviously, it is very difficult to handle when there are many different parts kept together in an inventory. To take care of these variety parts, a complex inventory system and expert operators are need.

To correspond with a pull system, at first, a sewing schedule representing a sequence of jobs that will be sewn in a sub-assembly and assembly process is created. Furthermore, in this sewing schedule, a tardiness job is not permitted to be occurred. Subsequently, this created schedule is sent backward to a cutting room in order to plan for a cutting process. In cutting room, a cutting schedule is created based on a given sewing schedule. With this cutting schedule many bundles of cut parts must be arrived at a sub-assembly and assembly room before or on time. Finally, these two schedules are sent backward to a marker planning process to generate a marking plan or a set of markers that will be later used as cutting templates in a cutting room. Implicitly, this marking plan is generated based on both two given schedules.

1.1.2 General background of marker planning process.

In garment industry, fabric rolls are processed into the desired finished goods. Figure 1 shows flow of garment processes as well as flow of materials. The cutting process, the function of this process is to cut fabric rolls into bundles of required cut pieces or parts. The sub-assembly process, the function of this process is to sew cut pieces into semi-product, e.g. sleeves, collars. This process usually appears with manufacturers who produce medium to high complex products. Finally, the assembly process, the function of this process is to assemble semi-products and/or parts into the desired products. All garment products must be sequentially processed on these three processes to become the finished products.

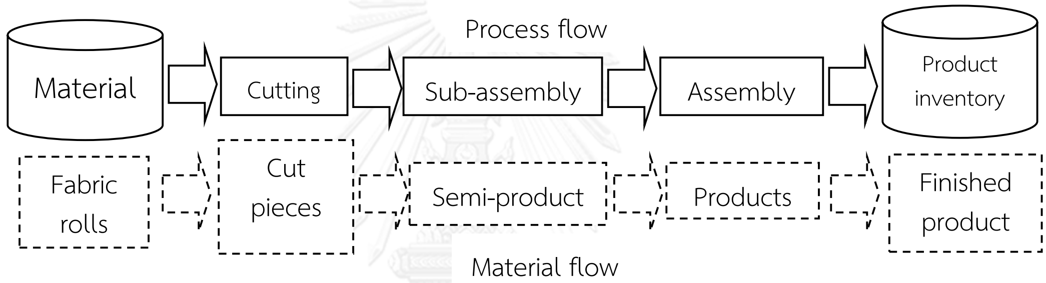

Figure 1 The flow in garment industry.

A cutting process is an upstream process which generates bundles of cut pieces used as an input to all other downstream processes. Apparently, a cutting process controls sequence of jobs that will be processed, and production smoothness in the downstream processes. Hence, this process should be efficiently managed with systematic method.

In garment industry, a marker planning process is used to plan for cutting process. The function of this process is to generate a set of markers which are used as cutting guidelines or cutting patterns in a cutting process. By definition, marker planning process can be defined as follows. (1) marker planning process is to arrange cut templates to execute the fabric cutting operation [1]. (2) marker planning is to find an optimal combination of markers to cover the work order [2]. (3) marker planning is to determine the set of cut templates needed including the garment sizes in each cut template, quantities of garments from each size and number of fabric plies that will be cut under each cut template [3]. (4) Marker planning is the process of arranging all the patterns of the component parts of one or more garments on a piece of paper [4]. Data input into marker planning process is a customer order which consist of order detail, bill of material, and assembly chart. Generally, a customer order comprises of two dimensions, namely, size and color. An output from this process is a set of markers which are indicated by 3 important questions [5] as follows.

(1) Which part should be assigned to which marker with how many copies?

(2) How many fabric plies is appropriate for each marker?

(3) How many markers should be used to satisfy demand?

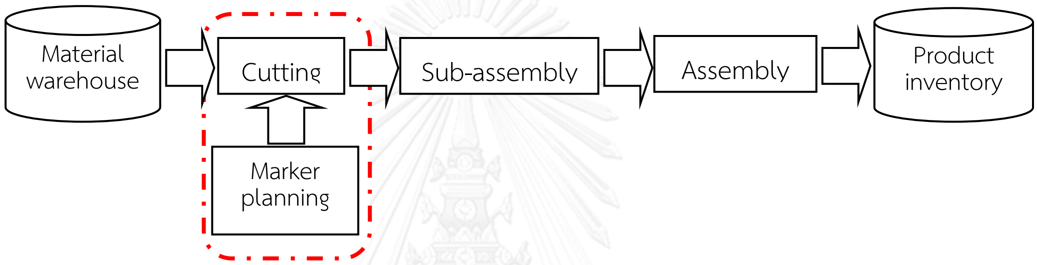

Figure 2 The Flow of garment processes with marker planning.

As can be seen in Figure 2, a set of makers which is an output of marker planning process is cut into many bundles of parts in a cutting room. These bundles are subsequently, sewn into the desired products in sub-assembly and assembly process. Therefore, marker planning can be seen as planning step which partially controls what and how many parts to cut which, also, controls production sequence and smoothness of sub-assembly and assembly process. Apparently, an output of marker planning can affect to the performance of the whole system.

1.2 Marker planning terminologies.

In marker planning process, there are many specific terms used which can confuse readers that are not familiar with a garment industry. To well understand this research, readers should get familiar with the following terms.

1.2.1 Marker.

A marker is a combination of parts or stencils arranged on a rectangular shape block which is later used as a cutting guideline or cutting pattern in a cutting process. In [6], marker is defined as garment pattern pieces of different sizes and styles that are laid out on a sheet of paper with fixed width and arbitrary length in order to achieve the highest marker efficiency. In each marker, many parts are arranged so as to achieve the desired objective, such as minimization of material usage, minimization of over production units, minimization of number of markers used, and etc.

A marker in garment industry is the same as a batch in other manufacturing industries. Sai fallah [5] states that processing parts in batches is preferable to the processing when setup times are significant. In the same way, parts are combined to create marker or batch in order to reduce set up occurred in generating and using that marker.

Furthermore, markers can be categorized into three groups with respect to a combination of sizes on a marker. Firstly, markers that have only one size, e.g. S-S-S, M-M-M and etc. Secondly, markers that have at least two sizes which all sizes are absolutely different, e.g. S-M-L, M-L-XL and etc. Finally, markers that have at least two sizes which some sizes are repeatedly used on the same marker, e.g. S-S-M, M-M-L and etc.

On the top of each marker, there is a marker pattern which is a combination of parts or stencils of one size or many sizes. Furthermore, this pattern is affected by four factors, i.e. number of sizes required in a customer order, total number of units required, the distribution of demand to all sizes and number of plies used in each marker.

In this research, a stencil is used as a unit in creating marker pattern as in most reviewed papers [2, 3, 5, 7-13]. A stencil is a complete set of parts for one size of a required product, e.g. a stencil of size L, a stencil of size S, and etc. However, to agree with a scope of marker planning process, an arrangement of parts in a stencil is omitted.

Figure 3 Example of marker pattern.

In marker planning process, stack is one of terminologies that are mostly used. Generally, stack is a bundle of parts of one size from one marker. A height of each stack is equal to a height of marker which that stack is cut out. As stated before, this research uses a stencil (a complete set of parts for one size) instead of a single part. So, meaning of a stack is slightly changed from a bundle of parts to a bundle of stencils.

Each marker can be described by three dimensions, namely, length, width and height. Marker width is varied depending on a width of fabric roll used which is typically assumed to be constant in many researches [7, 14]. A length of each marker is restricted to some specific upper bounds which its value depending on a planner or a cutting table length. Generally, ply height is restricted to two values which correspond with equipment limitations. One is lower bound whereas the other one is upper bound on ply height. In some researches, ply height can compose of different color fabrics which is called “multi-color marker” [7, 15] while in practical situation, it is hard to manage different color parts or stencils that are cut out simultaneously.

In most papers, a demand input (a customer order) used to create markers is tabulated as shown in Table 1. In Table 1, there are two colors (black and green) and three sizes (size S, M, and L). Each cell in this table displays a demand quantity of a specific color and size, e.g., there are 100 units of size S which are in black color.

Table 1 Demand table.

Size / Color	S	M	L
Black	100	50	50
Green	150	50	100

In each marker, there are many areas involved as described below.

(1) Total assigned stencil area – this area is the summation of all stencil areas that are assigned to the considered marker.

(2) Waste area – due to irregular shape, some assigned parts may not completely fit to others on the same stencil and marker. An inevitably unused area between or among these parts are considered as waste area.

(3) Remaining area – remaining area is a difference between the maximum allowable area which correspond with a cutting table area and a total assigned stencil area.

(4) Allowance area – these areas are located on head and tail of each marker. Marker locking equipments are placed on these two areas to lock a marker with a cutting table.

(5) Total area of marker – this area is the summation of total assigned stencil area, waste area, and allowance areas. Therefore, this area is equal to total fabric used for one ply of each marker.

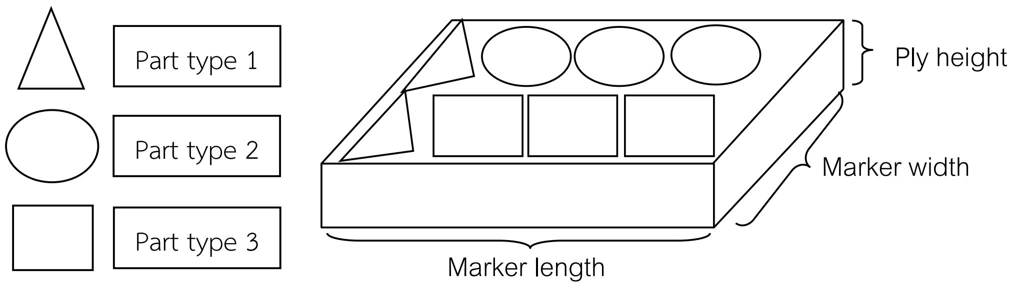

Figure 4 The first example of marker.

In the first example, a marker pattern is in the form of a combination of demand parts. There are three types of part which are type1, 2, and 3 used in this example. A major benefit of using this form of marker pattern is obviously when a planner emphasizes on minimizing material usage.

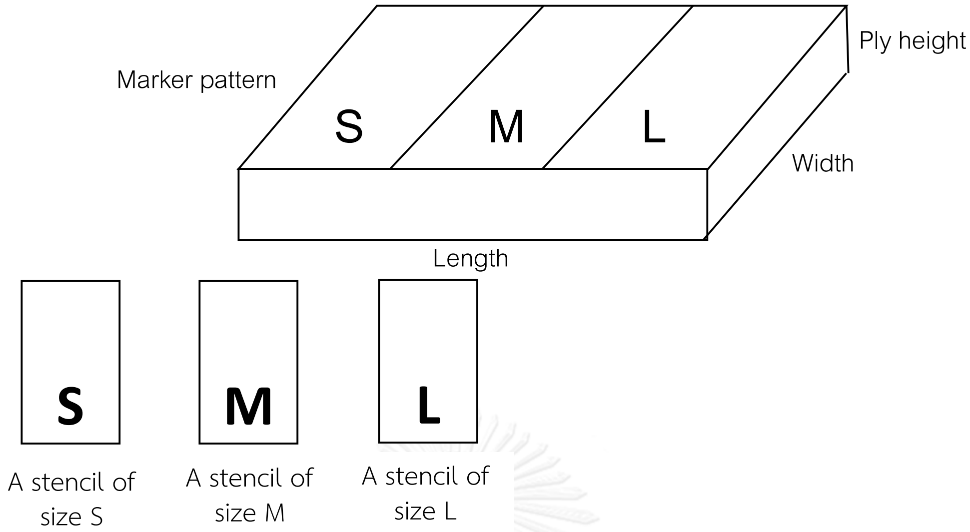

Figure 5 The second example of marker.

In the second example, a marker pattern is in the form of a combination of demand stencils. There are three types of stencil which are stencil of size S, M, and L used in this example. Each stencil contains all parts required for one product of one size, e.g. a stencil of size S must contain all parts required for producing a product of size S. However, an arrangement of parts in each stencil is out of scope of marker planning process. This research uses this form of marker pattern which corresponds with the objective function.

1.2.2 Marker planning.

The major function of marker planning process is to generate a set of markers that are used as cutting templates in a cutting process. Furthermore, it consists in dividing every garment's order into sections, assigning the sizes to them, and determining their lengths and numbers of layers such that the total fabric length is minimized [14]. This process is very helpful and useful in the situation that numbers of units required are very large. In such situation, efficient plan is relatively hard to compute with traditional manual method.

Figure 6 and 7 show a flow of data from a customer order to marker planning process. The flow begins with a customer order which composes of three important data. Firstly, order detail, this data is usually represented in the form of table. Rows of table are colors of the desired product while columns are sizes. Numbers of demand for each size and color are in the table. Secondly, bill of material (BOM), this data tells planner what parts and how many of each part are needed to assemble to the desired product. In some products, bill of material is very complex and is drawn in the form of hierarchy which each level represents intermediate products or work in process (WIP), e.g. shirt, overcoat. Thirdly, assembly chart, this data shows how to assemble cut parts into the desired product. It also gives detail of operation sequence and production lead time. An input of marker planning process is called demand table which is a combination of order detail and bill of material. In demand table, demand quantities are in unit of part, e.g. part 1 and size S, part 2 and size L. The output of marker planning process is a set of markers which will be used later as cutting guidelines in a cutting process. Furthermore, quantities of parts derived from this set of markers must satisfy a demand quantity in a demand table.

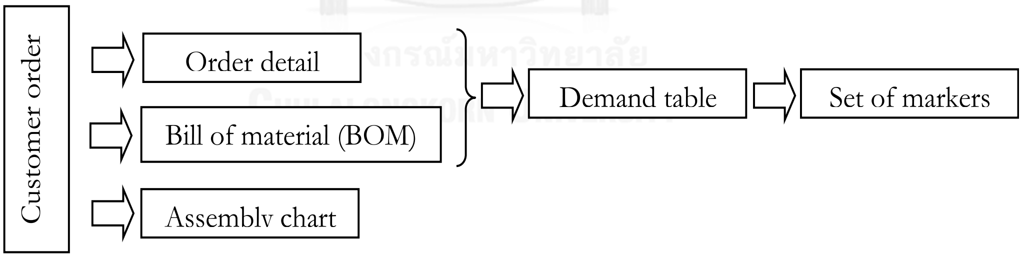

Figure 6 Flow of data of marker planning process.

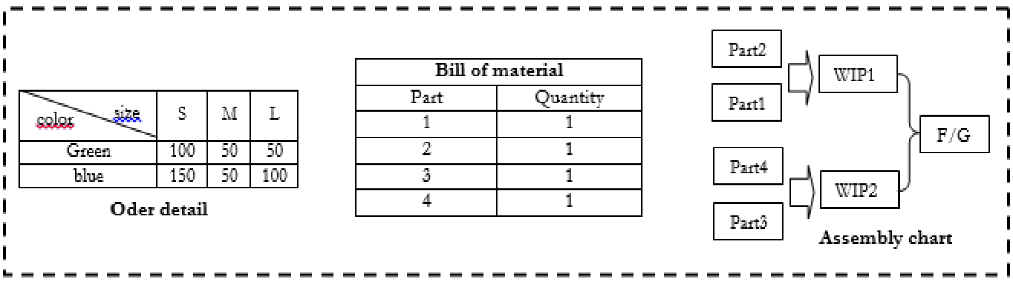

Figure 7 Examples of order detail, bill of material, and assembly chart.

To illustrate marker planning process, a demand input as shown in Table 1 is transformed to markers with a simple method which is usually used in industrial practice. Conceptually, this simple method tries to eliminate number of color-size demand entities by each generated marker to simplify the problem. First of all, two S and one M are assigned to marker 1. The last black color demand is size L which should be assigned to marker 2. Subsequently, the green color is considered, three size S are assigned to marker 3. Lastly, one of size M and two of size L are assigned to marker 4. All ply heights are equal to 50 which is the maximum allowable ply height. The resulted marking plan with four markers is shown in Table 2.

Table 2 Output table.

Marker no.	Color	Pattern	Ply
1	Black	S-S-M	50
2	Black	L	50
3	Green	S-S-S	50
4	Green	M-L-L	50

In Table 2, there are four markers used (with no waste area and excess unit occurred) to satisfy a customer demand. This marking plan is feasible with respect to the area and ply height limitation. However, there are many feasible marking plans besides this one.

The previously shown example is quite small compared to real industry demands. In practical, for each customer order, more than four markers have to be used. Therefore, this planning process is further complicated when facing with larger customer orders.

In industrial practice, this process mostly relies on planner experiences which usually result in feasible but not optimal solution [10]. Planners try to combine smaller size units with larger size units because sometimes smaller size units can be inserted into unused space between larger size units. Moreover, they try to assign parts as many as possible to each marker to maximize material utilization. They solely focus on material utilization or amount of fabric used per one customer order. Additionally, in many cases, planners often use the same marker patterns repeatedly with different customer demands which require the same product and sizes but difference in total number of units required and a distribution of demand. As a result, it can cause many excess units which are seen as additional cost in some situations.

In academic point of view, marker planning problem has been interested for more than 15 years. Almost researches found are based on the similar scopes and assumptions of the problem. The major differences are in their objective functions and solution approaches. These differences will be explained in detail later. However, most of papers found are extended from the basic model which is formulated as integer nonlinear programming model (INLP.). The details of the model are presented as follows.

Set

I set of all required stencils.

K set of all markers

Decision variable

$\mathbf{X_{ik}}$ = integer = number of copies of part i in marker k, $\forall$i in I, $\forall$k in K.

This decision variable is used to answer the question "Which part should be assigned to which marker with how many copies?".

$\mathbf{Y_k}$ = integer = number of plies of marker k, $\forall$k in K.

This decision variable is used to answer the question "How many fabric plies is appropriated for each marker?".

$\mathbf{Z_k}$ = binary = 1 if marker k is selected.

0 otherwise, $\forall_k$ in K.

This decision variable is used to answer the question "How many markers should be used to satisfy demand?".

Parameters

$\mathbf{a_i}$ = required area of a stencil *i*.

d_i = demand quantity of a stencil *i*.

L = maximum allowable area of each marker.

UB = maximum allowable ply height.

LB = minimum allowable ply height.

SC = unit set up cost.

$$\min(SC \times \sum_k Z_k) \quad (1)$$

$$\sum_k (X_{ik} Y_k) \geq d_i \forall_i \quad (2)$$

$$\sum_i (X_{ik} \times a_i) \leq L \times Z_k \forall_k \quad (3)$$

$$Y_k \geq LB \times Z_k \forall_k \quad (4)$$

$$Y_k \leq UB \times Z_k \forall_k \quad (5)$$

Eq.(1), the objective function is to minimize set up cost which is the product of total number of markers used and unit set up cost. **Eq.(2)** satisfy demand constraint stated that total number of cut stencils must greater than or equal to the demand stencils. **Eq.(3)** max area limitation stated that the total used area must less than or equal to the maximum allowable marker area which is equal to the available cutting table length multiplies by the average width of all fabric rolls used. This area is mostly assumed to be constant value. **Eq.(4)** and **Eq.(5)** maximum and minimum allowable ply height restriction. This height range from the lower allowable to the upper allowable which both correspond with the equipment limitation. This limitation depends on the type and performance of a cutting equipment used.

The structure of this problem can be viewed as an extension of the multiple knapsack problem (MKP) which is the problem of assigning a subset of n items to m distinct knapsacks, such that the total profit sum of the selected items is maximized, without exceeding the capacity of each of the knapsacks [16]. Readers who are interested in marker planning problem can start the study with this problem.

Alan A. Farley [17] proposes relatively different models based on cutting-stock problem. He states that an objective of marker planning problem should be maximization of long-run profitability rather than minimization of only waste. He proposes two alternative models to represent this idea. Moreover, his proposed models incorporate all relevant costs, contributions and, constraints ranging from fabric warehouse to sewing process. These models are very complex and hard-to-use in real-world industry situation. However, these complex models can be seen as examples or frameworks for development of more sophisticated models.

1.3 Paradigm shift in the garment industry.

1.3.1 The major changes in garment industry.

Over the last decade, there have been three changes occurred in garment industry which directly affect all garment manufacturers [18]. Firstly, an occurrence of new information technologies which enable an accurate, efficient, and effective collection of customer requirements. Moreover, with these technologies, garment manufacturers can easily communicate with individual customer to get accurate customer needs. On the other hand, with these information technologies, customers want to buy only products that are closely agreed with their requirement. Secondly, a rapid change in customer requirements which make product life cycles shorter than ever. In this situation, it is hard for manufacturers to precisely respond to target customers which can change their requirements rapidly. To correspond with a rapid changing, a more flexible production strategy is needed. Finally, due to a progress in logistics system, high fashion and premium brand garment manufacturers shift their attention from a local market to a global market. Their garment products are worldwide distributed to many regions of the world. Therefore, their production amounts are substantially increased which makes current planning methods do not work. On the other side, this worldwide market gives not only a benefit but also a threat to garment manufacturers. This threat is in the form of many new competitors from around the world. For example, nowadays, garment manufacturers in Far East Asia can be a competitor of garment manufacturers in East Europe. To survive in such high competitive market, garment manufacturers should improve their competitive ability. Moreover, this improvement should be on both planning and operating system of these manufacturers.

1.3.2 Responses of garment manufacturers to changes.

To cope with the three major changes described above, two popular concepts are introduced to garment manufacturers. A first concept, a mass customization production strategy, this concept is a combination of two old production strategies, i.e., a custom production and a mass production. A second concept, a lean manufacturing concept, an application of this concept will support the use of a mass customization production. To successfully use such flexible production strategy like a mass customization, a lean manufacturing concept is necessary. With this concept, a non-value added workload should be reduced from a production line. The details of these two concepts are described as follows.

1.3.2.1 A mass customization production strategy.

In the past, there are two production strategies used in garment industry, i.e., a custom production strategy [19], and a mass production strategy, where each strategy is appropriate for different types of manufacturers. A custom production strategy is suitable for fashion product manufacturers which produce high price and premium brand fashion products. Products of these manufacturers always use high value fabrics and accessories. Furthermore, customer orders usually come in small lot size with a nonsmooth demand pattern. While the mass production strategy is suitable for basic product manufacturers, which produce standard brand products, low to medium price fabrics and accessories are used to produce these basic products. Moreover, customer orders usually come in large lot size with a smoother demand pattern than custom production.

Generally, manufacturers in these two groups emphasize on different production planning aspects. Manufacturers that use a custom production strategy usually deal with small lot size and high-valued products. In this scenario, an importance of excess cost in terms of overproduction units seem to be higher than, or at least equal to an importance of set up cost in terms of number of markers used. Therefore, their attention should be orderly paid on excess cost and set up cost, respectively. On the other hand, manufacturers that use a mass production strategy usually deal with large lot size and low-to medium-valued products. In this scenario, an excess cost seems to have less importance than a set up cost. Two major reasons are related to an amount of excess units compared to a total produced amount and price of fabrics used. Therefore, their attention is tentatively toward set up cost.

Obviously, a mass production does not satisfy the three major changes described previously because of its inflexibility. The mass strategy is not suitable for a rapid changed demand. On the other hand, a custom production also does not satisfy these changes because of its production cost which reflects in expensive products. The custom strategy cannot fulfill a cost dimension of garment manufacturers. Therefore, using only custom production strategy or mass production strategy, can’t correspond with the aforementioned three changes. To cope with this changed environment, a mass customization strategy which is a combination of customization and mass production [20]should be applied to garment industry.

A mass customization was first introduced by Pine [21] in his book of mass customization as providing individual customers with customized products and producing those with principles of mass production. In [20], a mass customization is defined as producing customized goods as craft production while producing goods in a large scale as mass production. A more concise definition is presented in [22], they stated that a mass customization is the mass production of individually customized goods and services.

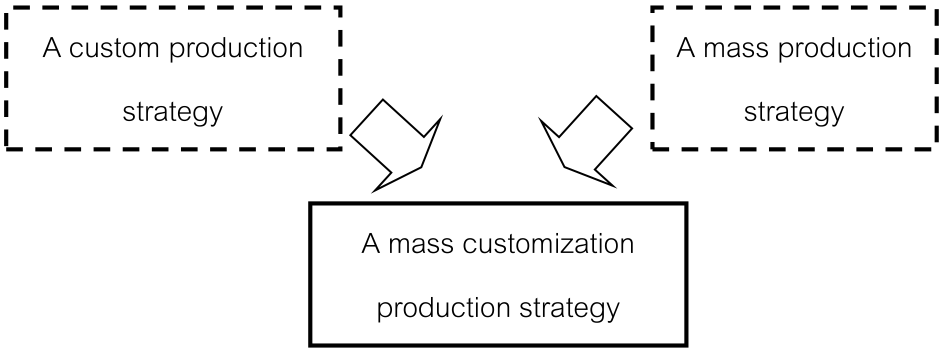

Figure 8 A mass customization production strategy.

With mass customization production strategy, manufacturers still produce high value garment products which compose of high price fabrics and accessories but in larger lot size and smoother demand pattern. As a demand is higher, a set up cost which is directly related to number of markers used should be still in consideration and to agree with a production of high value products, an excess cost is also still included in consideration. Hence, a decision criteria of marker planning process in mass customization is composed of set up cost plus excess cost. Moreover, to better correspond with a mass customization concept, areas of stencils of different sizes should be unequal as a result of high-valued fabric used in production. The last impact of applying a mass customization in garment industry is associated with a higher amount of demand than in a fashion industry. It is quite straight forward that when demand is higher, a number of markers used should be increased proportionally which makes marker planning process more complex. However, using mass customization concept does not alter marker planning constraints. The current used constraints are still working such as ply height limitation, marker area limitation, and demand constraints.

1.3.2.2 A lean manufacturing concept

In the previous Section, a concept of mass customization production is introduced to garment manufacturers in order to cope with the major changes. In this Section, a lean manufacturing concept which can, in many cases, support the use of a mass customization production is applied. Moreover, this concept is very useful, especially with garment manufacturers that are not familiar with a mass customization production.

The concept of lean manufacturing is first introduced in 1990 in the book “the machine that changed the world”[23]. In [24], lean manufacturing is defined as “the systematic approach to identifying and eliminating waste through continuous improvement by flowing the product or service at the pull of your customer in pursuit of perfection”. Furthermore, the core idea of lean manufacturing is to identify and eliminate waste from a production line. Generally, waste is defined as any workload or activity that doesn’t add value to finished products. Waste is classified into seven basic types, i.e. over production, waste of unnecessary motion, waste of inventory, production of defects, waste of waiting, waste of transportation, and waste of over-processing.

To successfully use a mass customization strategy which is relatively flexible, a concept of lean manufacturing should be applied. From literature, it is found that this concept is popular among many types of garment manufacturers in many regions of the world [22, 24-29]. With this concept, garment manufacturers should reduce their non-value-added workload from their production lines. This reduction will make their production lines more slim which are more appropriated for using a mass customization strategy. In this research, a work-in-process inventory is seen as an important non-value added workload that should be reduced first. The occurrence of this workload is explained as follow.

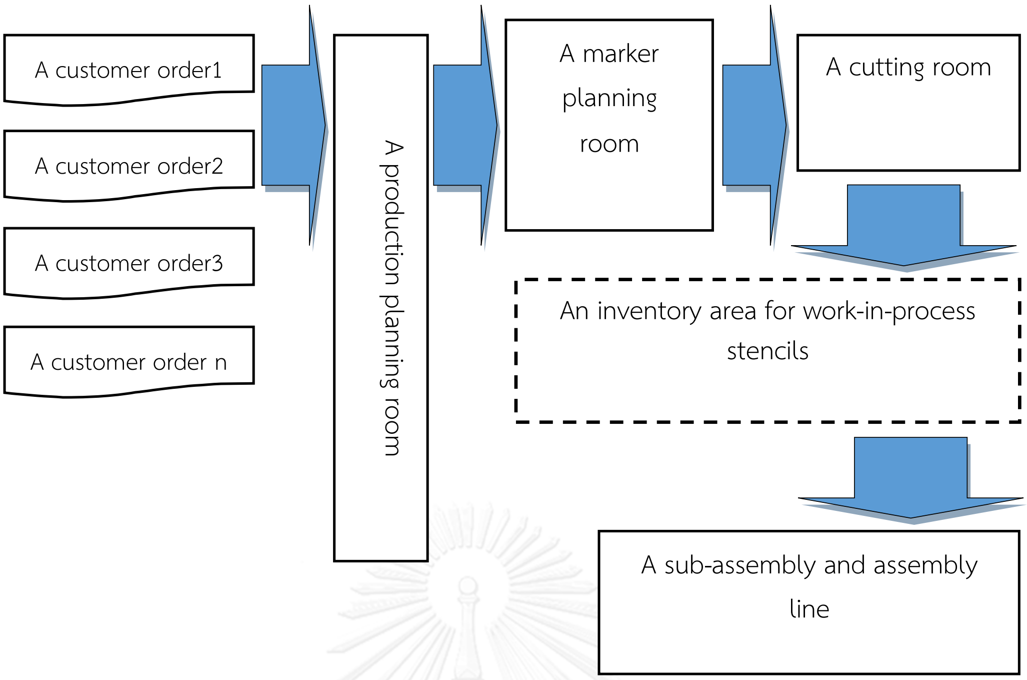

Figure 9 A configuration of an interested production line.

Figure 9 shows a configuration of an interested production line. In this line, there are three major processes located consecutively which are a marker planning, a cutting, and a sub-assembly and assembly process. Furthermore, in this configuration, all customer orders are assumed to use a common production line. At first, a received customer order is transformed into a sewing schedule which shows a sequence of sizes that will be assembled in a sub-assembly and assembly process. A sewing schedule together with a customer order detail will be continuously operated from a marker planning process to a sub-assembly and assembly process. In front of a sub-assembly and assembly process, there is a large inventory area used to keep work-in-process parts or stencils derived from a cutting process. This inventory is caused from an arrival of stencils to a sub-assembly and assembly process before their time of use. These stencils are kept in this area until their assembly times which will be called "due date" from now on. However, to maintain a sewing schedule, stencils from cutting process are restricted to arrive at a sub-assembly and assembly line before or at least on their time of use. From Figure 19, it is obvious that this work-in-process inventory is increased proportional to two major parameters Firstly, a number of customer orders, an amount of work-in-process inventory tend to be higher when facing a large number of customer orders with different due dates. Secondly, a marker pattern, as stated before, a function of marker is to use as a cutting template in a cutting process. Apparently, a difference marker pattern can result in a difference set of stencils arriving at an inventory area. Therefore, an adjustment in marker patterns can, in some cases, reduce this workload.

To reduce this work-in-process inventory, a sewing schedule in terms of a due date of each size is incorporated into consideration. This due date is used to represent a sewing start date of that size. Hence, stencils arriving at a sewing line on their due dates are incurred no workload while stencils arriving at a sewing line before their due dates are certainly incurred inventory workloads.

1.4 Statement of problem

The major changes in garment industry cause a significant impact to marker planning problem as explained previously. At first, with a mass customization production strategy, an amount of demand is between 1,000-3,000 units which are larger than an amount of demand in a custom production garment. Therefore, it is straight forward that a number of markers used are higher than in a custom production garment. A demand pattern which is used to represent a distribution of demand amount is smoother than in a custom production garment. However, this demand pattern is still more fluctuated than a demand pattern in a mass production garment. Finally, a number of sizes in each customer order are the same as in a custom production garment which is higher than in a mass production garment. Furthermore, to make the problem more realistic, areas of fabric required for different sizes of product are assumed to be unequal which is different from other reviewed researches [2, 7-11, 14, 30, 31].

With a lean manufacturing concept, a sewing schedule in the form of due dates is included into consideration. Each due date is used to represent a time that each size is operated in a sub-assembly and assembly process. Hence, it means that stencils from one size are fixed with one due date no matter what marker they are located. Additionally, to maintain a manufacturer's goodwill, all units must be cut out before their due dates. So, in a cutting room, each marker will be cut at the minimum due date of all sizes located on that marker. It is apparent that adding these due dates makes a marker planning problem more complicated.

In an application of mass customization and lean manufacturing concept, three objective components are incurred in an objective function, i.e. set up cost, excess cost, and work-in-process inventory workload. Minimization of these three objective components simultaneously is very difficult. However, as explained previously, a marking plan which is a result of marker planning process is created based on given two schedules, i.e., cutting and sewing schedules. Together with a function of marker planning process which is to generate a set of markers (a marking plan) for using later in a cutting room, this research can be divided into two research areas which each area correspond with different objective components. The first area is to improve a marker planning methodology which is to minimize a set up cost plus excess cost. The second area is to improve a work-in-process inventory workload which is used to represent a relation between a cutting and sewing schedules. Moreover, to tackle these two research areas appropriately, concept of lexicographic goal programming is applied. With this concept, the interested problem is separated into two problems which each problem is laid on a different level. In the first level, only effect of a mass customization to marker planning process is considered. In this level, two objective components which are set up cost and excess cost are incurred. To solve this problem, a marker planning heuristic designed based on a context of mass customization production strategy is proposed. In the second level, a lean manufacturing concept is applied addition to a mass customization. In this level, only a work-in-process inventory workload is incurred. A marking plan derived from a heuristic proposed in the first level is further improved with respect to a work-in-process inventory workload. To solve this problem, a specific heuristic designed especially for reducing inventory workload is proposed.

The purpose of this thesis is to develop two marker planning heuristics which are used for two related problems. The first heuristic is designed for solving unequal-area marker planning problem in a context of mass customization garment. In the first heuristic, an objective function consists of a set up cost and an excess cost. The second heuristic is designed for marker planning problem with lean manufacturing concept. With this concept, a sewing schedule in terms of due dates from a sub-assembly and assembly process is included into consideration. In the second heuristic, an objective function consists only of a work-in-process inventory workload.

The summary of related literatures is presented in the next Section. In Section 3, a marker planning problem in a context of mass customization is described. In Section 4, a marker planning problem with lean manufacturing concept is studied. In Section 5, a conclusion, research limitation, and future research are drawn. Finally, a reference is provided in Section 6.

Chapter 2
Literature review

2.1 Marker planning problem

In this Section, marker planning papers are summarized and presented by 5 model components. In each model component, important details are explained clearly. The first component, objective function, there are 4 major objectives found. The second component, constraint, a set of standard marker planning constraints is described. Moreover, additional constraints addressed in some papers are also explained. The third component, model formulation, there are many types of model used to formulate this problem ranged from a nonlinear model to a linear model. The fourth component, solution approach, these approaches can be divided into 2 broad groups with respect to their purpose of use. The first group is pre-processing method and the second group is solving method. The last component, performance measurement, there are 2 important issues which are sources of problem instances and lower bounds.

2.1.1 Objective function

There are 4 major objectives found which each objective function composes of a set of costs. The first objective function is minimization of set up cost. This objective is represented in 3 forms which are all nearly the same in meaning. Firstly, it is directly represented in the form of minimum number of markers or lays used [12, 30, 32]. When a number of markers is tried to minimized, number of units in each marker should be maximized. Therefore, the second form is maximum number of units in each marker [3, 33]. Naturally, marker planning is an iterative process which each iteration try to satisfy a customer demand with a generated marker. Hence, to minimize number of markers used, each iteration should generate a marker that can maximize number of eliminated pieces from a work order [2].

However, these 3 objective functions are probably different when using. Fister, I., et al. [31] argue that "maximizing number of eliminated pieces at each step does not lead to a minimum number of markers or lays to cover the work order". Therefore, using minimum number of markers as objective function has more chance of leading to the desired target.

The second objective function is minimization of set up plus excess cost [7, 8, 11]. At first, the objective is to minimize these 2 costs simultaneously but this objective is difficult to solve. To simplify this difficulty, in [7, 8], they use mathematical equation to calculate the minimum number of markers used to satisfy a customer demand. Subsequently, they fix a number of markers in model to this minimum number. The objective function of these papers is reduced to minimize only excess cost. Furthermore, this excess cost is represented in the form of a number of units produced which is used to show the attempt to minimize the gap between produced quantity and demand quantity. Especially in [34], the authors add an objective component that is used to represent a variation of due date in each marker. This objective component is in the form of standard deviation of due date of each marker. When this time based component is added to the objective function, the original problem becomes a multi-objective problem which is harder to solve.

The third objective function is minimization of material cost. The important assumption of most papers in this group is to assume that a fabric width is constant. So, minimization of fabric area used is equal to minimization of total fabric length used [14, 35]. This objective function is used based on the insertion effect. This effect state that small-size parts can be inserted into gaps between large-size parts when they are assigned to the same marker. Subsequently, an amount of fabric used can be reduced. With this objective, planners try to combine different parts with various sizes into one marker. However, in[36], set of fabric rolls with different widths are used. This paper implicitly assumes that the total length of fabric used to satisfy demand is constant no matter what patterns are used. In this case, the total amount of fabric used can be reduced by trying to use a smaller width fabric rolls first. Moreover, a number of fabric rolls with each width is restricted to certain number.

The fourth objective function is minimization of set up plus material plus machine cost. The objective function in this group is divided into 2 subgroups which are 1.including machine cost and 2.not including machine cost. In the first subgroup, including machine cost, an objective function consists of material cost, set up cost, and machine cost [33]. As explained before, a machine cost is referred to an electricity cost occurred when using a computerized cutting machine. Moreover, this cost is proportional to length of fabric used for all markers. In the second subgroup, not including machine cost, an objective function consists of material cost and set up cost [10, 12, 15]. In this group, there are 3 forms of objective function found. Firstly, in [37], the author assumes that an amount of fabric used per lay is minimized when number of units/lay are maximized. Therefore, numbers of units/marker are fixed at maximum and, subsequently, fabric or material cost is eliminated from the objective. Secondly, in [10], the initial objective function is to minimize total cost composed of fabric cost, spreading cost, cutting cost, and increased marker making cost. In developing solution approach, the authors assume that fabric cost which is proportional to fabric length used is the most important cost. Cost components that don't relevant with the fabric length are eliminated from consideration. Therefore, only fabric cost remains in the objective function. Finally, in [31], the authors state that minimizing preparation cost which consists of minimizing material consumption, marker making cost, spreading and cutting cost is the most important in marker planning process.

In the development of new data systems that can efficiently collect data through a whole production line and subsequently, transform it into useful information. A collaborative planning concept can be applied to garment production line. With this concept, information such as due date, constraints and, etc., from downstream processes can be delivered to upstream processes. As a special case of applying this concept, due dates which is time information from cutting, sub-assembly and, assembly process can be included into marker planning process. In this case, a time-based objective component will be added to a single cost-based objective. Hence, an original single objective marker planning will become a multi-objective marker planning problem.

In the future when economic situation is improved, customers tend to require high quality fabrics which are relatively expensive. Such situation makes a material cost more important than any other relevant costs. As a result, excess and material cost can dominate other costs occurred in generating and using markers.

2.1.2 Constraint

Almost papers [3, 8, 10, 11, 14, 30, 31, 33-35, 37] used only a set of basic constraints addressed in the basic marker planning model as shown in Section 2.2. However, in [12, 32], they add a constraint that allows no excess to occur. To simplify the problem, Fister, I., et al. [2] add an additional constraint used to represent a restriction on the maximum number of sizes allowed on each marker in each iteration. This constraint help reduce number of feasible solutions and amount of computation time. Lastly, in [38], a constraint used to limit an available time for cutting a set of markers is applied. This constraint expresses that a summary of preparation, spreading, and cutting time must be less than or equal to a demand time from a sewing process. Degraeve, Z., et al. [7] constrain on minimum number of stencils used for each size and lower, upper bound on number of stencils needed in one pattern to reduce number of pattern variables. As a result, when numbers of pattern variables are reduced, an amount of computation time is also reduced. In [34], a set of soft constraints which are used to express target goals in multi-objective problem is added.

With standard cutting equipment, i.e. hand knife and band knife, both lower and upper allowable ply height must be restricted. However, with laser cutting machine which is a new trend for garment industry, only upper allowable ply height must be included. This laser cutting machine can cut even one ply marker. Consequently, a solution search space is larger which results in larger number of alternative solutions. Nevertheless, a computation time is also significantly increased.

In [36], a constraint on the fabric stock available for each width is used to restricted number of fabric rolls of each width that can be selected.

2.1.3 Model formulation

Most of reviewed papers [2, 3, 7, 8, 11, 12, 14, 30-32, 35, 37, 38] are done based on the basic marker planning model. This model is in a type of integer nonlinear programming (INLP) which is relatively hard to solve. Nonlinear terms appeared in both objective and demand satisfaction constraints are the product of pattern or stencil assignment variable and ply height variable. To eliminate these nonlinear terms, Jacobs-blecha, C., et al. [10] use the variable substitution method which substitutes the nonlinear terms with a variable z_j. Obviously, value of a variable z_j is either 0 or a ply height of lay j. One important thing making this method work is that they use pattern assignment which generates all possible patterns outside the model. Apparently, these possible patterns are seen as only input of the model While in [8], they state that additional to nonlinearity, an area limitation constraint which is in a type of knapsack constraint makes the problem more complicated. To cope with the nonlinearlity, they use the variable discrete expansion which allows them to linearize the product of variables $a_{ij}z_j$ (number of units produced in each marker) by defining an additional set and variable. To cope with the knapsack constraint, they choose to reformulate to the network formulation. Many constraints are introduced to maintain the meaning of the original problem. In [2], the original marker planning model is transformed into knapsack model which known to be NP-hard problem [3]. Subsequently, they use knapsack-based concept to develop 2 heuristics to solve the transformed problem.

Degraeve, Z., et al. [7]tackle a difficulty in the original model by presenting 2 alternative models. In the first alternative, two decision variables are introduced, namely, a_ip_j (binary) and v_ip_j (integer). The major concept of this model is to assign size to empty positions in a marker and decide number of plies of that marker. Furthermore, this model is linearized by adding 3 new constraints into the model. To eliminate a vast amount of feasible solutions, they develop 2 sets of constraints that impose an ordering of sizes both within each pattern and across patterns. In the second alternative, 2 decision variables are introduced, namely, $y_{(j1,...,jq)}$ (binary) and $z_{(j1,...,jq)}$ (integer). The objective of this model is minimum total production. The major concept is to create possible patterns outside the model and use them as input to generate markers. Subsequently, each pattern is selected and numbers of layers of this pattern are decided.

2.1.4 Solution approach

There are 2 types of methods used in solving this problem as summarize in Table 6. Firstly, pre-processing method, the major purpose of methods in this group is to simplify the original problem. These methods try to relax or redefine decision variables or reformate the original problem to an easier-to-solve problem. Nevertheless, the simplified problems must keep the meaning of the original problem as much as possible. Secondly, solving method, the major purpose is to search for the best solution or good solution or a set of feasible solutions for the original problems or the simplified version. Some papers use both methods together while others used only solving method.

Table 3 The summary of solution approach methods.

Pre-processing method	Solving method
1. The variable discretization.	1. The enumerative approach.
2. The variable substitution.	2. The mathematical method.
3. The network or dynamic reformulation.	3. The heuristic approach
4. The elimination by assumption.	4. The meta-heuristic approach
5. The knapsack problem reformulation.	5. The hybrid approach.

To solve this problem mathematically, they firstly transform or reformulate the original model as explained in sub-Section 4.3 into easier-to-solve model. Degraeve, Z., et al. [7, 8]try to mathematically solve this problem with 3 different models. Moreover, these 3 models are based on 3 different modeling concepts.

The basic 5 heuristics based on constructive concept are developed in [14]. The first 4 algorithms (H1-H4) are inspired from rule of thumb used by experts of the garment industry whereas the last algorithm (H5) is a random search which randomly generates a set of markers satisfying demand orders.

Rose, D.M., et al. [12] propose an enumerative approach based on branch and bound concept. The developed solution approach composes of 2 stages. Firstly, generating partitions, minimum number of markers and all possible combinations of plies for a set of full markers are calculated. Hence, output of this stage is a set of alternative empty markers. Secondly, all possible combinations are tested one by one to search for the best solutions. In this stage, branch and bound search tree is used to test each combination. There are 2 search strategies employed which are style distribution tree and marker filling tree. Any solutions that can completely branch to the last node are classified as feasible solutions. Jacobs-blecha, C., et al. [10] develop 3 greedy heuristics to solve the transformed problem. Firstly, saving heuristic, assign size combination to a lay on the basis of the fabric saving achieved by combining them into one section. Secondly, cherry picking heuristic, build lays by combining certain sizes based on the best utilization of fabric. This algorithm picks the first and second most numerous quantity in the remaining order and places them in unfulfilled lays. Lastly, improvement heuristic, take a current solution and try to improve it by exchanging sizes in different sections or by combining existing sections into one section. Fister, I., et al. also develop a greedy heuristic which its steps are 1.order the sizes in the work order, 2.pick the sizes one after another and 3.put them into the marker until reaching the maximum number of sizes (m^k). Furthermore, this heuristic orders the sizes based on Cauchy-Schwartz inequality. In [34], decomposition concept is used to tackle this multi-objective problem. This concept tries to decompose the original problem into a set of smaller sub-problems. Subsequently, these sub-problems are sequentially solved to achieve a final solution corresponding with the original problem. The difficulty of using this concept is how to keep the core meaning of the original problem.

Genetic algorithm or evolutionary algorithm is a very popular meta-heuristic used in this area. Filipi, B., et al. [33] develop 2 heuristics based on evolutionary algorithm (EA). Firstly, an EA with penalty function – the concept is to assign lower fitness value to invalid solutions. As a result, fitness function in this approach is determined by subtracting the penalty term from the original objective function. Moreover, there are 3 types of penalty functions, i.e. logarithmic, linear and quadratic which are different in the growth rate of penalty. Secondly, an EA with repair function – the concept is to repair invalid solutions and, then, evaluate their fitness function again. Moreover, there are 3 repairing approaches used, i.e. heuristic, greedy and random. Martens, J., [11] proposes 2 genetic algorithms (GA1 and GA2) based on 2 model which are integer nonlinear programming model (INLP) [8] and integer programming (IP) [7]. For GA1 (GA. based on the INLP. model), the penalty function consist of the amount of overproduction cost plus the amount of underproduction cost. Moreover, a dynamic penalty policy that regularly updates the penalty for demand underproduction is applied. For GA2 (GA. based on the IP. model), the penalty function compose of only the amount of overproduction cost. The next important issue is how to develop GA operators, for GA1, the authors use a uni-crossover operator together with a classic mutation operator. For GA2, an enhanced, schemata based one-and two-point crossover operator and a dynamic adaptation mutation are used. Furthermore, to boost up performance, auxiliary heuristics are developed for both GA1 and GA2. For GA1, a simple hill climbing algorithm is applied while for GA2, a network algorithm called “a flow redirection algorithm” is used. In [14], their initial population of individuals is a set of feasible solutions to CT which are generated with constructive algorithms H1-H4. In this approach, the best local position method (BLP) is used to assess the minimal length of every new or modified section. Wonk, W.K., et al. [38]

propose 2 encoding methods which correspond with 2 different binary strings. Fister, I., et al. [31] propose a hybrid self-adaptive evolutionary algorithm for marker optimization. To solve the problem, firstly, candidate solutions are randomly generated. All these solutions are either improved or repaired by the three modes of repairing, i.e. heuristic, random and greedy. The developed algorithm has 6 essential components as, i.e. representation of individuals, evaluation of the objective function and local search improvement, the population model, parent selection, mutation operator and neutral survival selection. Another variation of GA-based approach is presented in [3]. They develop a canonical GA approach which is a popular stochastic search technique. Moreover, their GA is divided into 3 major topics. Firstly, encoding chromosomes, a candidate solution or a size ratio will be encoded as an integer string to form a chromosome. Secondly, selection, the selection policy employed a combination of the roulette wheel selection and the elitism strategies. This combination can ensure higher fitness chromosomes become parents of new chromosomes. Lastly, cross over and mutation operations for mating chromosomes – uniform order based crossover method was used to execute crossover operation. Mutation operator is equipped to search global optima in the solution space with the mutation probability equal to 0.1.

Simulate annealing (SA) which is a flexible and robust stochastic search is applied in [14]. This approach starts from an initial solution and, then, moves to a neighbor in hope of further improving the current solution. Furthermore, there are 2 types of neighbor with respect to the objective function value that are a neighbor that can improve the objective value and vice versa. This iterative process continues until the stopping criterion is reached. In this research, the SA process is stopped after 3 successive plateaus without improvement of the current solution.

In hope of solving this problem more efficient, many combined GA are developed. In[32], the hybrid approach which is a combination of a conventional heuristic method and a standard GA. The aim of combining these 2 methods is to reduce number of initial populations and also amount of execution time. At first, they use a conventional heuristic to generate a suggested size ratio which will be used as encoding mask string in generating initial population for GA. With this encoding mask string, number of initial populations represented as chromosomes will be reduced. Okuno, H., et al. [35] propose a genetic annealing (GAn) method which is a combination of a genetic algorithm (GA) and a simulate annealing (SA). At first, GA is used to generate solutions with the best possible fitness value. Subsequently, SA which is a local search concept is applied to improve the solutions. In SA Stage, a concept of uphill moves which allows moves from a current solution to a neighbor in hope that it leads to a minimal cost one. M'Hallah, R., et al. [14] also develop a genetic annealing (GAn) method. This approach can be seen as a modification of GA because the main structure is based on GA except a replacement strategy and a mutation mechanism. These modifications accelerate the search without leading it to premature convergence and stagnation in local minimum.

In purpose of solving larger-size problem, Deng, H., et al. [30] present the two stages optimization method based on probability search and genetic algorithm to solve cut order planning (COP) problem. The major concept is to decompose the original COP problem into 3 sub-problems which each sub-problem corresponds with only one decision variable. In the first stage, there are 2 related sub-problems. The first sub-problem is to determine number of markers or cutting tables. The second sub-problem is used to randomly generate number of layers for each cutting table. In the second stage, sizes combinations are randomly generated for each cutting table based on the solutions from the first stage. The final solutions are feasible with respect to both a maximum allowable cutting table length limitation and a demand satisfaction constraint.

In literatures, there are 2 assignment units found, i.e. stencil and pattern assignment units. With these 2 units, all parts required for each produced item are restricted to locate on the same marker. Furthermore, these 2 units are not only used in academic researches but also used in practice. The reason is mainly related to an intermittently distribute of fabric color. In the future, if a new efficient and effective dying technology which can produce uniformly color-distributed fabric is developed, a part assignment unit can be an alternative in generating markers. With part assignment unit, all required parts are independently assigned to any generated markers. As described earlier, with this method, there is a great chance to create better fit marker patterns. Hence, a number of markers used and amount of fabric area used are hoped to be reduced with better fit marker patterns.

2.1.5 Performance measurement

To measure performance of the developed models and methods, computational experiments must be conducted. There are two major issues in designing experiments.

Firstly, a source of problem instances, there are three sources as follows.

Table 4 Sources of problem instances.

Sources	Papers
1. Problem instances from real-world industry.	[2, 3, 8, 10, 14, 31-33, 38]
2. Problem instances from program generating	[11, 37]
3. Problem instances from other papers	[12, 14]

Secondly, a lower bound, there are 4 types of lower bound used to compare as follows.

Table 5 Types of lower bound.

Type of lower bound	Papers
1. Compare with lower bounds from a commercial software	[3, 10, 14, 32, 33, 35, 37, 38]
2. Compare with lower bounds from other heuristics	[7, 8, 10, 11, 31-33]
3. Compare with optimal solution	[11]
4. Compare with solutions from an expert	[2]

2.1.6 Summary

The solutions obtained from the mathematical method are guaranteed to be optimal for only small-size problem instances whereas for large-size problem instances, very large computation times are needed for both finding the best solution and proving the optimality conditions of this solution. Hence, this solving method is appropriated for solving only small-size problem instances which are often occurred with fashion product manufacturers. These manufacturer's products are highly fashion produced in a relatively small lot size. Moreover, demand patterns of these orders are usually non-smooth. Furthermore, an objective function of marker planning in this scenario usually composes of a set up cost and an excess cost.

The enumerative method is somewhat similar to the mathematical method in the sense that this method can guarantee to obtain the optimal solutions because this method generates all feasible solutions and, subsequently, selects the best one. However, numbers of possible solutions are growth exponentially with respect to size of problems. Hence, only very small-size problem instances can be solved with a reasonable computation times.

The heuristic, meta-heuristic, and hybrid methods seem to be the promising methods with respect to the special characteristics of this problem. Moreover, among these three methods, the meta-heuristic method, e.g. GA and SA, is the most popular method used. However, from literature survey, it can be observed that little information is used in designing the mechanism of these methods. Furthermore, almost methods are designed based on fashion garment industry which are capable of efficiently solving only small size customer orders such as customer orders of local brand fashion product manufacturers. With mass customization production strategy, a size of customer order is large compare to a size of customer order found in literatures. Therefore, a more efficient marker planning method is need. Additionally, there is only one paper found [34] concerning due dates in an objective function. However, a method used to calculate a work-in-process inventory workload is different. Moreover, a demand pattern of a customer order in that paper is relatively smoother than a demand pattern in this research.

2.2 Multi-objective problem

In high complex situation such as problems in engineering, industry, and environmental management, several objectives are involved. These objectives are usually defined in incompatible units and moreover, they usually present some degree of conflict among them [39].In this situation, all involved objectives cannot be improved (minimize or maximize) simultaneously which means one objective cannot be improved without decreasing of any other objectives [39]. To cope with such problem, goal programming was invented in [40] to deal with executive compensation method. Additionally, a clear definition of goal programming is given in [41]. Orumie [42] stated that goal programming is one of the oldest multi criteria decision making techniques used in optimization of multiple objective goals by minimizing the deviation for each of the objective from the desired target. To do this, two deviational variables are introduced, i.e., positive deviational (d^+), and negative deviational (d^-) variables. A positive deviational variable is used to represent an amount over the desired target while a negative deviational variable is used to represent an amount under the desired target. In [43], goal programming is classified into two variants, i.e., distance metric based variants, and decision variable and goal-based variants which are briefly described as follow.

Decision variable and goal-based variants

In this group, goal programming is further divided into three types with respect to the mathematical nature of the goals and/or decision variables.

- *Fuzzy goal programming* – this type of goal programming utilizes fuzzy set theory [44] to deal with a level of imprecision in the goal programming model [43]. The fuzziness around the target goals can be measured in many ways which lead to a different fuzzy membership function. In general, there are four common linear fuzzy membership functions [43], i.e., right-sided (positive deviations penalized) linear function, left-sided (negative deviations penalized) linear function, triangular (both deviations penalized) linear function, and trapezoidal (both deviations penalized with an interval of complete satisfaction).
- *Integer and binary goal programming*–in this type of goal programming, at least one decision variable is restricted to be an integer variable. Especially in binary goal programming, at least one decision variable is restricted to be zero or one. As stated in [43], this type of goal program is harder to solve than similarly sized linear programs because of their complexity. Furthermore, a situation where this method is appropriate is when formulating problems that have both logical conditions and multiple, conflicting goals.
- *Fractional goal programming*–this type of goal programming has one or more goals of the form.

$$\frac{f_{q\,(x)}}{g_{q(x)}} + n_q - p_q = b_q$$

Romero [45] stated that this type of goal programming arise in the field of financial planning, production planning, and engineering. It is apparent that this type of goal programming is in the form of nonlinear problem which is more difficult to solve than linear problem. To deal with this difficulty, heuristics such as multi-objective evolutionary methods was developed [46].

Distance metric based variants

In this group, goal programming is also further divided into three types with respect to the methods to deal with deviational variables. Moreover, objective functions of these three types are managed in different ways. The details of these goal programming are explained as follow.

- *Chebyshev goal programming* – this type of goal programming is introduced by Flavell in [47]. With this type, the maximal deviation from any goal is minimized which is known as Chebyshev means of measuring distance. In some researches, this goal programming is called minmax goal programming. The most appropriate situation is when a balance between the levels of satisfaction of the goals is needed [43]. The major advantage of this variant is that this method can find optimal solutions for linear models that are not located at extreme points.
- *Weighted goal programming* –with this type, weights are attached to each of the objectives to measure the relative importance of deviations from their targets [42]. Subsequently, all objective components are placed in a weighted single achievement function which allows for direct trade-offs between all unwanted deviational variables [43]. This type of goal programming is sometimes called non-pre-emptive goal programming. Obviously, with this method, weights assigned to each of the goals directly affect final solutions. Hence, different sets of weights can result in different sets of solutions. Jones and Tamiz [48] reported that until year 2000, this weighted goal programming received more attention compared to other types.
- *Lexicographic goal programming* –in lexicographic or pre-emptive goal programming, the objectives or goals are ranked or prioritized in order of

importance by the decision maker from the most importance (goal 1) to the least importance (goal m) [39]. With this structure of goals, an attainment of first goal is much more important than attainment of second goal which is much more important than attainment of third goal, etc., [42]. Tamiz, et.al. [49]stated that a lexicographic minimization being defined as a sequential minimization of each priority whilst maintaining the minimal values reached by all higher priority level minimizations. One important constraint applied from second priority goal to the least priority goal is constraints that are used to retain solutions derived from the higher priority goals. This type of goal programming is useful in two situations. A first situation is when a decision maker can clearly specify a priority of each goal. A second situation is when there is more than one optimal solution with respect to only one objective component or goal. In the second situation, solutions from lower levels are used as the second, third, etc., criteria to the problem in case that solutions from higher levels are tie. Thus, in the worst case, a decision maker has to carry out k single objective optimizations (k is a constant represented a number of priority levels specified by a decision maker).

Especially in a situation when the goals or objectives can be categorized into groups and in each group, the goals are of equal importance, a lexicographic can be combined with a weighted goal programming to create a new method called prioritized goal programming[42]. In each group, because all goals are of equal importance, a weighted goal programming is used. Between each group, because of difference in priority levels, a lexicographic goal programming is applied.

Until now, lexicographic goal programming is widely applied in many areas of problems such as social economic planning, production planning, finance, accounting, inventory management, investment planning, forest planning, agricultural planning, urban and environmental issues, network planning, and etc [50, 51].

As explained previously, three costs incurred in this research, i.e., set up, excess, and inventory holding costs, can be ranked by their importance into three levels which are set up cost, excess cost, and inventory holding cost, respectively. Therefore, a lexicographic is most appropriate for dealing with the studied marker planning problem.

2.3 An integrated problem

Christos T.Maravelias, C.S. [52], also present three solution strategies to tackle the integration problem in which the first and second methods are lied in the first group while the third method is in the second group. Details of these methods are as follows.

1. Hierarchical method – data from higher level decision or predecessor process will be fed to lower level or successor process as input of the model. In this method, no feedback loop is included which means that the solution from higher level can’t be adjusted even though it sometimes generates infeasible scheduling result.

2. Iterative method – additional to hierarchical method, this method includes feedback loop into consideration. This will result in more flexible solution approach because lower level problem can sometimes send back a higher level solution that cause an infeasible solution in lower level. Subsequently, higher level must generate another alternative solution that is expected to result in feasible and better solution in lower level. This procedure will continue until the best solution is found. In some problem environment, this method can cause long computational time. In some literatures, the integer cut method is used to prevent the same set of solutions from being found again.

3. Complete large single model or full-space method [53] – all characteristics of all processes or planning levels that are integrated together will be incorporated into a single large model. Obviously, this model will be complex and very time-consumption model. In the other hand, this model often results in more accurate

solution. Many literatures show that full-space method should be used with relaxed or integrated model to reduce some computational complexities.

Moreover, Mahamed K.Omar, et.al, [54] introduced a three-level hierarchical production planning and scheduling approach to cope with planning problem in resin factory. In this research, planning decisions are divided into three levels which each level is strongly related to the others. The first level, the aggregate planning model is modeled with mixed integer programming (MIP) to decide the produced quantity of each product family. Objective of this MIP model is to minimize the total cost which consists of production cost, setup cost, inventory cost, and workforce cost. The second level, the disaggregate planning model which is used to decide the produced quantity of each product item in each product family. The disaggregate planning model is used to disaggregate the plan resulted from the aggregate planning. This level is modeled with integer programming model (IP) which objective is to minimize the total cost consisting of backorder cost, over production cost, under inventory cost, and under utilization of regular time cost. The third level, the shop-floor scheduling model which is used to decide the sequence of products to be produced in each production line. Objective of this level is to sequence products in each line so as to minimize the total weighted tardiness. In summary, the first level is used to generate the aggregate plan which will be disaggregated in the second level and, finally, the second plan will be scheduled in the third level.

An integrated system for hierarchical production planning [55] is developed to cope with the integration system in assembly plant. This research separates the considered planning problem into 4 major relevant decision problems. Firstly, the monthly dispatch schedule together with the other required data are processed through integer programming model. This IP model is used to determine the quantity f the given products to be assembled in a given period. Secondly, the similar IP model is used to determine the sub-assembly quantity per period and, then, sequence this quantity with respect to the assembly schedule. Thirdly, lot-sizing model is used to determine batch size and due date of each batch. The last problem is to schedule all generated batches of parts in job shop production environment. The major contributions of this research are to select the appropriate solution approaches which are ready to implement for each decision problem and to design the linkage between these selected solution approaches.

B.Verlinden, et.al, [56], developed an integrated production planning methodology specifically based on sheet metal working factory. They selected two important operations that are related to each other, laser cutting and air bending, to be studied. These two operations are viewed as two-stage flow shop system which sheet metals are cut at first stage and bended to form finished goods at the second stage. The integration method of this research can be group into 2 phases. In the first phase, each operation is analyzed and converted to the standard well-known problem. Laser cutting is converted to bin packing problem (BP.) which objective is to minimize a number of used metal sheets and air bending is converted to travelling salesperson problem (TSP.) which objective is to minimize total sequence-dependent setup time. In second phase, these two problems are combined to be the vehicle routing problem (VRP.) which relaxes some original characteristics of the problem. The combined model objective is to minimize total setup time appearing in air bending operation. B.Verlinden, et.al, [57] proposed another integer programming (IP.) model to deal with the same problem in sheet metal factory. The purpose of this model is to assign work pieces that use the same production layout (in air bending) to metal sheets so as to minimize total time spend in air bending process. Total time in the objective function consists of setup time due to the number of production layouts used in each metal sheet plus processing time due to each used production layout. According to number of sheets used to satisfy demand orders, they also present a traveling salesperson problem based algorithm to solve this sequence problem in order to minimize total setup time occurring between consecutive sheets. This model also uses a single relaxed model as use in the other developed model described previously.

Chapter 3
A marker planning problem in a context of mass customization production

In this Section, a marker planning problem that is affected from using a mass customization production is studied. Details of this Section are separated into four topics, i.e., problem statement, solution approach, computational experiments, and conclusion.

3.1 Problem statement

3.1.1 Problem description

The research in this Section focuses on solving marker planning process which transforms a customer order into a set of markers. This set of markers is later used as cutting guidelines in a cutting room. To generate each marker, stencils of required sizes are assigned to rectangular shape fabric to generate a marker pattern. Each marker pattern can contain only one size or various sizes depending on planners. There are two types of limitation used to limit number of stencils that can be assigned to each marker. Firstly, it is straightforward to limit the maximum number of stencils per marker. Secondly, the limitation is expressed in terms of the maximum area of each marker. After a marker pattern is completely fulfilled, ply height of each marker must be determined. Generally, ply height is restricted by both lower and upper bounds which is corresponding to cutting equipment limitation.

Marker planning problem studied in this paper usually occurs in global brand fashion product manufacturers with a context of mass customization production strategy. In this scenario, customer orders are ranged between 1,000-3,000 units which is relatively large for high value products. Apparently, these customer orders are larger than customer orders occurred in fashion garment industry studied in [7, 8, 11]. For an academic standpoint, larger size of a customer order makes the problem more complex and difficult to solve with the methods found in literatures [7, 8, 11].

Therefore, a more efficient heuristic approach which is capable of solving larger-sized marker planning problem is needed.

Especially in this paper, all required stencils are assumed to be rectangular shape block which their areas are varied depending on sizes of a product. This variation in stencil area is called unequal area in later Sections. When areas of stencils are unequal, there is an important issue that must be further considered in each marker generating iteration. The order in which stencils are assigned to partial marker is important. Because stencil areas are unequal, e.g., 0.1 m^2, 0.3 m^2, 1 m^2, 1.2 m^2, and etc., each selection of stencil directly affects to number of stencils and what sizes that can be selected later. Obviously, each selection determines feasible combinations of sizes that can be used later.

3.1.2 Mathematical model

<u>Assumption</u>

1. The fabric width is assumed to be constant. Subsequently, the widths of all markers are also constant.

2. The shade of color of all used fabrics is assumed to uniformly distribute along the length of the fabric rolls used.

3. All markers are not allowed to split. This means that every marker must be continuously cut on one cutting table until all garment units in this marker are cut out.

4. To simplify the problem, sub-assembly and assembly processes are assumed to sew only one size per time period.

5. A cutting time per marker is relatively small compare to other operation times in a production chain. Hence, an effect of a cutting time to a sewing schedule is neglected.

6. In this research, a sewing schedule which shows due date of each size is assumed to be given. These due dates are used to represent sewing start times of all sizes in a sub-assembly and assembly process.

Scope

1. This thesis focuses only on single-color marker because this type of marker is usually used in the real-world industry. A multi-color marker is rarely used in industry because it is hard for operators to simultaneously manage cut parts of different colors. Moreover, it is very time-consumption to set up spreading machine or equipment for the case of multi-color marker.

2. The demand input of marker planning process is characterized by size only because in current practice, it is easier for manufacturers to manage single-color marker. Moreover, the same product with different color can be individually processed with the same model.

3. This thesis doesn't concern the effect of insertion between smaller parts and larger parts. Therefore, material consumption or area of fabric used is in the form of linear function.

4. This research covers only marker planning problem which is to find the optimum combination of parts or stencils on each marker. The problem of marker making which is to find the exact position of parts or stencils on each marker is out of scope.

Parameters

$\mathbf{a}_i$ = a required area of each stencil *i*,

$\mathbf{d}_i$ = a demand quantity of stencil *i*.

L = the maximum allowable area of each marker,

UB and **LB** = the upper and lower allowable ply height.

SC = unit set up cost,

EC = unit excess cost.

Decision variable

$\mathbf{X}_{ik}$ = *integer* = number of copies of stencil *i* in marker *k*.

This variable is used to answer the question "Which stencil should be assigned to which marker with how many copies?".

$\mathbf{Y}_k$ = *integer*=number of plies of marker *k*.

This variable is used to answer the question "How many fabric plies in each marker?".

Z_k = *binary* =selection variable.

This variable is used to answer the question "How many markers should be used to satisfy demand?". Its value is very useful when set up cost is in consideration.

<u>Model</u>

Objective; $\text{minimize [set up cost } + \text{ excess cost]}$

$$; \ \text{minimize}\ [(\text{sc} \times \textstyle\sum_k Z_k) + (\text{EC} \times \sum_i \text{EXCESS}_i)] \tag{6}$$

Constraint;

$$\textstyle\sum_k (X_{ik} Y_k) \geq d_i \ \forall i \tag{7}$$

$$\textstyle\sum_i (X_{ik} \times a_i) \leq L \times Z_k \ \forall k \tag{8}$$

$$Y_k \geq LB \times Z_k \ \forall k \tag{9}$$

$$Y_k \leq UB \times Z_k \ \forall k \tag{10}$$

$$\text{EXCESS}_i = \textstyle\sum_k \{(X_{ik} Y_k) - d_i\} \times a_i \ \forall i \tag{11}$$

$$X_{ik} \text{ and } Y_k \geq 0, Z_k = 0 \text{ or } 1 \tag{12}$$

Eq. (6) is an objective function which comprises of a set up cost and an excess cost. **Eq. (7**) is a demand satisfaction constraint where total number of cut stencils must be greater than or equal to the demand. **Eq. (8**) represents maximum area limitation where the area used must be less than or equal to the maximum allowable area. **Eq.(9) and (10)** shows maximum and minimum ply height restriction. Ply height of each marker is ranged from the lower allowable to the upper allowable which both correspond with an equipment limitation. **Eq.(11)** is used to calculate number of occurred excesses of each stencil. Excesses are a quantity of stencils of each size that are produced over the demand. Finally, **Eq.(12)** controls sign restriction.

In this model, there are two costs incurred which are related with the interested scenario. These two costs are described as follows.

Set up cost –this cost occurred when each marker is generated and used in four activities which are marker planning, marker making, cut scheduling, and cutting. Furthermore, this cost can be divided into two cost components, namely, labor cost and opportunity cost. Generally, set up cost is proportional to a number of markers used for one customer order. Hence, minimization of set up cost is the same as minimization of a number of markers used. With this objective, each marker must be forced to contain as maximum as possible number of demand products. In some cases, especially when a demand pattern is not smooth, trying to use minimum number of markers can cause many excesses products.

Excess cost – this cost is fabric cost incurred when cut out parts or units are over a customer demand amount. These over demand amount are considered as waste in some manufacturers, e.g. original equipment manufacturers (OEM). With objective to minimize set up cost, each marker used tends to contain many sizes. Together with nonsmooth demand pattern, numbers of excess products have a higher chance to occur. Therefore, adding this cost to the objective function will make this objective more balanced.

3.1.3 Complexity analysis

From literature, this problem is very hard to solve for many reasons. Firstly, this problem is proved to be NP-complete problem in many researches [2, 7, 8]. Secondly, Bogdan F, et.al. [33], explain that nonlinear terms which are a product of ply height variable and marker pattern variable make the problem more complicate. These nonlinear terms make solution spaces become irregular shape which is difficult to find the optimal or even a feasible solution in some cases. It is hard to decide which direction will lead to the better solutions because in nonlinear problem, only information about the current point and stored information about past visited points are known [36].

Moreover, we found that number of possible solutions exponentially grow with four parameters as shown in **Eq.13**. It is obvious that number of markers used have major impact on number of possible solutions which directly affect to a computation time. This is an important reason why a computation time grows very fast when number of markers or amount of total demand are increased.

$$Number\ of\ possible\ solutions\ =\ \left\{\left[max(X_{ik})^{\#sizes}\right]\ \times\ \left[max(Y_k)\right]\right\}^{(\#markers)} \quad (13)$$

Max(X_{ik}) = the highest value of X_{ik} that can occurred in any markers without violating area constraint. This value is equal to an integral part of a quotient of the maximum allowable area per marker divided by the minimum required size area.

#Sizes = number of sizes given in a considered customer order.

Max(Y_k) = the maximum allowable value of variable Y_k (ply height). This value is given by a model user or planner.

#markers = number of markers used which are varied depending on an amount of total demand. At least, these markers must be able to contain all required garment units.

Finally, from testing run the previously presented model with ILOG-CP, more than 10 hours are needed to prove the optimality even with small- to medium-sized problems. Therefore, a heuristic approach is more appropriated for solving this problem.

3.2 Solution approach

In this Section, the key concepts which are used as a framework and guideline for developing the heuristic for a marker planning in a mass customization garment and details of the heuristic are described. This Section is divided into 2 topics which are the key heuristic concepts and the detailed procedure as explained below.

The first concept is an improvement heuristic concept. With this concept, the proposed heuristic will begin with an initial solution and, subsequently, this initial solution will be improved through all later processes. **The second concept** is randomization which is used to escape from a local optimum by randomly generate initial solutions to the heuristic. **The third concept** is to decompose the original marker planning problem into five related sub-problems. The first sub-problem is to generate an initial solution containing minimum number of markers. The second sub-problem, ply height determination, is to reduce excessive ply height of each marker with respect to an excess ratio. The third sub-problem, stack relocation, is to reduce ply height of individual stacks in order to reduce excesses contained in those stacks. The fourth sub-problem, ply height reduction, is to reduce ply height of each marker by two-step method. The first step is to reduce ply height of a selected marker with no consideration of the demand constraint. The second step is to correct a feasibility condition of a solution derived from the first step. The fifth sub-problem, marker pattern randomization, is to randomize marker patterns of all current markers to create a new set of markers. This iterative process is run until the stopping criterion is reached.

3.2.1 The key heuristic concepts

1. Improvement heuristic concept – in general, there are two types of heuristic with respect to their method used for finding solutions: Constructive heuristic and improvement heuristic. Constructive heuristics, take the input data and construct feasible solutions using intuition, clues, and guidelines found in the mathematical model and a specific structure of the problem [10, 36]. Examples of constructive heuristics are Johnson algorithm, Palmer algorithm, and CDS algorithm for flow shop scheduling problem. Improvement heuristics, begin with an existing feasible solution and attempt to change the solution in some manner so that the objective function is improved while feasibility is maintained [10, 36]. Examples of improvement heuristics are GA, SA, and Tabu search.

As explained previously, marker planning is in the class of NP-complete. It is relatively hard to find a good solution or even a feasible solution of large-sized problem in a reasonable computational time. Therefore, an improvement heuristic concept is selected. Furthermore, this concept corresponds with a decomposition concept which decomposes marker planning problem into five sub-problems.

Subsequently, these sub-problems are sequentially improved until the stopping criterion is met.

In this research, initial solutions are solutions to marker planning problem which have minimum number of markers used. These minimum solutions are derived from running the linearized marker planning model in the ILOG C-PLEX solver.

2. Randomization concept – Figure 10 illustrates an example of a marker planning problem search space which is nonlinear integer programming. A large irregular area represents a possible solution region which encloses many feasible regions represented in a form of small irregular units. In each small irregular area (feasible region), there is at least one local optimal point. Moreover, among these feasible regions, there is only one global optimal point addressed in one feasible region.

As explained before, the developed heuristic begins with an initial solution, and subsequently this solution is continuously improved through later processes. If an initial solution is located at point A as depicted in Figure 10, there is a very long distance from point A to the global optimal point. Furthermore, starting at point A often result in getting stuck with a local optimal point. Conversely, if an initial solution is located at point B as depicted in Figure 10, there is a shorter distance from point B to the global optimal point. However, it is very difficult to accurately designate such point as an initial solution. Therefore, in this heuristic, a random concept is applied in a marker pattern randomization process. The purpose of applying this concept is to generate many different initial solutions in order to start the heuristic with various starting points. This concept can help avoid from getting stuck with a local optimal point as stated in [5].

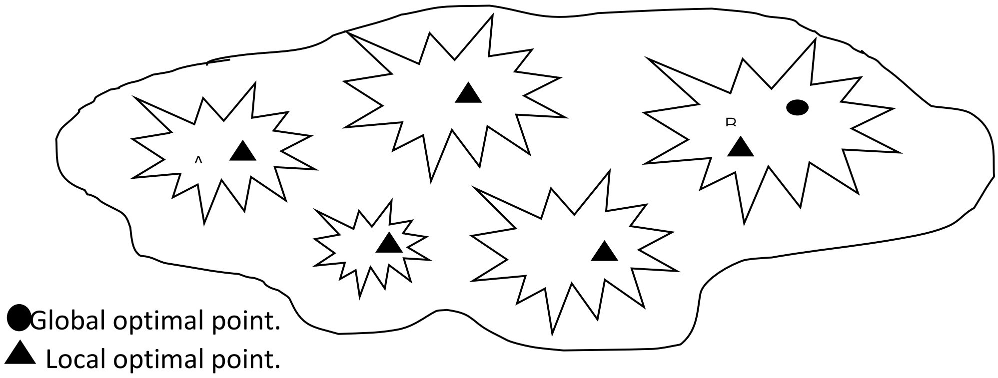

Figure 10 Example of a search space of marker planning problem.

3. Decomposition concept – as explained before, marker planning heuristics which are capable of solving small-sized problems (with the same objective as used in this research) are proposed in [7, 8, 11]. When a situation is shifted to a mass customization, total demand per customer order is surely increased. This higher demand is not only increase number of markers used but also enlarges a solution search space. Consequently, heuristic in [7, 8, 11] cannot efficiently solve these larger size problems. The purpose of using decomposition concept is to simplify the original marker planning problem by decomposing it into many smaller sub-problems which are easier to solve. These sub-problems are varied in size depending on contents of the original problem they contain. Furthermore, each sub-problem is not restricted to hold all of the original problem's constraints. In some sub-problems, one or many hard constraints are relaxed which result in easier-solving problem. However, solutions from these relaxed sub-problems are not feasible for the original problem but they can give some useful information about the better solutions. To successfully decompose, there are two issues that must be concerned as follows.

1. How to decompose – the criterion used is to divide this problem into many sub-problems which each of them corresponds with a major question occurred when improving a solution. An answer to each question is hoped to be a better solution for the original problem. An example of these questions is "Given a marker pattern, what is an appropriate ply height for each marker?". In fact, there are many more questions in improving a solution but from the analysis, these imposed questions are found to

cover most area of a search space. The important assumption behind this concept is that the global or near global optimum is still be able to find after solving all of these sub-problems. All these questions will be stated along with each process in Section 3.2.2.

2. How to maintain the original marker planning problem – the original marker planning problem as represented by the model in Section 3.1.2 composes of three major components

- *Objective function* – the objective is to minimize a total cost which is a combination of set up cost and excess cost.
- *Decision variable* – there are three decision variables which are copies variable, ply height variable, and selection variable. These three variables completely represent a marking plan which is a set of markers.
- *Constraints* – there are six constraints as stated in the model. A solution to marker planning problem is feasible if it satisfies all these constraints.

A solution from the developed heuristic is considered as feasible if it can fulfill the three components stated above. In this heuristic, a final output of each iteration is designed to contain all decision variables which their values satisfy all six constraints. Moreover, in each iteration, an objective value derived from each process is restricted to be equal to or smaller than an objective value of the previous processes. This restriction will force an objective to be continuously improved along the sequence of heuristic processes.

3.2.2 The detailed procedure

In this Section, details of the heuristic designed based on three major concepts explained above are clearly explained. At first, with an improvement heuristic concept, an initial solution is generated by a linearized marker planning model and subsequently used as an input to later processes. With a decomposition concept, the original marker planning problem is decomposed into five related sub-problems as shown in Figure 11 and 12, i.e., initial solution generation, ply height determination, stack relocation, ply height reduction, and marker pattern randomization. Finally, a concept of randomization is applied in the form of the last process (marker pattern randomization). With this concept, a number of initial solutions are randomly generated and re-input to the heuristic in order to avoid getting stuck with a local optimum point.

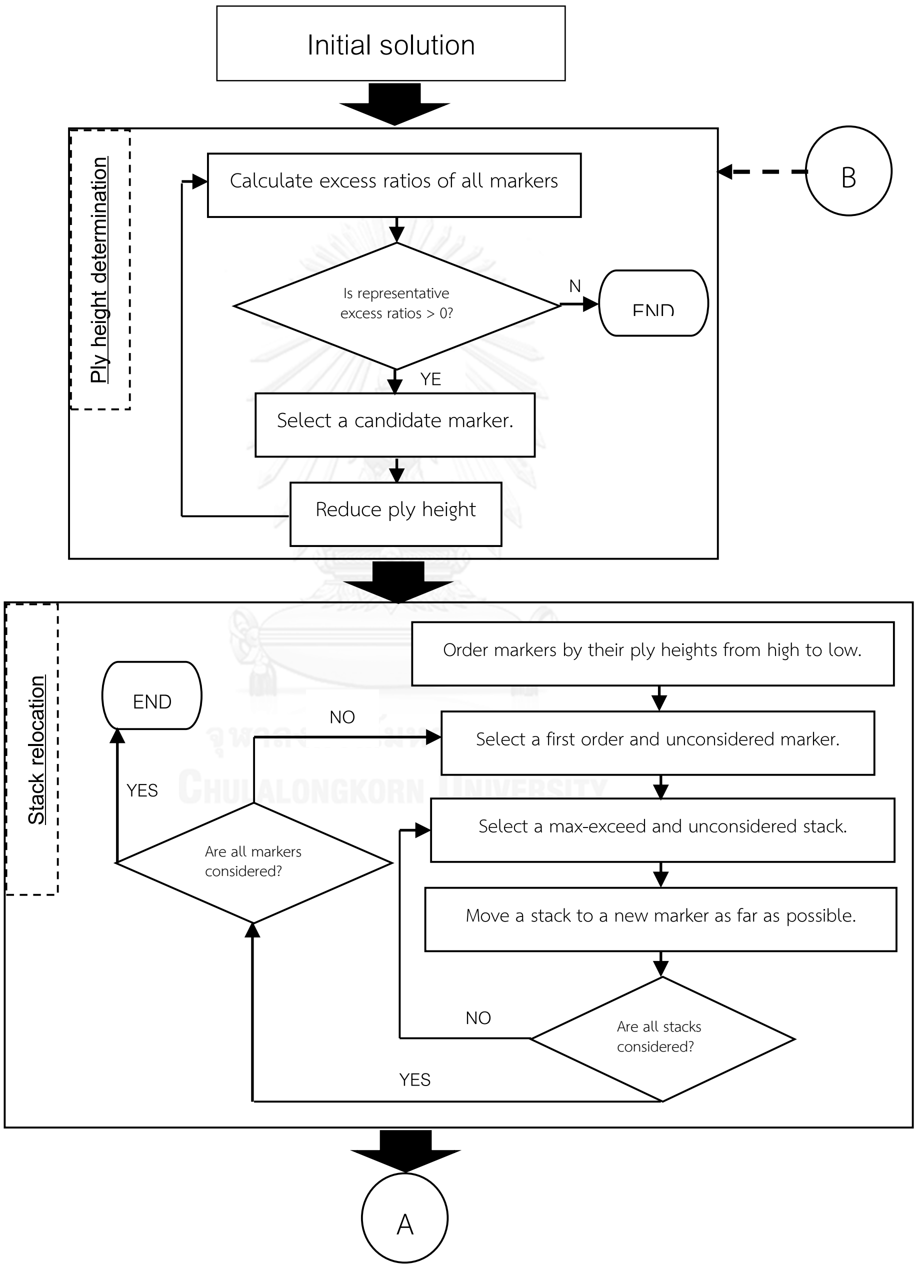

Figure 11 Flow of the proposed heuristic part I.

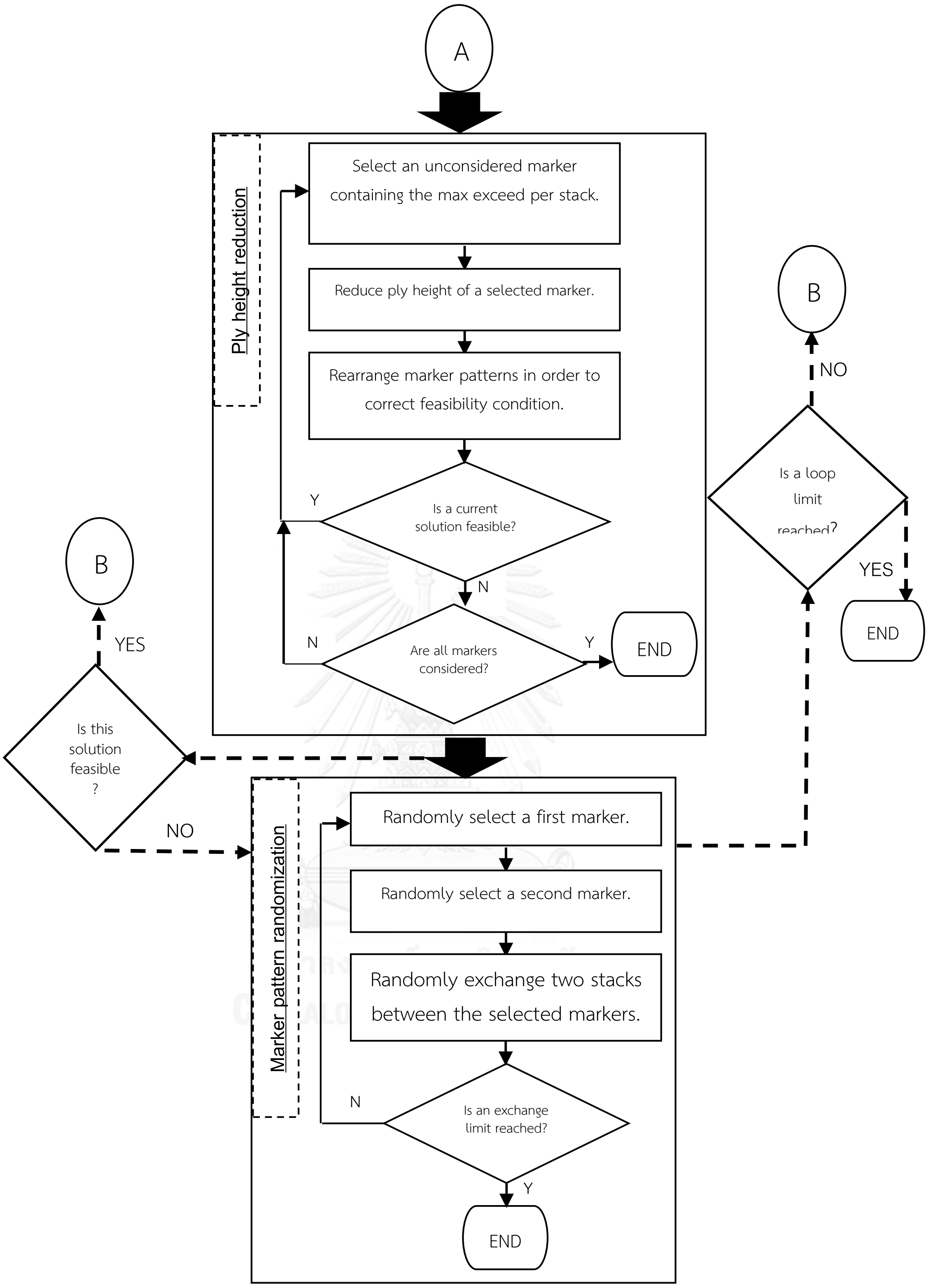

Figure 12 Flow of the proposed heuristic part II.

<u>Step 0</u> **Initial solution generation**

Input; a single color customer order.

Output; a set of feasible markers (a marking plan) which is used as an initial solution. Ply heights of all markers in this set are fixed at the maximum allowable ply height.

Parameter setting;-

Description; this process is used to generate an initial solution which is used as an input to the developed heuristic. Furthermore, this process also answers the question "what is the minimum number of markers used to satisfy a considered customer order?". An initial solution is generated with the linearized marker planning model as shown below. In this model, a set of markers will be created with respect to only set up cost which is represented in the form of number of markers used. Moreover, ply height of all markers are fixed at the maximum allowable ply height which helps eliminate 2 nonlinear terms from the original marker planning model. Subsequently, ILOG C-PLEX is used to solve this linearized model. However, with this model, many unnecessary plies are generated which also result in too many excesses occurred.

<u>Linearized marker planning model</u>

<u>Decision variable</u>

$\mathbf{X_{ik}}$ = integer = number of copies of stencil *i* in marker *k*. This variable is used to answer the question "Which stencil should be assigned to which marker with how many copies?".

$\mathbf{Z_k}$ = binary = selection variable. This variable is used to answer the question "How many markers should be used to satisfy demand?". Its value is very useful when set up cost is in consideration.

<u>Parameter</u>

$\mathbf{a_i}$ = a required area of each stencil *i*.

d_i = a demand quantity of stencil *i*.

L = the maximum allowable area of each marker,

UB and **LB** = the upper and lower allowable ply height.

Y = constant = the maximum allowable ply height.

Objective; minimize[a number of markers used]

$$\mathrm{Min}(\textstyle\sum_k Z_k) \quad (14)$$

$$\textstyle\sum_k (X_{ik} Y) \geq d_i \forall_i \quad (15)$$

$$\textstyle\sum_i (X_{ik} \times a_i) \leq L \times Z_k \forall_k \quad (16)$$

$$Y \geq LB \times Z_k \forall_k \quad (17)$$

$$Y \leq UB \times Z_k \forall_k \quad (18)$$

$$X_{ik} \text{ and } Y \geq 0, Z_k = 0 \text{ or } 1 \quad (19)$$

Eq.14, an objective function which is to minimize set up cost or a number of markers used.**Eq.15**, demand satisfaction constraint, total number of cut stencils must greater than or equal to the demand. **Eq.16**, maximum area limitation, the area used must be less than or equal to the maximum allowable area. **Eq.17 and 18**, maximum and minimum ply height restriction. Ply height of each marker is ranged from the lower allowable to the upper allowable which both correspond with an equipment limitation. **Eq.19**, sign restriction.

<u>Step 1</u> **Ply height determination**

Input; a set of markers from step 0 which all ply heights are equal.

Output; a set of markers with various ply heights.

Parameter setting; -

Description; this process answers the question "How many plies are appropriated for each marker with respect to only excess cost?". The set of markers from previous step contains too many excesses which are resulted from fixing ply height to the maximum value. To reduce these excesses, unnecessary plies should be reduced. An excess ratio which is a quotient of number of excesses and number of stacks of a considered size in a considered marker is used as an indicator in reducing ply height. Moreover, this ratio is calculated by Eq.20. The number of plies of each marker that can be reduced is equal to the integral part of the minimum excess ratio of the considered marker. Furthermore, to maximize number of excesses reduced, these markers are considered in a maximin sequence. This sequence can be explained by 5 steps as explained below.

1. In each marker, calculate excess ratio of each size.

2. Select the minimum excess ratio as a representative excess ratio for each marker.

3. Among all representative excess ratios (from all markers), select the maximum representative excess ratio and a marker that own this ratio as a candidate for reducing ply height.

4. Reduce ply height of the selected marker. A number of plies that can be reduced is equal to an integral part of the selected excess ratio.

5. Repeat step 1-4 until no ply height can be reduced anymore.

To retain feasibility condition, ply height and demand constraints must be maintained. A result of this process is a set of feasible markers which ply heights of all markers are not necessary to be equal. Moreover, a solution from this step is restricted to use only the minimum number of markers.

$$\text{Excess ratio of marker k} = \frac{\text{a number of excesses of a considered size}}{\text{a number of stacks of a considered size}} \tag{20}$$

The procedure of step 1 is shown in Figure 13.

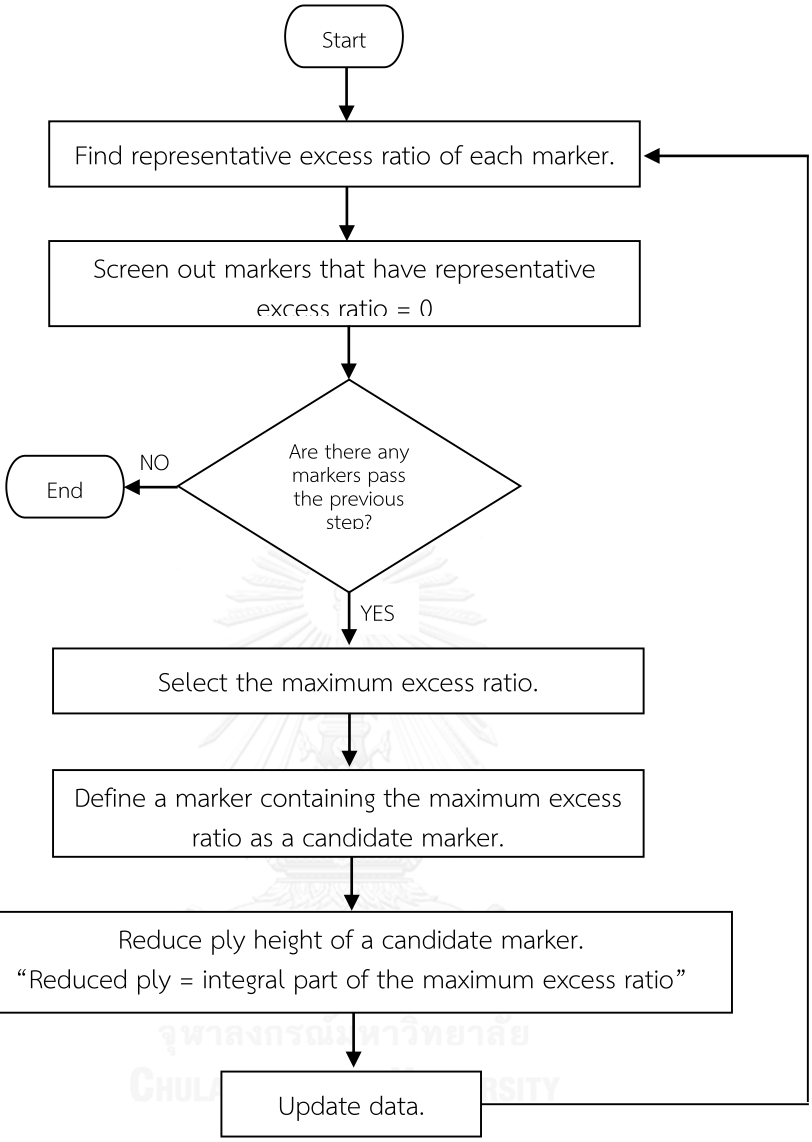

Figure 13 A procedure of ply height determination step.

This procedure starts with an initial solution which is a set of markers from step 0. With this set of markers, excess ratios of all sizes in each marker is calculated. In each marker, choose the maximum excess ratio as a representative excess ratio. Subsequently, screen out markers that have representative excess ratios equal to zero because in these markers, there is no need for improvement with respect to an excess cost. Among the remaining markers, select a marker that has maximum excess ratio. In the selected marker, reduce ply height equal to an integral part of an excess ratio of that marker. This procedure will be run until all markers are considered.

<u>Step 2</u> **Stack relocation**

Input; a set of markers with various ply heights.

Output; a feasible set of markers.

Parameter setting;-

Description; this process answers the question “what is an appropriated marker pattern for each marker”. The key idea of this process is to relocate some selected stacks of stencils to the better matched height markers. This process tries to reduce a gap between marker ply height and actual demand (or actual height) of each stack as shown in Figure 14. The actual demand of each stack is equal to marker ply height minus by number of excesses contained in that stack. Hence, if this gap is reduced, number of excesses will be reduced automatically. Obviously, only stacks of stencils that contain excesses are in consideration of this step. With this concept, only stencils in higher ply markers will be relocated to markers with lower ply by locating them on a remaining area. To retain a feasibility condition, ply height, area, and demand constraints must be maintained in each relocation. This process will be stop if no stack can be relocated with an improvement. A result from this process is a set of feasible markers.

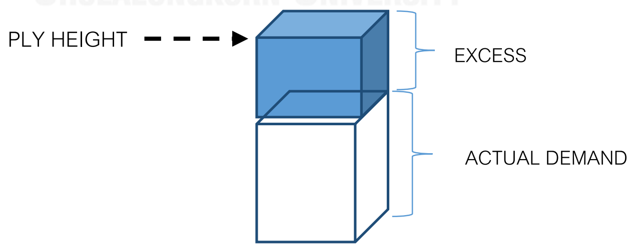

Figure 14 Example of a stack.

As explained previously, in this step, stacks that contain excesses will be moved from higher height markers to lower height markers. So, the first step is to order markers with respect to ply heights from high to low. Before going to the next step, any markers which all of their excess ratios are equal to zero are excluded. Among remaining markers, select a candidate marker which is a first order marker that is still not considered. In a candidate marker, choose a size that is still not considered and contains the maximum number of excesses as a candidate size. The last step is to find an appropriate destination for a candidate size. This appropriate destination marker is defined by these three conditions as stated below.

1. Remaining area of a destination marker ≥ area of a candidate size.
2. Ply height of a destination marker ≥ actual demand of a candidate stack.
3. A gap between an actual demand level of a candidate size and a destination marker ply height is minimum.

This procedure will be run until no stack can be moved with an improvement anymore. The procedure of this step is shown in Figure 15.

<u>Step 3</u> **Ply height reduction**

This process answers two questions which are "if we want to reduce a specific amount of excesses in a specific marker, what is an appropriated marker pattern and how many appropriated ply for that marker?". However, consideration of these two questions simultaneously is very difficult and hard to solve in a reasonable computation time. To simplify the search, this step is divided into two sub-steps which are ply reduction and feasibility correction.

<u>Step 3.1</u> **Ply reduction**

Input; a feasible set of markers.

Output; an infeasible set of markers.

Parameter setting; a number of internal loops controlling a number of times that a feasible solution will continue improving in this process.

Description; in some cases, especially for a nonlinear problem, a path from an initial point to a target point which is a global or a near-global optimum point is very far or impossible if this path is restricted to only a feasible area. Therefore, the algorithm of this step will expand a problem search space of marker planning problem. The old search space is expanded to an infeasible area in hope of finding better solutions or finding the old solution in a shorter computation time.. Nonetheless, these better solutions are usually infeasible and need to be corrected.

At first, in each marker, a reducible excess per stack of each size is calculated. Additionally, it can be calculated by dividing amount of excesses of each size by a number of stacks of that size on a considered marker. Subsequently, calculate reducible excesses of all sizes in all markers. In each marker, choose the maximum reducible excess as a representative value. Finally, a marker with the maximum reducible excesses per stack is selected. In the selected marker, numbers of plies which are equal to the maximum reducible excess per stack are reduced. However, this reduction always results in demand constraint violation which means demands of some sizes are not satisfied. To correct this violation, the second sub-step is applied.

In each marker, calculate a potential reducible ply height which is equal to an integral part of the maximum excess ratio that is still not considered. Among all markers, screen out markers that all sizes on that marker have excess ratios equal to zero. In the set of remaining markers, select a marker having the maximum potential reducible ply height. In the selected marker, reduce ply height equal to a potential reducible ply height. As a result, demands of some sizes are not satisfied which make a solution from this infeasible. This infeasibility will be corrected in the next step.

<u>Step 3.2</u> **Feasibility correction**

Input; an infeasible set of markers.

Output; a feasible set of markers.

Parameter setting; a number of internal loops controlling a number of times that a feasible solution will continue improving in this process.

Description; an input of this step is a set of infeasible markers derived from the previous step. With marker's heights given from the first step, marker patterns are rearranged in order to adjust produced volume. It is relatively straight that a solution is feasible if demand constraint can be satisfied. Therefore, a purpose of marker pattern rearrangement is to increase produced volume of nonsatisfied demand. Moreover, a marker pattern is rearranged by exchanging stacks of any sizes between a marker that ply height is reduced and any markers in a set. However, to correspond with a purpose of this step, stacks of nonsatisfied demand are solely moved to higher ply marker. Each exchanging is feasible, if area and ply height constraints are maintained. This process is run until no stack can be exchanged with an improvement.

The stopping point of this process can be divided into two ways, i.e. 1.all demands are satisfied and 2.some demands are not satisfied. The first case, all demands are satisfied, in this case, produced amount of all sizes are higher than or equal to demand amount. With this stopping, a solution will be fed back to step 1 (ply height determination) in order to further improve because marker patterns of some markers are changed. The second case, some demands are not satisfied, in this case, produced amount of some sizes (often only one size) are lower than demand amount. With this stopping, a solution will be sent forward to the next process to create a new input (a new set of markers).

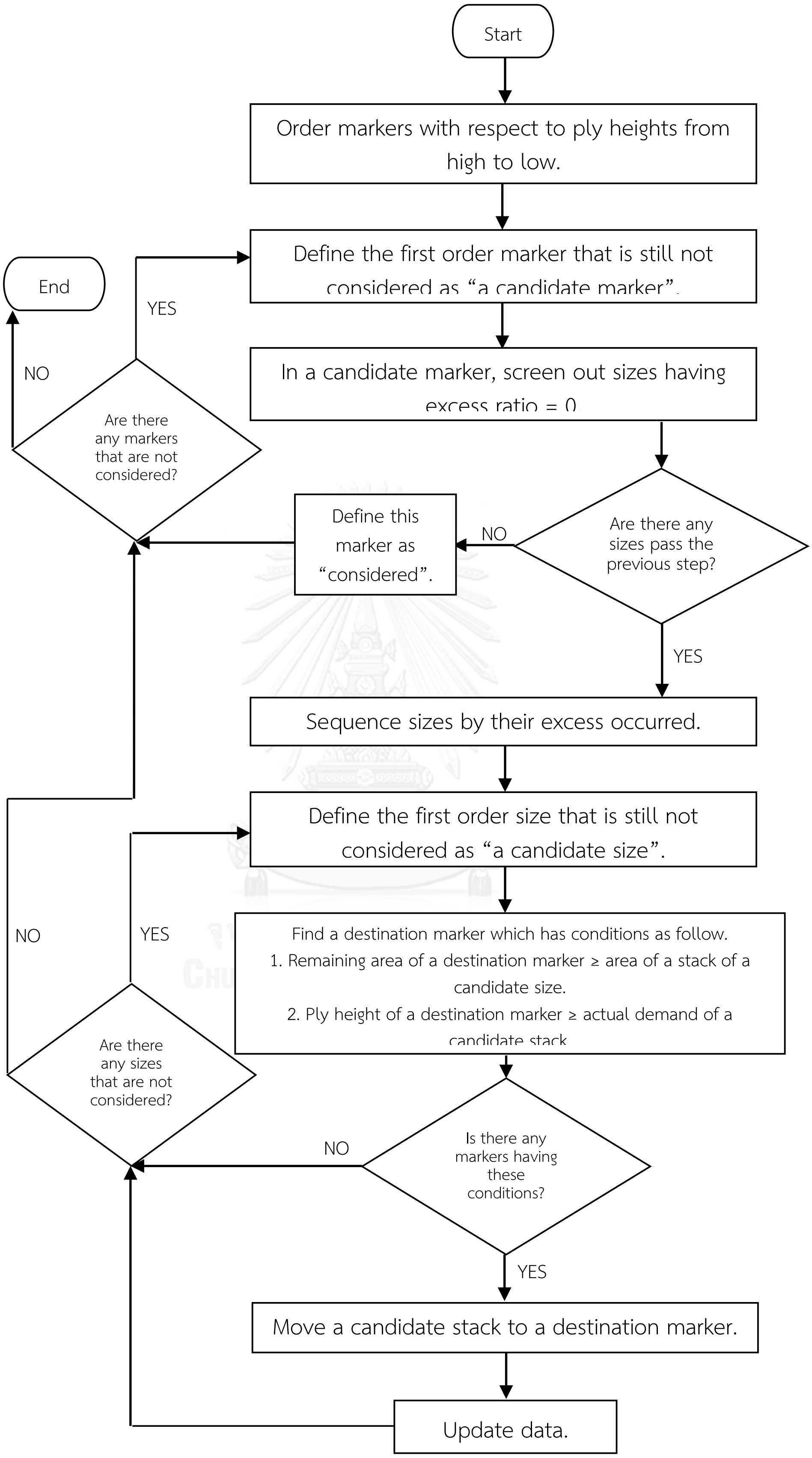

Figure 15 A procedure of stack relocation step.

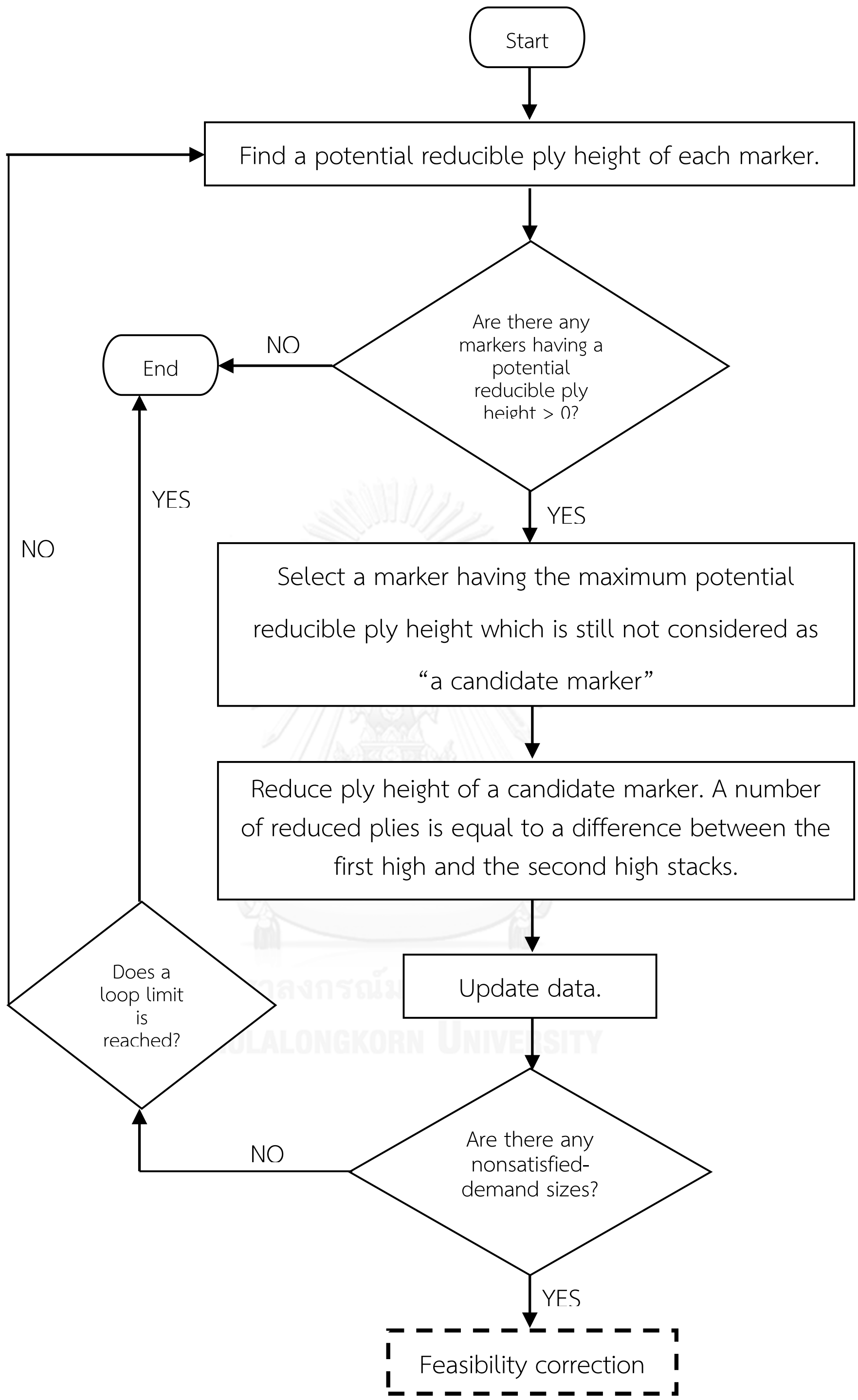

Figure 16 A procedure of step 3.1, ply reduction.

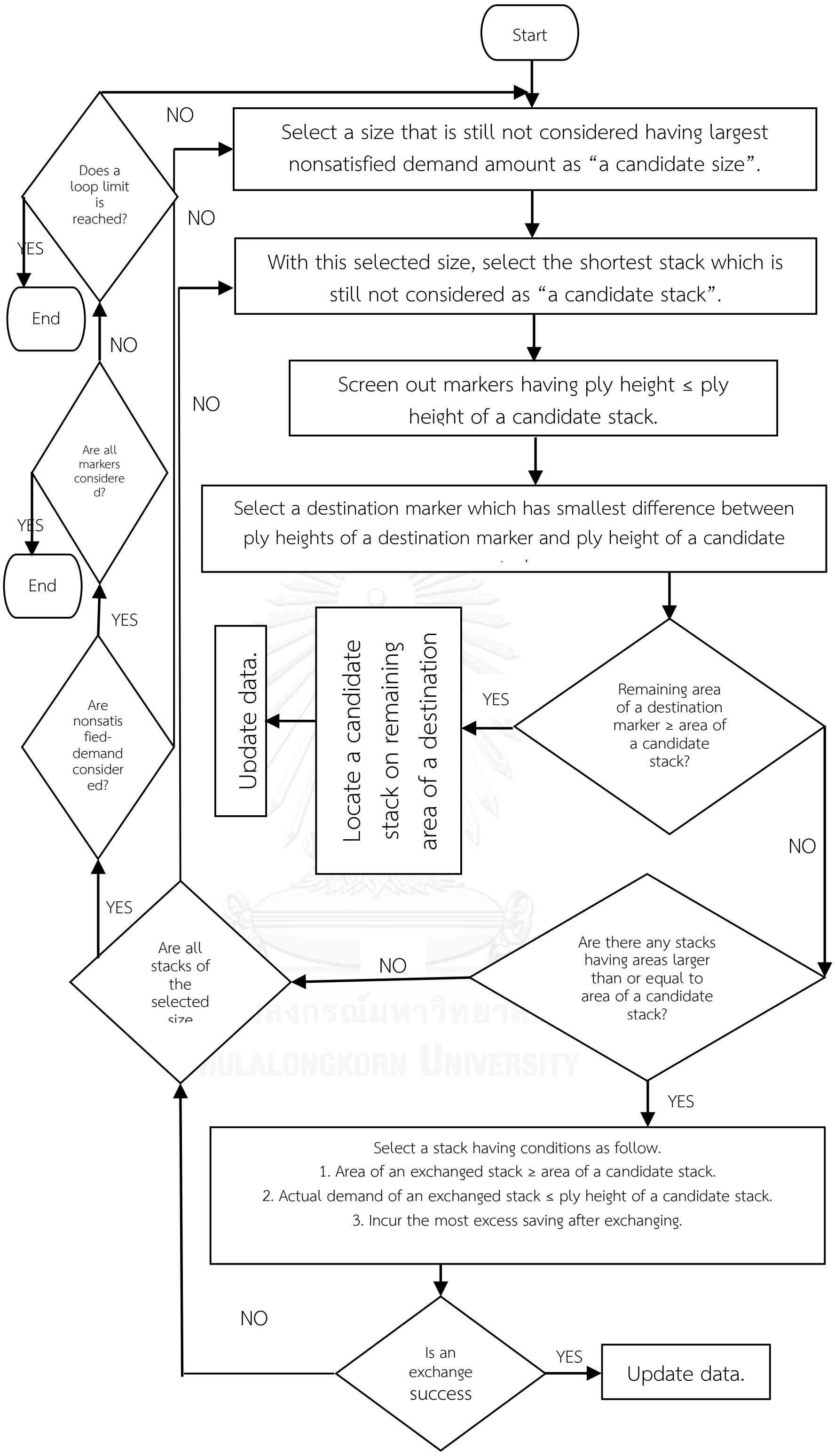

Figure 17 A procedure of step 3.2, feasibility correction.

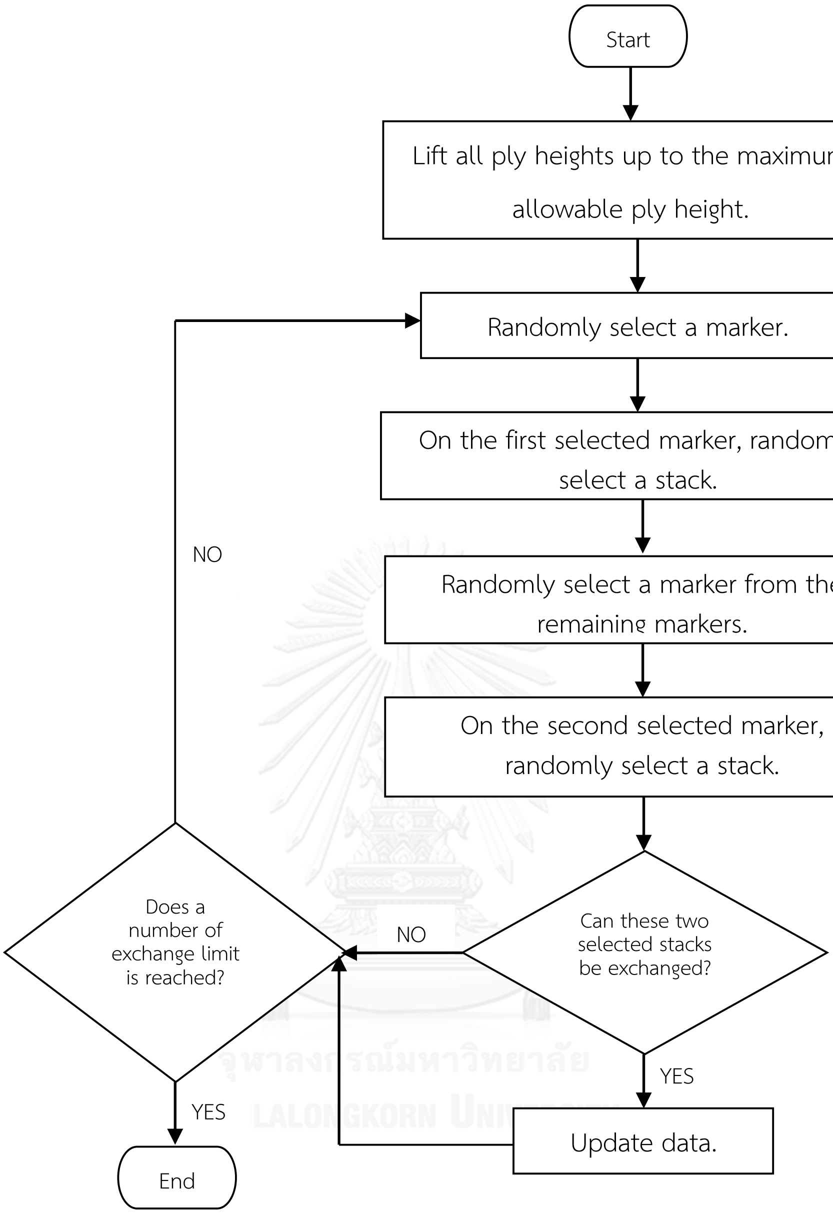

Figure 18 A procedure of marker pattern randomization step.

<u>Step 4</u> **Marker pattern randomization**

Input; a feasible set of markers.

Output; a feasible set of markers with new marker configurations.

Parameter setting; there are two parameters that must be set in this process.

1. An exchange rate, this rate will control a number of couples of stacks that will be exchanged between two selected markers.

2. A number of external loops, this number will control a number of iterations that the developed heuristic will be run from step 0 to step 4.

Description; the purpose of this process is to escape from a local optimum by generating a random and different initial solution for the next iteration. This process is separated into 2 steps which are ply raising and marker pattern perturbation. The first step, ply raising, ply heights of all markers are lifted up to the maximum allowable value. The purpose of this action is to remove ply height differences among all markers in the set. Thus, when these differences are removed, demand constraint can be relaxed from consideration of the next step. A result from the first step is a set of markers which ply height of all markers are equal to the maximum allowable ply height. The second step, marker pattern perturbation, marker patterns are randomly changed with respect to only area constraint. These changes are done by exchanging stacks among markers in a random manner. Furthermore, a number of random exchanging is limited by a given exchange rate.

3.3 Computational experiments

The purpose of this Section is to evaluate performance of the proposed heuristic using various sizes of marker planning problems. To satisfy this purpose, two numerical experiments are conducted. The first experiment, uses one set of test instances from [7, 8], and two sets of problem instances from [11]. In this experiment, the optimal solution and GA solution are used as lower bound. The second experiment uses a set of problem instances which is randomly generated based on major characteristics of mass customization garment. Due to the problem complexity, the optimal solutions cannot be found in reasonable times for this experiment. Therefore, solutions from a modified genetic algorithm1 (MGA1) which is a modification of GA1 proposed in [11] are used to compare with solutions from the developed heuristic. Details of each numerical experiment are presented as follows.

3.3.1 Experiments on small- and medium-sized problems.

The main purpose of this experiment is to verify that the proposed heuristic is able to solve small-and medium- sized problem instances from [7, 8, 11]. As explained previously, a mass customization scenario can be seen as an extension of fashion garment industry presented in [7, 8, 11]. It is reasonable that a marker planning heuristic designed for a mass customization garment should be able to solve smaller size problem occurred in fashion garment. This Section is composed of three experiments which are small-sized problems as shown in Table 16 and 17 of appendix A, and a medium-sized problem as shown in Table 18 of appendix A.

3.3.1.1 Test problem parameters

In this experiment, there are five parameters that affect size and complexity of the problems as shown in Table 6. In this Table, a column experiment shows all three numerical experiments conducted in this Section. Experiment 1-1 is an experiment on small-sized problem instance set 1 while experiment 1-2 is an experiment on small-sized problem instances set 2. Experiment 1-3 is an experiment on medium-sized problem instances. All demand data of these test problem instances are shown in appendix A. Additionally, columns 1, 2, 3, 4, and 5 are used to represent five parameters as stated below.

1. A number of sizes in each customer order.
2. A maximum allowable number of stacks per marker.
3. An amount of total demand per customer order.
4. The minimum allowable ply height per marker.
5. The maximum allowable ply height per marker.

Table 6 Test problem parameters of small-and medium-sized problems.

Experiment	1	2	3	4	5
1-1	5	4	200-400	1	35
1-2	4 or 6	3 or 5	40-880	1	10, 50
1-3	13-20	3-7	200-600	1	20, 25, 30

Experiment 1-1 and 1-2 are classified into small-sized problems with respect to a number of sizes per customer order and an amount of total demand per customer order. Although amount of total demand of some customer orders in experiment 1-2 are higher than or equal to demand amount in experiment 1-3, a number of sizes are obviously different. This difference in number of sizes seriously affect complexity of a problem. As a result, problem instances in experiment 1-3 are classified as medium-sized problem with respect to both number of sizes and amount of total demand per customer order. The demand data of all these problems are shown in appendix A.

3.3.1.2 Computational results

In this Section, computational results of small-and medium-sized problems are summarized and discussed.

Experiment 1-1

These 12 instances are solved to optimum by a mathematical method in [7, 8]. It can be seen that all solutions from the proposed heuristic which are shown in column Heuristic are able to reach to optimum of both number for markers and number of excesses.

Table 7 Results of experiment on small-sized problem instance set 1.

Case	Number of markers				Number of excesses			
	Optimal	GA1	GA2	Heuristic	Optimal	GA1	GA2	Heuristic
a	3	*3*	*3*	3	1	*1*	*1*	1
b	3	*3*	*3*	3	3	*3*	*3*	3
c	3	*3*	*3*	3	1	*1*	*1*	1
d	3	*3*	*3*	3	1	*1*	*1*	1
e	3	*3*	*3*	3	3	*3*	*3*	3
f	3	*3*	*3*	3	2	*2*	*2*	2
g	3	*3*	*3*	3	1	*1*	*1*	1
h	3	*3*	*3*	3	0	*0*	*0*	0
i	3	*3*	*3*	3	4	*4*	*4*	4
j	3	*3*	*3*	3	9	*9*	*9*	9
k	3	*3*	*3*	3	1	*1*	3	1
l	3	*3*	*3*	3	2	*2*	*2*	2

In column GA1 and GA2 of Table 7, solutions from genetic algorithm1 (GA1) and genetic algorithm2 (GA2) proposed in [11] are presented. With respect to number of markers, solutions from the heuristic are equal to solutions from GA1 and GA2 in all problem instances. Moreover, these solutions are able to reach to optimum in all instances. With respect to number of excesses, it is obvious that all solutions from the proposed heuristic shown in column Heuristic are equal to solutions from GA1 and GA2 except an instance k that a heuristic solution is better than a solution from GA2.

Experiment 1-2

These 22 instances can be solved to optimum as shown in Table 8. It can be seen that all solutions from the proposed heuristic shown in column heuristic are able to reach to optimum of both number of markers and number of excesses.

In Table 8, solutions from genetic algorithm1 (GA1) and genetic algorithm2 (GA2) proposed in [11] are presented. With respect to number of markers, solutions from the heuristic are equal to solutions from GA1 and GA2 in all problem instances. Moreover, these solutions are able to reach to optimum in all instances. With respect to number of excesses, it is apparent that all solutions from the heuristic shown in column Heuristic are equal to solutions from GA1 and GA2 except instance o, p, and x that solutions from the heuristic are better than solutions from GA2 as stated in Table 8.

Table 8 Results of experiment on small-sized problem instances set 2.

	Number of markers				Number of excesses			
Case	Optimal	GA1	GA2	Heuristic	Optimal	GA1	GA2	Heuristic
a	2	2	2	2	5	5	5	5
b	2	2	2	2	8	8	8	8
c	2	2	2	2	17	17	17	17
d	2	2	2	2	31	31	31	31
e	2	2	2	2	3	3	3	3
f	2	2	2	2	4	4	4	4
g	2	2	2	2	10	10	10	10
h	2	2	2	2	27	27	27	27
i	3	3	3	3	1	1	1	1
j	3	3	3	3	1	1	1	1
k	3	3	3	3	2	2	2	2
l	3	3	3	3	9	9	9	9
m	3	3	3	3	0	0	0	0
n	3	3	3	3	0	0	0	0
o	3	3	3	3	0	0	1	0
p	3	3	3	3	1	1	3	1
q	4	4	4	4	0	0	0	0
r	4	4	4	4	0	0	0	0
s	4	4	4	4	0	0	0	0
u	4	4	4	4	0	0	0	0
v	4	4	4	4	5	5	5	5
x	4	4	4	4	0	0	5	0

Experiment 1-3

In this experiment, with respect to number of excesses, these eight instances are unable to solve to optimum because of high complexity. However, J. Martens [11] used some methods to estimate the upper bounds on the optimal solutions for these instances except for case 10 which he can estimated the exact optimal solution. However, with respect to number of markers, the optimum numbers of markers of these eight instances are found. These upper bounds are listed in column Optimal in Table 9.

Table 9 Results of experiment on medium-sized problem instances.

Case	Number of markers				Number of excesses			
	Optimal	GA1	GA2	Heuristic	Optimal	GA1	GA2	Heuristic
8	**5**	*5*	*5*	**5**	<=2	**4**	8	6
10	**5**	*5*	*5*	**5**	0	4	5	**0**
14	**6**	*6*	*6*	**6**	<=2	5	9	**4**
15	**7**	*7*	*7*	**7**	<=7	**8**	10	**8**
17	**5**	*5*	*5*	**5**	<=10	11	14	**9**
18	**6**	*6*	*6*	**6**	<=5	**8**	13	**8**
19	**6**	*6*	*6*	**6**	<=5	**7**	15	9
20	**5**	*5*	*5*	**5**	<=19	27	41	**18**

In column GA1 and GA2 of Table 9, solutions from genetic algorithm1 (GA1) and genetic algorithm2 (GA2) proposed in [11] are presented. With respect to number of markers, the heuristic, GA1, and GA2 are able to reach to optimum in all problem instances. With respect to number of excesses, it is obvious that the heuristic is superior to GA2 in all instances. Compare to GA1, four solutions are better than, two solutions are equal to, and two solutions are slightly worse than solutions from GA1. Therefore, it can be concluded that the developed heuristic can perform better than both GA1 and GA2. Especially for GA2, the developed heuristic can perform absolutely better for all problem instances.

3.3.2 Experiment on large-sized problems

The main purpose of this experiment is to evaluate performance of the developed heuristic in solving large-sized marker planning problem which is the emphasis of this paper. Furthermore, to correspond with a structure of the heuristic, a performance is divided into two aspects, i.e., a computational time in terms of number of runs until the best solution is found and quality of a solution. Problem instances in this experiment as shown in appendix B are generated based on key characteristics of a mass customization garment as stated below.

1. A number of sizes per customer order are high

2. A demand pattern is smoother than a demand pattern in fashion garment.

3. Total demand per customer order is larger than total demand in fashion garment.

3.3.2.1 Test problem parameters

In this experiment, there are also five parameters that affect size and complexity of the problems as stated below.

1. A number of sizes in each customer order is equal to 10 sizes.
2. A maximum allowable number of stacks per marker is between 4-5 stacks.
3. An amount of total demand per customer order is between 1,100-2,700 units.
4. The minimum allowable ply height per marker is equal to 1 ply.
5. The maximum allowable ply height per marker is equal to 40 plies.

The aim of this experiment is on solving large-sized problems which is classified with respect to their sizes and amount of total demand per customer order. Demand data of these problems are shown in appendix A.

Unfortunately, the optimal solutions of these instances are difficult to be determined in reasonable computational times. Hence, GA1 from [11] which is designed for only equal area problem is modified in order to be able to solve unequal area problem. This modified GA1 which is called MGA1 will be used to compare with the proposed heuristic. The compared results are used as an indicator in evaluating the performance of the proposed heuristic.

To evaluate performance of the heuristic, for each problem instance, the best solutions from the heuristic and MGA1 are compared. These best solutions are derived from performing 60 independent runs of each method. After performing these 60 runs, the best solution and a number of runs that this solution is found are collected.

3.3.2.2 Computational results

In this Section, compared results between the proposed heuristic and MGA1 are shown and discussed. The solutions from heuristic and MGA1 are compared with respect to two aspects. Firstly, a computational time which is represented in terms of a number of runs until the best solution is found. Secondly, a quality of solutions, the best solutions of each problem instance from both methods are compared (column Best solution in Table 10). The compared results with respect to a quality of solutions are shown in Table 10.

Table 10 Results of experiment on large-sized problem instances.

Case	Best solution				Case	Best solution				Case	Best solution			
	Marker		Excess			Marker		Excess			Marker		Excess	
	H	MGA1	H	MGA1		H	MGA1	H	MGA1		H	MGA1	H	MGA1
1	10	10	0	2	**13**	12	12	0	5	**25**	12	12	4	8
2	11	11	3	1	**14**	13	13	0	1	**26**	14	14	1	3
3	12	12	3	6	**15**	16	16	0	2	**27**	12	12	3	6
4	13	13	0	0	**16**	12	12	4	8	**28**	11	11	4	5
5	13	13	2	4	**17**	14	14	5	6	**29**	12	12	8	10
6	14	14	0	2	**18**	12	12	2	6	**30**	13	13	1	7
7	16	16	1	1	**19**	14	14	1	1	**31**	12	12	3	4
8	17	17	2	5	**20**	16	16	1	2	**32**	16	16	4	8
9	17	17	4	4	**21**	16	16	2	3	**33**	13	13	0	1
10	18	18	2	2	**22**	16	16	1	2	**34**	12	12	4	21
11	16	16	0	2	**23**	17	17	0	1	**35**	11	11	1	2
12	12	12	5	9	**24**	17	17	1	2					

From Table 10, with respect to a number of excesses, the best solutions of the heuristic are better than the best solutions of MGA1 in 30 problem instances which are equal to 86% whereas the best heuristic solutions are equal to MGA1 best solutions in 5 problem instances which are equal to 14%. Obviously, it can be concluded that the proposed heuristic can perform superior than MGA1 in most of problem instances. Furthermore, with respect to a number of markers used, the two methods can perform equally in all problem instances.

However, it can be observed from the experiment that in some problem instances, MGA1 can perform or equal to the proposed heuristic. The reason of this phenomenon is related with characteristics of the problem. From the experiment, it can be concluded that the heuristic can perform well when an amount of demand area together with a degree of smoothness are high. These two parameters are briefly described as follows.

1. An amount of demand area – this area is an actual required fabric area per customer order which is equal to total number of demand units multiply by their required areas. When an amount of this area is large, it means that an amount of remaining area is small which directly affect an ability to exchange stacks of the proposed heuristic. Apparently, when an amount of remaining area is small, a number of possible solutions tend to be low which can shorten a computation time or help the proposed heuristic find a better solution with the same computation time.

2. A degree of smoothness – this parameter is used to present a fluctuation of demand among required sizes. It shows how large of a degree of smoothness of a considered customer order. As explained previously, customer demands in a mass customization garment which are an emphasis of this research are usually smoother than customer demands in fashion garment. When this degree is high, it means that differences of demands between sizes in a customer order are low. Moreover, when this degree is high, an actual demand of each stack tend to be equal which make the problem more easier to improve with respect to an excess unit occurred.

The compared results with respect to a number of runs until the best solution is found are summarized as shown in Figure 19.

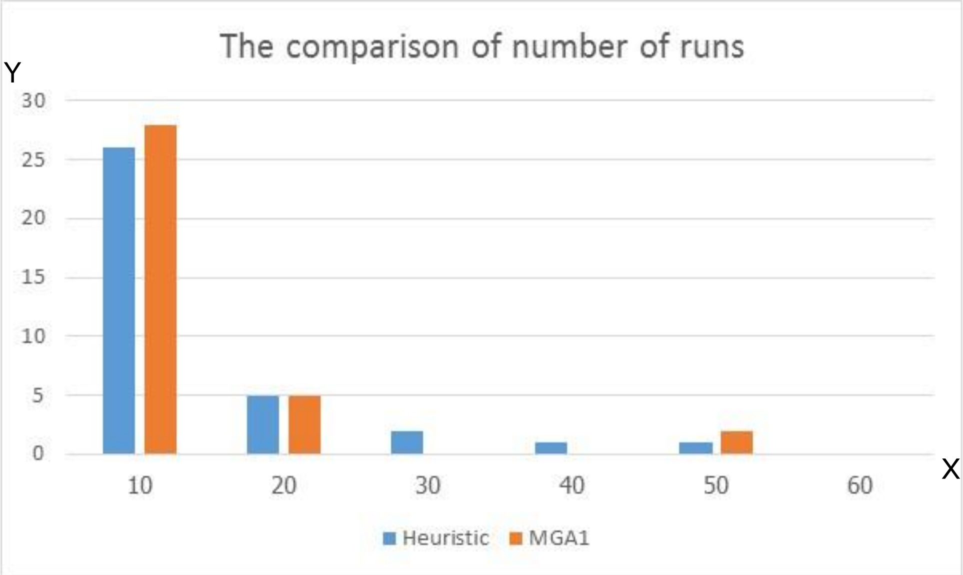

Figure 19 A summary of compared results with respect to a number of runs.

In Figure 19, a horizontal axis (X axis) represents a number of runs until the best solutions are found whereas a vertical axis (Y axis) represents a number of problem instances. Almost best solutions are found in the first 10 runs. Thus, it can be concluded that two methods can perform equally with respect to a number of runs until the best solution is found.

3.4 Conclusion

This section focuses on marker planning problem in which areas of different sizes are unequal and an objective function is to minimize set up and excess costs. From literature review, this problem is studied based on fashion industry which has total demand per customer order not exceed 1,000 units. Furthermore, there are two methods applied in literature, i.e., mathematical method and GA, which are tested to solve only small-and medium-sized problems. Conversely, this research interests on marker planning problem occurred in mass customization garments which usually produce high value products and, additionally, their total demands per customer order are higher than in fashion garments whereas their demand patterns are smoother. Nevertheless, their required sizes per customer order are still high.

Thus in this Section, a heuristic is constructed for marker planning problem with unequal area stencils occurred in mass customization garment. This heuristic is designed based on three major concepts, i.e., improvement heuristic concept, decomposition concept, and randomization concept. With an improvement heuristic concept, an initial solution is generated by a linearized marker planning model and subsequently used as an input to the next process. With a decomposition concept, the original marker planning problem is decomposed into five related sub-problems, i.e., initial solution generation, ply height determination, stack relocation, ply height reduction, and marker pattern randomization. All these sub-problems are solved consecutively until a given stopping criterion is met. Finally, a concept of randomization is applied in the form of the last process (marker pattern randomization). With this concept, a number of initial solutions are randomly generated and re-input to the heuristic in order to avoid getting stuck with a local optimum point.

To evaluate performance of this heuristic, two types of experiment are conducted. The first type is to verify that the proposed heuristic is able to solve small- and medium-sized problem instances from [7, 8, 11]. Moreover, in this type of experiment, two sets of small-sized and one set of medium-sized problem instances are tested. The second experiment is to evaluate performance of the proposed heuristic in solving large-sized marker planning problems which are often occurred in a mass customization garments. In this experiment, a set of test problem instances are generated based on key characteristics of a mass customization garment.

The numerical results show that the proposed heuristic can reach to the optimal solutions for all small instances. For medium instances, the heuristic can reach to the optimal solutions in 3 out of 8 instances. Compare to GA1 and GA2, the heuristic can perform equally as GA1 but superior to GA2 in most instances. In the experiment, the optimal solutions are unknown because of high complexity. Therefore, solutions from a modification of GA1 [11] (MGA1) is used to compare with solutions from the proposed heuristic. In summary, the heuristic can perform superior to MGA1 in 30 out of 35 problem instances while the solutions are equal in 5 problem instances.

From the experiment, it can be observed that in some problem instances, MGA1 can perform equal to the proposed heuristic. The reason of this phenomenon is related with characteristics of the problem. From the experiment, it can be concluded that the heuristic can perform well when an amount of demand area together with a degree of smoothness are high. These two parameters are briefly described as follows.

1. An amount of demand area – this area is an actual required fabric area per customer order which is equal to total number of demand units multiply by their required areas. When an amount of this area is large, it means that an amount of remaining area is small which directly affect an ability to exchange stacks of the proposed heuristic. Apparently, when an amount of remaining area is small, a number of possible solutions tend to be low which can shorten a computation time or help the proposed heuristic find a better solution with the same computation time.

2. A degree of smoothness – this parameter is used to present a fluctuation of demand among required sizes. It shows how large of a degree of smoothness of a considered customer order. As explained previously, customer demands in a mass customization garment which are an emphasis of this research are usually smoother than customer demands in fashion garment. When this degree is high, it means that differences of demands between sizes in a customer order are low. Moreover, when this degree is high, an actual demand of each stack tend to be equal which make the problem more easier to improve with respect to an excess unit occurred.

Additionally, the reason why the heuristic can perform well with large-sized problems is related with a decomposition concept which is a key concept of the heuristic. A decomposition concept which decomposes the original marker planning problem into many related sub-problems helps reduce an original search space to only a set of important search areas. These search areas are hoped to contain good or even the best solutions. Subsequently, the heuristic will search through only these important areas of a search space. As a result, the proposed heuristic is able to find good solutions in reasonable times.

Finally, future researches should emphasize on the integration between marker planning process and other relevant processes. The integration can be done with either previously processes, e.g., product design, purchasing, etc., or later processes, e.g., marker making, sewing, etc. Moreover, the levels of integration are relatively varied depending on planner’s decisions. For example, in some cases, only data from other relevant processes are included whereas, in some cases, marker planning is combined with other processes to form a new larger problem that can cover a wider range of production decision. In case of time information, e.g. due date, production start date, from downstream processes are included into marker planning process, a single objective function will become a multi-objective function.

Chapter 4
A marker planning problem with consideration of a sewing schedule in a mass customization production

In this Section, a marker planning problem in a context of a mass customization production strategy presented in Section 3 is further studied. The emphasis is on improving an existing marking plan with respect to a work-in–process inventory workload. This workload is incurred when stencils or parts from a cutting process are arrived at a sub-assembly and assembly line before their due dates. Details of this Section are separated into four topics, i.e., Problem statement, solution approach, computational experiments, and conclusion which are explained as follows.

4.1 Problem statement

4.1.1 Problem description

As explained in the introduction Section, this thesis focuses on a marker planning problem in a context of mass customization production strategy. The previous Section proposes a marker planning heuristic corresponding with using this production strategy. Moreover, from computational experiments, it is obvious that a proposed marker planning heuristic can perform well in variety of problem instances. However, to successfully apply this flexible production strategy, garment manufacturers should adjust their production lines in a way that non-value added workloads are reduced. The purpose is to increase a flexibility of their production lines in order to agree with a mass customization strategy. This reduction in a non-value added workload is similar to a lean manufacturing concept which is currently popular in garment industry [16, 20, 22, 24, 25, 27-29].

In this research, a work-in-process inventory is seen as an apparent non-value added workload that should be eliminated first. The occurrence of a work-in-process inventory and a disadvantage are explained as follows.

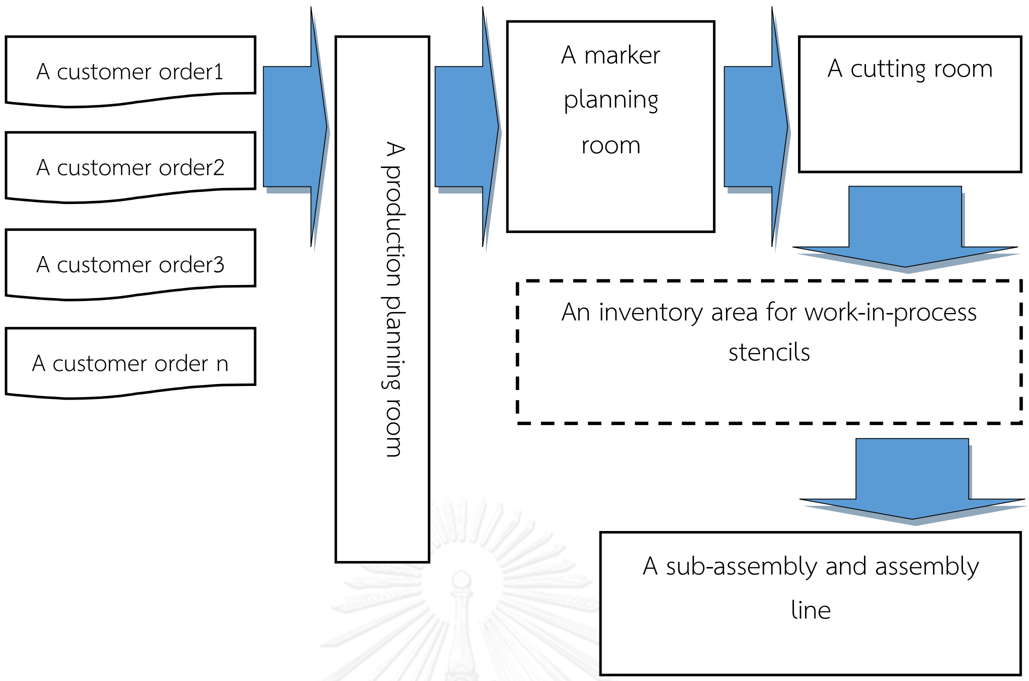

Figure 20 A configuration of an interested production line.

Figure 20 shows a configuration of an interested production line. In this line, there are three major processes located consecutively which are a marker planning, a cutting, and a sub-assembly and assembly process. Furthermore, in this configuration, all customer orders are assumed to use a common production line. At first, a received customer order is transformed into a sewing schedule which shows a sequence of sizes that will be assembled in a sub-assembly and assembly process. A sewing schedule together with a customer order detail will be continuously operated from a marker planning process to a sub-assembly and assembly process. In front of a sub-assembly and assembly process, there is a large inventory area used to keep work-in-process parts or stencils derived from a cutting process. This inventory is caused from an arrival of stencils to a sub-assembly and assembly process before their time of use. These stencils are kept in this area until their assembly times which will be called “due date” from now on. However, to maintain a sewing schedule, stencils from cutting process are restricted to arrive at a sub-assembly and assembly line before or at least on their time of use. From Figure 20, it is obvious that this work-in-process inventory is increased proportional to two major parameters Firstly, a number of customer orders, an amount of work-in-process inventory tend to be higher when facing a large number of customer orders with different due dates. Secondly, a marker pattern which is a combination of sizes lied on a top of each marker. As stated before, a function of marker is to use as a cutting template in a cutting process. Apparently, a different marker pattern can result in a difference set of stencils arriving at an inventory area. Therefore, an adjustment in marker patterns can, in some cases, reduce this workload.

To reduce this work-in-process inventory, a sewing schedule in terms of a due date of each size is incorporated into consideration. This due date is used to represent a sewing start date of that size. Hence, stencils arriving at a sewing line on their due dates are incurred no workload while stencils arriving at a sewing line before their due dates are certainly incurred inventory workloads. Moreover, no stencil is permitted to arrive after their due dates because it will directly affect a sewing schedule.

With a sewing schedule incorporated into consideration, there is a time dimension attached to each size addition to an area and a required quantity. Each size will be assigned a different due date which, in this research, these due dates are ranged from 1 to 15 corresponding with 10 sizes in each customer order. Moreover, time unit used for a due date is day. In practice, it means that all sizes are not simultaneously required in a sub-assembly and assembly process. In academic point of view, a due date is viewed as an additional dimension to consider in generating marking plan. Obviously, this additional dimension will make the problem more complicated which is difficult or, even, unable to solve by current methods [2, 3, 7-10, 14, 30, 32, 35].

Moreover, to make the problem more realistic, all required stencil areas are varied depending on size of a product. This variation in stencil area is called “unequal area” in later of this Section. When areas of stencils are unequal, there is an important issue that must be further considered in each marker generating iteration. The order in which stencils are assigned to partial marker is important. Because stencil areas are unequal, e.g. 0.1 m^2, 0.3 m^2, 1 m^2, 1.2 m^2, and etc, stencil of what size selected is directly affected to number of stencils and what sizes that can be selected later.

Obviously, each selection determines feasible combinations of sizes that can be used later.

In improving each marker, a marker pattern which is a combination of required sizes is rearranged with respect to area limitation, demand constraint, ply height constraint, no tardiness constraint, a restriction on a number of markers used, and a restriction on a number of excesses occurred.

The purpose of this Section is to develop a marker planning heuristic used to improve a marking plan derived from a proposed heuristic presented in Section 3. Hence, an input to this heuristic is a marking plan which a number of markers used is minimum and a number of excesses occurred is already improved. The aim of a heuristic is to reduce an amount of work-in-process inventory which is kept in an inventory area in front of a sub-assembly and assembly line.

From literature, there is only one paper concerning these sewing due dates in generating marking plan [34]. However, there are two major differences between a research in [34] and this paper. The first difference is a method used to calculate an inventory workload. In [34], an inventory workload is calculated from a standard deviation (SD.) occurred in each marker while in this paper, this workload is calculated from a difference between the minimum due date of a considered marker and other due dates on the same marker. The second difference is a relation between objective components. In [34], a weighted goal programming concept is applied which let all objective components trade off between each other. In this Section, a lexicographic goal programming concept is used instead. With a lexicographic goal programming, the interested marker planning problem is separated into two levels as described before. The first level composes of a set up and an excess cost while the second level incurs only a work-in-process inventory workload. Therefore, a set up cost and an excess cost in level one will not be traded off with an inventory workload in level two but these two costs are used as constraints in this research.

4.1.2 Mathematical model

There are assumptions and scopes enforced in this research as follows.

<u>Assumption</u>

1. The fabric width is assumed to be constant. Subsequently, the widths of all markers are also constant.

2. The shade of color of all used fabrics is assumed to uniformly distribute along the length of the fabric rolls used.

3. All markers are not allowed to split. This means that every marker must be continuously cut on one cutting table until all garment units in this marker are cut out.

4. To simplify the problem, sub-assembly and assembly processes are assumed to sew only one size per time period.

5. A cutting time per marker is relatively small compare to other operation times in a production chain. Hence, an effect of a cutting time to a sewing schedule is neglected.

6. A cutting and sewing capacity are assumed to be sufficient for all resulted marking plan which means many markers can be able to cut and sew simultaneously.

<u>Scope</u>

1. This thesis focuses only on single-color marker because this type of marker is usually used in the real-world industry. A multi-color marker is rarely used in industry because it is hard for operators to simultaneously manage cut parts of different colors. Moreover, it is very time-consumption to set up spreading machine or equipment for the case of multi-color marker.

2. The demand input of marker planning process is characterized by size only because in current practice, it is easier for manufacturers to manage single-color marker. Moreover, the same product with different color can be individually processed with the same model.

3. This thesis doesn't concern the effect of insertion between smaller parts and larger parts. Therefore, material consumption or area of fabric used is in the form of linear function.

4. This research covers only marker planning problem which is to find the optimum combination of parts or stencils on each marker. The problem of marker

making which is to find the exact position of parts or stencils on each marker is out of scope.

Parameter

a_i = a required area of each stencil *i*,

d_i = a demand quantity of stencil *i*.

L = the maximum allowable area of each marker.

UB and **LB** = the upper and lower allowable ply height.

$Duedate_{[i]}$ = a sewing due date of each size *i*.

EXCESS = a total number of excess units occurred which is a result of the problem presented in Section 3.

Decision variable

X_{ik} = integer = number of copies of stencil *i* in marker *k*. This variable is used to answer the question "Which stencil should be assigned to which marker with how many copies?".

Y_k = integer = number of plies of marker *k*. This variable is used to answer the question "How many fabric plies in each marker?".

M_k = integer = the minimum due date of stencils in marker *k*. This variable is used to answer the question "What is the earliest due date of stencils in this marker?". Its value is important in calculating a work-in-process inventory workload.

HOLDING= integer = this variable is a multiplication of how long and how many units of each size that will be kept in inventory. It is used to represent a workload of operators in taking care of these holding units.

$BINARYPATTERN_{[i][k]}$ = binary =this decision variable is used to display a due date pattern of each marker in the form of binary. This binary pattern shows which due dates appear in a considered marker. A value 1 means a due date is occurred in a marker while a value 0 means a due date is not occurred. This variable is later used in Eq.28 to calculate how long each size will be kept in inventory before sewing in sub-assembly and assembly processes.

DUEDATEPATTERN$_{[i][k]}$ = integer = this decision variable is used to display a due date pattern of each marker in the form of integer. This integer pattern shows, in each marker, how long each size will be kept in inventory. These holding units certainly incur inventory workload which is the objective of this research.

<u>Model</u>

Objective; $\text{minimize[a work} - \text{in} - \text{process inventory workload]}$

$$\text{minimize[(HOLDING)]} \quad (21)$$

<u>Constraint;</u>

$$\sum_k (X_{ik} Y_k) \geq d_i \, \forall_i \quad (22)$$

$$\sum_i (X_{ik} \times a_i) \leq L \;\; \forall_k \quad (23)$$

$$Y_k \geq LB \;\; \forall_k \quad (24)$$

$$Y_k \leq UB \;\; \forall_k \quad (25)$$

$$\sum_i \sum_k \{(X_{ik} Y_k) - d_i\} \leq \text{EXCESS} \quad (26)$$

$$\text{BINARYPATTERN}_{ik} = \frac{X_{ik}}{\max(1, X_{ik})} \forall_i, \forall_k \quad (27)$$

$$\text{DUEDATEPATTERN}_{ik} = (\text{duedate}_i - M_k) \times \text{BINARYPATTERN}_{ik} \forall_i, \forall_k \quad (28)$$

$$\text{HOLDING} = \sum_k \sum_i (\text{DUEDATEPATTERN}_{ik} \times X_{ik} \times Y_k) \quad (29)$$

$$X_{ik}, Y_k, M_k, \text{DUEDATEPATTERN}_{ik}, \text{and HOLDING} \geq 0 \quad (30)$$

Eq.21, the objective function is to minimize a total number of holding units or a work-in-process inventory workload occurred in an inventory area in front of a sub-assembly and assembly line. **Eq.22**, demand satisfaction constraint, total number of cut stencils must greater than or equal to the demand. **Eq.23**, maximum area limitation, an area used in each marker must be less than or equal to the maximum allowable area. **Eq.24 and 25**, maximum and minimum ply height restriction. Ply height of each marker is ranged from the lower allowable to the upper allowable which both correspond with an equipment limitation.**Eq.26**, this equation is used to control total number of excesses which are a quantity of stencils that are produced over the demand. Produced excesses must be less than or equal to a number of total excesses derived from the first level problem (the problem presented in Section 3). **Eq.27**, this equation is used to find a pattern of due dates in the form of binary occurred in each marker. This pattern is calculated by dividing each due date by its value. **Eq.28**, this equation is used to calculate how long each size will be kept in inventory. To correspond with no tardiness constraint and a just-in-time strategy, each marker will be cut on the minimum due date of that marker. Hence, in each marker, how long each size will be kept is equal to its due date subtract by the minimum due date of that marker. **Eq.29**, this equation is used to calculate numbers of units and times each size will be kept. These units and times are equal to **DUEDATEPATTERN**$_{[i][k]}$ variable multiply by a number of copies of a considered size and a number of plies of a considered marker. **Eq.30,** sign restriction.

In this problem, a number of markers used are restricted to the minimum number of markers given from the first level problem. This minimum value is derived from solving a relaxed or linearized marker planning model as explained in the previous Section.

4.2 Solution approach

To develop the heuristic for reducing a work-in-process inventory workload, three major concepts are applied, i.e. an improvement heuristic concept, a decomposition concept, and a concept used especially for reducing a work-in-process inventory workload. The first two concepts are already explained in detail in Section 3. Therefore, only the last concept that is used for reducing a work-in-process inventory workload is completely explained in this Section.

To reduce a work-in-process inventory workload, a marker pattern of each marker should be rearranged in the way that a difference among due dates on each marker is lower. Two key concepts are used as a framework for developing the heuristic. The first concept is to create new marker patterns by rearranging stencils on markers with respect to due date differences. The second concept is to adjust marker patterns by relocating some special-structure stacks to appropriate markers. The details of these two concepts and the developed heuristic are explained as follows.

4.2.1 The key heuristic concepts

1. How to reduce holding cost–as explained previously, a holding cost is incurred when there are many stacks that have different due dates locate on the same marker. Obviously, this holding cost can be reduced by recreating marker patterns composed of stacks of sizes that have the same or close due dates. However, with structure of this research, such marker patterns must be recreated under area, ply height, demand, and excess control constraints. With these constraints, it is very difficult to recreate marker patterns with respect to all these constraints. Therefore, a holding cost improving process will be divided into two steps as described below.

The first step–this step emphasizes on rearranging marker patterns of a set of markers derived from the previous process which is an excess improving process. To rearrange these patterns, considered markers must be subdivided into stacks which each stack represents a set of products of one size. To simplify and facilitate this rearrangement, stacks will be classified into groups with respect to stack heights. Stacks with the same stack height will be placed on the same group. Subsequently, in each group, stacks will be combined into marker patterns concerning only area constraint. This problem is viewed as a one-dimensional bin packing problem (1BPP) or a well-known knapsack problem. An empty marker is seen as a bin whereas a stack is seen as an item that must be assigned to a bin. A limitation of each bin is in the form of an area constraint. Finally, a profit of each bin is presented in terms of saving in holding cost.

The second step–this step emphasizes on fine tuning marker patterns from the first step. A set of markers from the first step will be improved by relocating some special-structure stacks among selected markers. Some special-structure stacks as shown in Figure 21, are stacks containing excess units. These excess units make stacks more flexible to move to other markers which have lower ply heights. The mechanism used to relocate these stacks is to exchange these stacks with other appropriate stacks from other markers. Subsequently, relocation of these special stacks are executed if it can cause saving in holding cost. However, demand, area, ply height, and excess control constraints must be hold in this step.

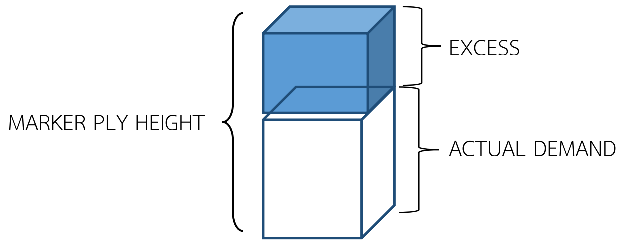

Figure 21 Example of a special-structure stack.

To reduce a search space in the second step, relocation cases occurred are classified into two groups which are an improvement group and a non-improvement group. To classify these cases, a holding cost saving equation (**Eq.30**) is formulated and analyzed.

A holding cost saving equation

At first, to facilitate readers, important terminologies used in this equation are explained as follows.

A candidate marker–in this step, a candidate marker is a marker with higher ply height compare to an exchanged marker. Moreover, a candidate stack must be located on this marker.

A candidate stack – a candidate stack is an unconsidered stack containing the maximum number of exceeds. In this step, this stack will be moved to another marker by exchanging with another appropriate stack.

An exchanged marker–an exchanged marker is a marker with lower ply height compare to a candidate marker. Furthermore, ply height of this marker is ranged between an actual demand of a candidate stack and a ply height of a candidate marker. An exchanged stack must be selected from this marker.

An exchanged stack–an exchanged stack is a stack on an exchanged marker which is the most appropriate for exchanging with a candidate stack. In general, a due date of this stack should be close to an average due date of a candidate marker.

In general, there are four components involved in this saving equation. The first two components are cost saving while the other two components are cost expense. Firstly, selection of a candidate stack, this component is used to represent a cost saving occurring when picking out one stack from a candidate marker. Secondly, selection of an exchanged stack, this component is used to represent a cost saving occurring when picking out one stack from an exchanged marker. Thirdly, locating of a candidate stack, this component is used to represent a cost expense incurring when locating a candidate stack to an exchanged marker. Finally, locating of an exchanged stack, this component is used to represent a cost expense incurring when locating an exchanged stack to a candidate marker so as to complete each exchanging. The relation of these components is stated by Eq.26 as follow.

Indices

c = a candidate stack or marker.

Ex= an exchanged stack or marker.

Nm= a new minimum on a candidate or exchanged marker.

Om= an old minimum on a candidate or exchanged marker.

Variables

HP = integer = ply height of a candidate marker.

LP = integer = ply height of an exchanged marker.

MIN.c = integer = the minimum due date of a candidate marker.

MIN.ex = integer = the minimum due date of an exchanged marker.

D_c= integer = due date of a candidate stack.

D_{ex} = integer = due date of an exchanged stack.

2^{nd}min.c = integer = the second minimum due date of a candidate marker.

2^{nd}min.ex = integer = the second minimum due date of an exchanged marker.

STACK.c = integer = a number of stacks of a candidate marker.

STACK.ex = integer = a number of stacks of an exchanged marker.

$\mathbf{D_{om,c}}$ = integer = the old minimum due date of a candidate marker. This is a before-exchanged due date of a candidate marker.

$\mathbf{D_{nm,c}}$ = integer =the new minimum due date of a candidate marker. This is an after-exchanged due date of a candidate marker.

$\mathbf{D_{om,ex}}$ = integer = the old minimum due date of an exchanged marker. This is a before-exchanged due date of an exchanged marker.

$\mathbf{D_{nm,ex}}$ = integer =the new minimum due date of an exchanged marker. This is an after-exchanged due date of an exchanged marker.

$$\mathrm{HP}\left[\mathrm{STACK.c}\left(\mathrm{D_{nm,c}} - \mathrm{D_{om,c}}\right) + \left(\mathrm{D_c} - \mathrm{D_{om,c}}\right) - \left(\mathrm{D_{ex}} - \mathrm{D_{om,c}}\right)\right] + \mathrm{LP}\left[\mathrm{STACK.ex}\left(\mathrm{D_{nm,ex}} - \mathrm{D_{om,ex}}\right) + \left(\mathrm{D_{ex}} - \mathrm{D_{om,ex}}\right) - \left(\mathrm{D_c} - \mathrm{D_{om,ex}}\right)\right] \quad (31)$$

This equation is a generalized version of a holding cost saving equation. This equation can be divided into two parts, i.e., a first part is used to represent exchanging operation on a candidate marker and a second part is used to represent exchanging operation on an exchanged marker. Moreover, each part comprises of three components which are orderly described as follows.

<u>A first component</u>

$$\mathrm{STACK.c}\left(\mathrm{D_{nm,c}} - \mathrm{D_{om,c}}\right) \text{ and } \mathrm{STACK.ex}\left(\mathrm{D_{nm,ex}} - \mathrm{D_{om,ex}}\right)$$

This component is used to calculate a cost saving or a cost expense incurred when the minimum due dates of a candidate marker and/or an exchanged marker are changed. When the minimum due date of a marker is changed, an effect is distributed to all other stacks on the same marker. Therefore, a number of stacks of a considered marker must be included in this component.

<u>A second component</u>

$$\left(\mathrm{D_c} - \mathrm{D_{om,c}}\right) \text{ and } \left(\mathrm{D_{ex}} - \mathrm{D_{om,ex}}\right)$$

This component is used to calculate a cost saving incurred when one stack (due date of this stack is not the minimum due date of a considered marker) is picked out from a candidate and an exchanged markers. Apparently, this component always contributes a saving in holding cost to an objective function.

A third component

$$(\mathrm{D_{ex}} - \mathrm{D_{om,c}}) \text{ and } (\mathrm{D_c} - \mathrm{D_{om,ex}})$$

This component is used to calculate a cost expense incurred when one stack (a due date of this stack is not the minimum due date of a considered marker) is located on a candidate and an exchanged markers. Obviously, this component always contributes an expense of holding cost to an objective function.

From this equation, there are nine cases that can be occurred with respect to a number of minimum-due date stacks in both a candidate and exchanged marker, a comparison between the minimum due date of a candidate marker and an exchanged marker, a second minimum due date of a candidate marker, a number of stacks on both markers, a due date of a candidate stack, and a due date of an exchanged stack. To simplify the search and to reduce a computation time, these nine cases are analyzed. The result of an analysis shows that there are 3 promising cases as stated below.

Case 1

Scenario: **HP** > **LP**, $\mathbf{D_c} \neq \mathbf{MIN._c}$, and $\mathbf{D_{ex}} \neq \mathbf{MIN._{ex}}$.

Improvement condition: $\mathbf{D_c} > \mathbf{D_{ex}}$ [always improve if a due date of a candidate stack ($\mathbf{D_c}$) is greater than a due date of an exchanged stack ($\mathbf{D_{ex}}$)].

Case 2

Scenario: **HP** > **LP**, $\mathbf{MIN._c} > \mathbf{MIN._{ex}}$, $D_c = MIN._c$, $D_{ex} > 2^{nd}MIN._c > MIN._c$, and there is only one minimum-due date stack on a candidate marker.

Improvement condition: improve if the equation shown below is satisfied.

$$\frac{(HP \times STACK.c) \times (2^{nd}\, MIN.c \times MIN.c)}{(HP - LP)(D_{ex} - MIN.c)} > 1$$

Case 3

Scenario: **HP** > **LP**, $\mathbf{MIN._c} > \mathbf{MIN._{ex}}$, $D_c = MIN._c$, $2^{nd}MIN._c > D_{ex} > MIN._c$, and there is only one minimum-due date stack on a candidate marker.

Improvement condition: always improve.

4.2.2 The detailed procedure

The proposed heuristic is used to reduce a work-in-process inventory occurred in an initial marking plan which is a result of a heuristic presented in Section 3. A flow of the heuristic is shown in Figure 22.

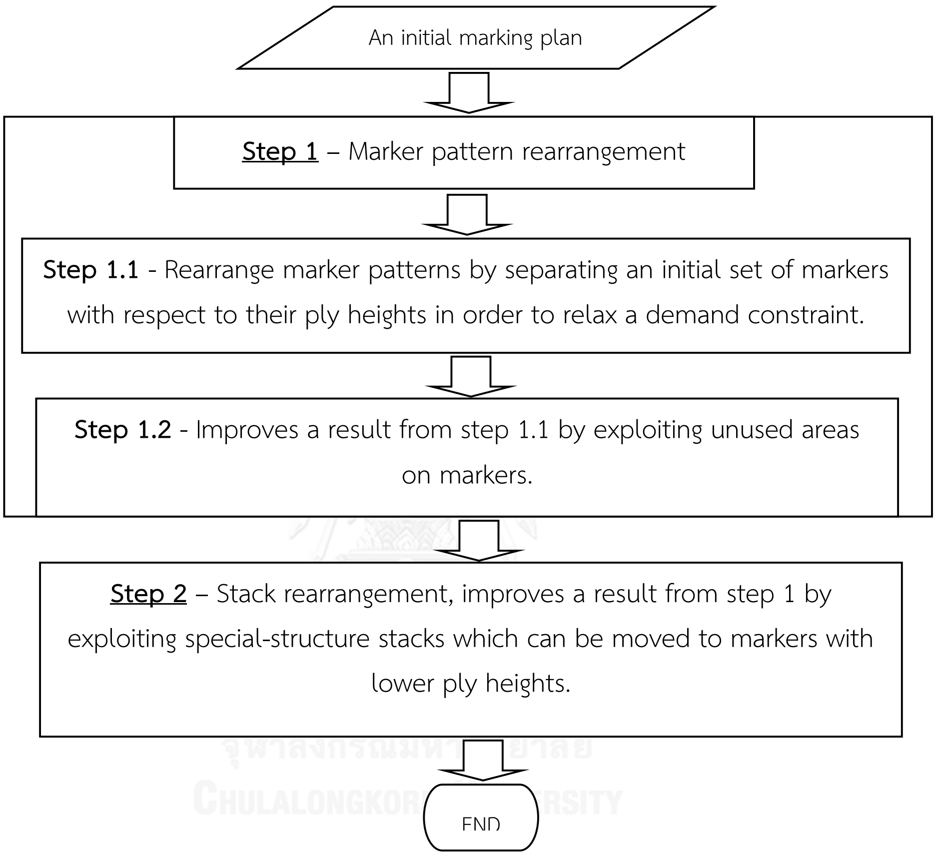

Figure 22 Flow of the proposed heuristic.

From Figure 22, step 1 and 2 are used to improve an inventory workload incurred in a marking plan derived from a heuristic proposed in Section 3. These two processes improve this non-value added workload by directly attacking to marker patterns of all markers. Some or all marker patterns should be rearranged in a way that this workload is reduced. Details of these two steps are explained below.

Step 1 Marker pattern rearrangement

Input; a feasible set of markers which is an initial marking plan derived from a proposed heuristic in Section 3.

Output; a feasible set of markers.

Parameter setting;-

Description; this process is used to improve holding cost of a marking plan from the previous process. A key concept is to minimize difference among due dates of stacks in each marker. A method used is to regroup existing stacks to recreate markers in a manner that stacks with nearby due dates are almost in the same marker. This regrouping method must be done in a way that all feasibility constraints of marker planning are satisfied. However, to avoid violating demand and ply height constraints, this regrouping method will be executed under smaller sets of markers which each smaller set contains only markers with the same ply height. Consequently, in each group, only area, excess control, and no tardiness constraints are hold. In each group, after all stacks are already assigned, there can be a remaining area appeared in the last considered marker. This area can be exploited to further improve holding cost. As explained previously, a holding cost is incurred when stacks that have different due dates are placed on the same marker. Moreover, a different combination of stacks may incur different amount of holding cost. Thus, with this remaining area, some stacks should be relocated in order to receive a better holding cost. To efficiently relocate, a method called “continuous exchange” is used. This method tries to continuously relocate a selected stack one by one until all stacks are completely located on markers. Furthermore, to reduce a computation time, a domain of possible solutions should be reduced. This reduction can be done by eliminating markers containing only one due date or incur no holding cost from a consideration. To finish this process, all these smaller sets must be considered. The stopping point of this process is separated into two cases. The first case, all stacks are completely regrouped to create a new set of markers. The second case, some stacks can’t be assigned to any markers in a considered set. Obviously, in this case, some demands are not satisfied which make a marking plan infeasible. It means a marking plan can’t be improved with this regrouping method. Apparently, this process can perform well in a situation that material usage rate is relatively low to medium because in this situation, existing stacks can be easily regrouped to create better marker patterns and also better marking plan. A procedure of step 1 is shown in Figure 23.

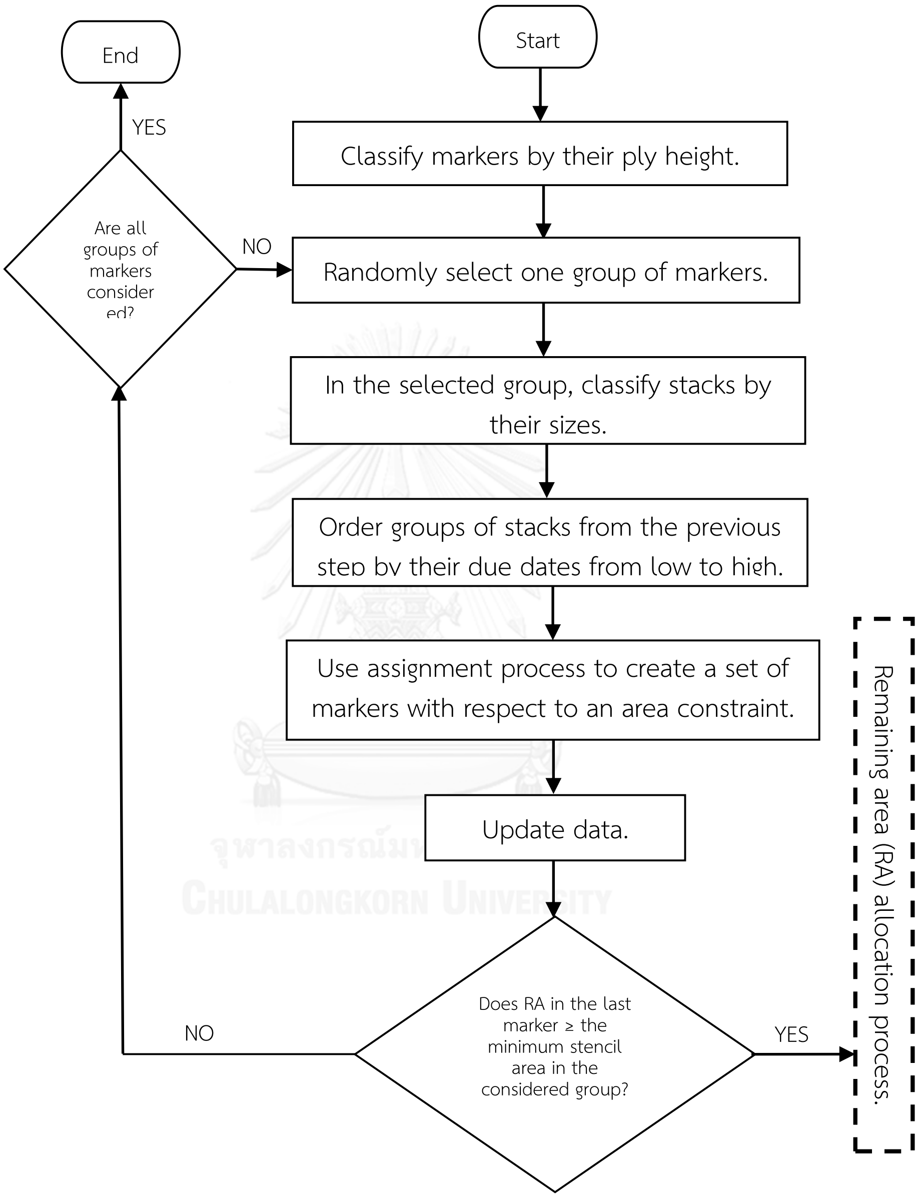

Figure 23 A procedure of marker pattern rearrangement process.

<u>**Assignment process**</u>

An assignment process as shown in Figure 24 is used to assign stacks to empty markers to recreate a set of markers with new marker patterns. In this process, stacks are orderly assigned to empty markers with respect to due dates from low to high.

Furthermore, each assignment of stack is feasible if an area constraint is satisfied. A process is terminated only when all stacks are completely assigned to empty markers.

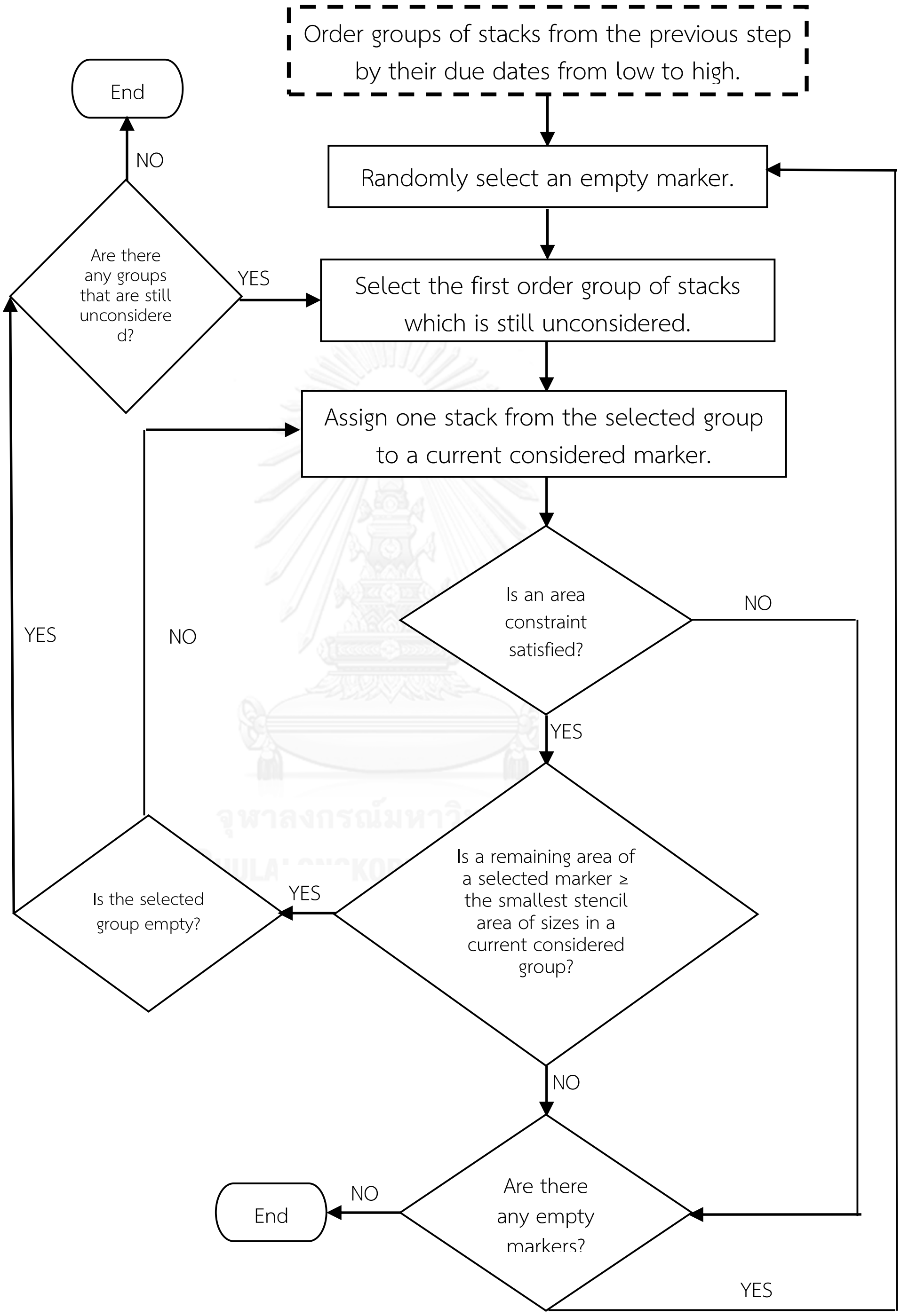

Figure 24 A procedure of an assignment process.

Remaining area allocation process

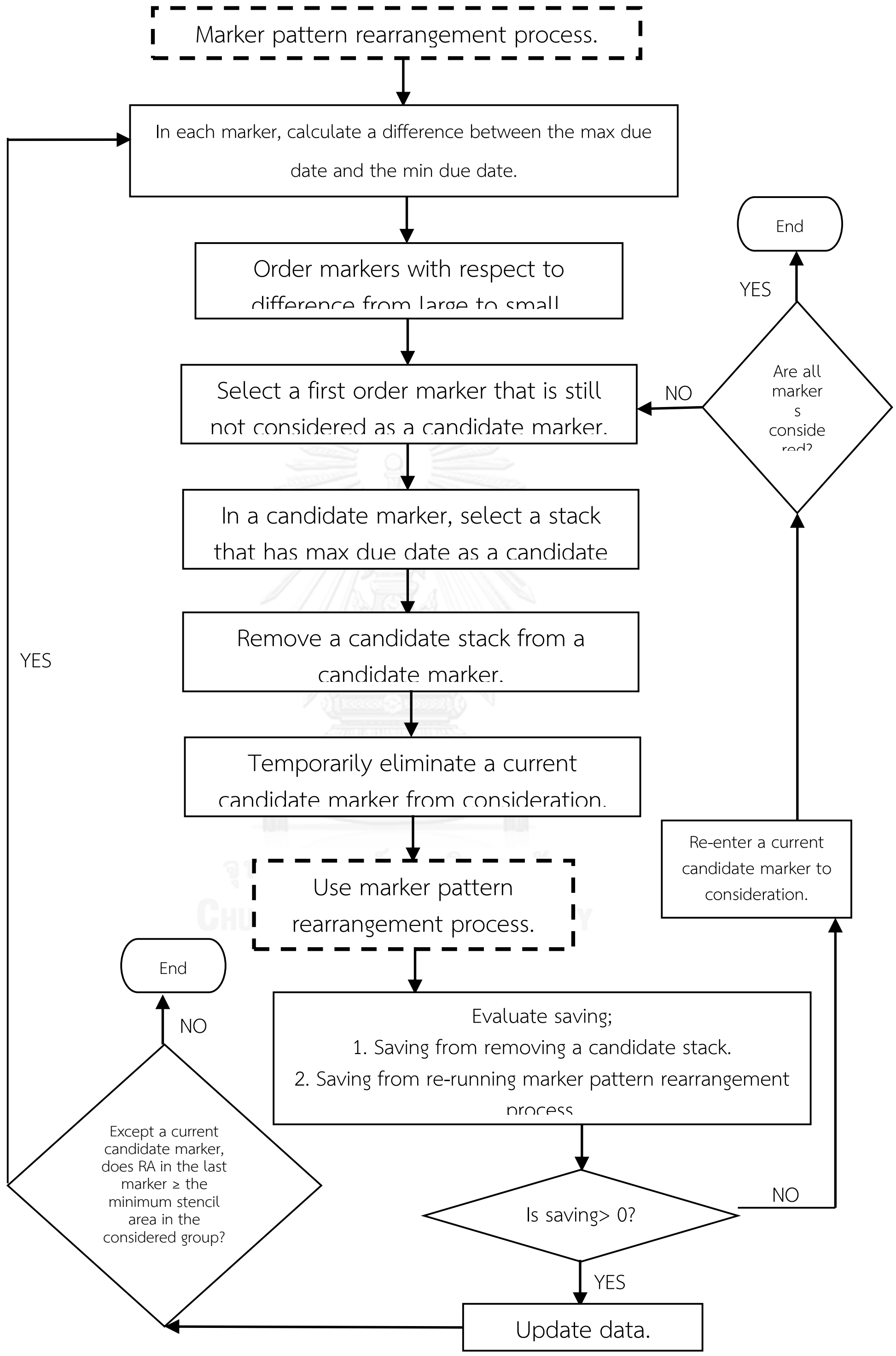

Figure 25 A procedure of a remaining area allocation step.

<u>Step 2</u> **Stack rearrangement**

Input; a feasible set of markers from step 1.

Output; a feasible set of markers.

Parameter setting;-

Description; this process is used to further improve holding workload of a marking plan from the previous process. A key concept of this process is to relocate stacks to more appropriated markers with respect to a difference between a considered stack's due dates and the minimum due date of a destination marker. One important structure of stack that facilitates this exchanging is related with excesses of each size occurred. These excesses are viewed as a flexible degree which enables a considered stack to move to a lower ply height marker without violating demand constraint. In this section, such stack is called a special-structure stack. Therefore, to maintain demand constraint, a gap between ply height of a considered stack and ply height of a destination marker must not exceed a number of excesses on a considered stack. Obviously, in this step, only stacks that contain excesses are involved. Furthermore, in each exchanging, demand, area, excess control, and no tardiness constraints are hold. This process will be run until no stack can be moved with an improvement.

This step begins with a set of markers derived from the first step. At first, to reduce solution search space, any sizes that incur no excess units are excluded. Subsequently, select an unconsidered size that incurs maximum excess units. Moreover, with the selected size, choose a stack which has maximum difference between due date of that stack and the minimum due date of a marker containing that stack. A destination marker must has ply height equal to or higher than an actual demand of the current selected stack. With these markers, select the highest ply marker. Finally, generate all possible solutions which each solution is a combination of the current selected stack and one stack from the highest ply marker.

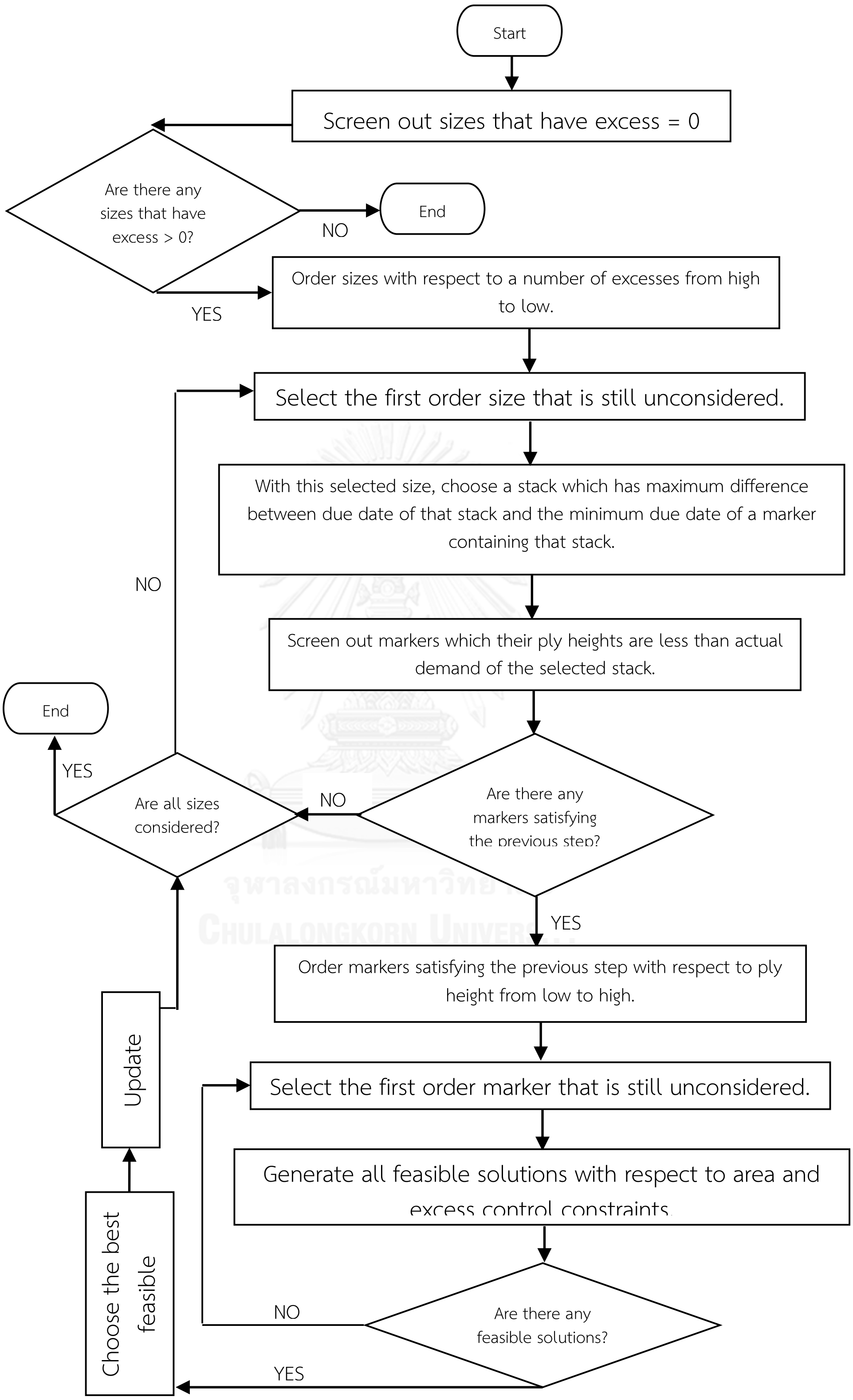

Figure 26 A procedure of stack rearrangement.

4.3 Computational experiments

The purpose of this Section is to evaluate performance of the proposed heuristic in solving large-sized marker planning problem with unequal area stencils with respect to a work-in-process inventory workload. To satisfy this purpose, three numerical experiments are conducted. In these three experiments, 140 problem instances are randomly generated based on key characteristics of a mass customization garment as stated below.

1. A number of sizes per customer order are still high.
2. A demand pattern is smoother than a demand pattern in fashion garment.
3. Total demand per customer order is larger than total demand in fashion garment.

In each experiment, a major parameter of marker planning problem is studied. In the first experiment, a number of sizes in each customer order are varied. In the second experiment, the maximum allowable area per marker is varied. Finally, in the third experiment, the maximum allowable ply height is studied.

To measure quality of solutions from the proposed heuristic, a modified genetic algorithm1 (MGA1) which is modified from a genetic algorithm approach proposed in [11] and is already used in Section 3, is further modified to cope with the problem in this Section. Subsequently, solutions from these two methods are compared and analyzed.

4.3.1 Test problem parameters

In marker planning problem, there are five parameters that affect size and complexity of the problems as shown below.

1. A number of sizes in each customer order.
2. The maximum allowable area per marker.
3. An amount of total demand per customer order.
4. The minimum allowable ply height per marker.
5. The maximum allowable ply height per marker.

In these three experiments, an amount of total demand per customer order is varied between 1000-3000 units per customer order. Additionally, this total demand is randomly distributed to all required sizes. A number of markers used for each customer order are set at the minimum number of markers which are between 8 and 25 markers. Especially in this research, areas of stencil of different sizes are unequal which makes the problem more realistic. These areas are set between 0.8 to 1 m^2. Moreover, sewing due dates of all these sizes are set at 1 to 15 as shown in Table 11. Finally, the minimum allowable ply height per marker is fixed at one ply.

Table 11 Areas and due dates of all required sizes in case of 5, 10, and 15 sizes.

Size	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
A case of 5 sizes.															
Area	0.8	0.85	0.9	0.95	1										
Due date	1	2	3	4	5										
A case of 10 sizes.															
Area	0.8	0.8	0.85	0.85	0.9	0.9	0.95	0.95	1	1					
Due date	1	2	3	4	5	6	7	8	9	10					
A case of 15 sizes.															
Area	0.8	0.8	0.8	0.85	0.85	0.85	0.9	0.9	0.9	0.95	0.95	0.95	1	1	1
Due date	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

The other three parameters, i.e. parameter 1 – a number of sizes in each customer order, parameter 2 – the maximum allowable area per marker, and parameter 5 – the maximum allowable ply height per marker are set as stated in Table 12.

Table 12 Test problem parameters of large-sized problem instances used in Section 4.

Experiment	1	2	5
1-1	5,10,15	4	40
1-2	10	3.3,4,4.9	40
1-3	10	4	30,40,50

In this table, a column experiment shows all three numerical experiments which are 1-1, 1-2, and 1-3. A column 1 states a setting up of a number of sizes per customer order whereas a column 2 states a setting up of the maximum allowable area per marker. A column 5 states a setting up of the maximum number of plies per marker.

With this parameter setting, seven sets of problem instances which comprise of 140 problem instances are generated as summarized in Table 13.

Table 13 Seven sets of problem instances.

Experiment	Problem instance		
1-1	Set 1 (5,4,40)	Set 2 (10,4,40)	Set 3 (15,4,40)
1-2	Set 4 (10,3.3,40)	Set 2 (10,4,40)	Set 5 (10,4.9,40)
1-3	Set 6 (10,4,30)	Set 2 (10,4,40)	Set 7 (10,4,50)

In experiment 1-1, a number of sizes per customer order are varied. In this experiment, three set of problem instances are tested. In the first, second, and third set, a number of sizes are set at 5, 10, and 15 sizes per customer order, respectively. In experiment 1-2, the maximum allowable area per marker is varied. In this experiment, three set of problem instances are tested. In the first, second, and third set, the maximum allowable are per marker is set at 3.3, 4, and 4.9, respectively. In experiment 1-3, the maximum allowable ply height per marker is varied. In this experiment, three set of problem instances are tested. In the first, second, and third set, the maximum allowable ply height per marker is set at 30, 40, and 50, respectively. With each parameter setting, 20 problem instances are generated. The demand data of these three experiments are shown in appendix B.

To measure performance of the proposed heuristic, MGA1 (modified genetic algorithm version 1) which is a modification of genetic algorithm presented in [11] is used. ThisMGA1 is already used as a lower bound to measure performance of a heuristic in Section 3. However, to solve problems in this Section, MGA1 is further modified. The major modifications are a fitness function to include an inventory workload component and a chromosome to include a due date attribute. To measure performance, each problem instance will be solved by both methods by the same computer. Moreover, to agree with a random character of both methods, each problem instance will be run 40 times by each method. Subsequently, the best solution from each method is collected and used as a representative solution for each problem instance. Finally, representative solutions from both methods are compared and analyzed.

4.3.2 Computational results

In this Section, computational results of all three experiments are summarized and discussed.

Experiment 1-1

As explained previously, in experiment 1-1, a number of sizes are varied which are 5, 10, and 15 sizes. With each number of sizes, 20 problem instances are generated and tested.

From Table 14, columns MGA1 show results from the MGA1 method while columns Heuristic show results from the proposed heuristic method. In each problem instance, a better solution is in italic style and underline. With 5 sizes, solutions of the proposed heuristic are better than solutions of the MGA1 in 19 instances which is equal to 95% of all instances. With 10 sizes, solutions of the proposed heuristic are better than solutions of the MGA1 in 19 instances which is equal to 95% of all instances. With 15 sizes, solutions of the proposed heuristic are better than solutions of the MGA1 in 19 instances which is also equal to 95% of all instances. Therefore, it can be concluded that the proposed heuristic can perform superior to the MGA1 in this experiment.

Table 14 computational results of an experiment 1-1.

Case	5 sizes		10 sizes		15 sizes	
	Heuristic	MGA1	Heuristic	MGA1	Heuristic	MGA1
1	*230*	456	*1105*	1400	*2828*	3574
2	*381*	442	*354*	497	*3935*	3995
3	*429*	543	*992*	1207	*3153*	3800
4	*418*	774	*1321*	1348	*3225*	3305
5	*397*	442	*1348*	2117	2815	*2560*
6	*307*	332	*1764*	2245	*3895*	4130
7	*325*	517	*1406*	1908	*3754*	3900
8	*331*	350	*1214*	1926	*3054*	3210
9	*356*	536	*1913*	2170	*1682*	1720
10	*413*	545	*695*	1005	*2788*	3270
11	*296*	786	*975*	1385	*3143*	3260
12	*455*	494	*1505*	1675	*2306*	2380
13	*336*	350	*1507*	1635	*2955*	3320
14	*493*	504	1267	*1107*	*3643*	3824
15	*338*	416	*862*	1011	*2855*	2946
16	396	*240*	*565*	611	*2132*	2404
17	*229*	254	*939*	1042	*2800*	2911
18	*383*	757	*1807*	2330	*3311*	3400
19	*380*	390	*1155*	1665	*1916*	2204
20	*534*	580	*526*	615	*2123*	3319

Experiment 1-2

As explained previously, in experiment 1-2, the maximum allowable area per marker is varied which are 3.3, 4, and 4.9 m^2. With each maximum value, 20 problem instances are generated and tested. However, problem instances with 4 m^2 are the same as problem instances with 10 sizes of an experiment 1-1. Thus, there are only 40 problem instances generated and tested in this experiment.

From Table 15, columns MGA1 show results from the MGA1 method while columns Heuristic show results from the proposed heuristic method. In each problem instance, a better solution is in italic style and underline. With 3.3 m^2, solutions of the proposed heuristic are better than solutions of the MGA1 in 19 instances which is equal to 95% of all instances. With 4 m^2, solutions of the proposed heuristic are better than solutions of the MGA1 in 19 instances which is equal to 95% of all instances. With 4.9 m^2, solutions of the proposed heuristic are better than solutions of the MGA1 in 19 instances which is equal to 95% of all instances. Therefore, it can be concluded that the proposed heuristic can perform superior to the MGA1 in this experiment.

Table 15 computational results of an experiment 1-2.

Case	3.3 m^2.		4 m^2.		4.9 m^2.	
	Heuristic	MGA1	Heuristic	MGA1	Heuristic	MGA1
1	*683*	995	*1105*	1400	*1475*	1560
2	*510*	636	*354*	497	*1091*	1724
3	*1097*	1124	*992*	1207	*1117*	1124
4	*1097*	1125	*1321*	1348	*947*	1024
5	*749*	910	*1348*	2117	*1816*	1877
6	*965*	995	*1764*	2245	*1604*	1723
7	*1256*	1295	*1406*	1908	*980*	1403
8	*1089*	1158	*1214*	1926	*1472*	1749
9	*1284*	1300	*1913*	2170	*1577*	2794
10	*1200*	1294	*695*	1005	*1543*	2018
11	*1183*	1294	*975*	1385	*1521*	3746
12	*1364*	1433	*1505*	1675	2214	*1418*
13	*1205*	1425	*1507*	1635	*1768*	2875
14	*1034*	1245	1267	*1107*	*1784*	2756
15	*906*	1100	*862*	1011	*825*	1083
16	910	*884*	*565*	611	*1352*	1430
17	*989*	1145	*939*	1042	*2009*	1699
18	*794*	1105	*1807*	2330	*2005*	2871
19	*975*	1098	*1155*	1665	*1005*	1943
20	*635*	995	*526*	615	*1200*	1920

Experiment 1-3

As explained previously, in experiment 1-3, the maximum allowable ply height is varied which are 30, 40, and 50 plies. With each maximum value, 20 problem instances are generated and tested. However, problem instances with 40 plies are the same as problem instances with 10 sizes of an experiment 1-1. Thus, there are only 40 problem instances generated and tested in this experiment.

From Table 16, columns MGA1 show results from the MGA1 method while columns Heuristic show results from the proposed heuristic method. In each problem instance, a better solution is in italic style and underline. With 30 plies, solutions of the proposed heuristic are better than solutions of the MGA1 in 18 instances which is equal to 90% of all instances. With 40 plies, solutions of the proposed heuristic are better than solutions of the MGA1 in 19 instances which is equal to 95% of all instances. With 50 plies, solutions of the proposed heuristic are better than solutions of the MGA1 in 19 instances which is equal to 95% of all instances. Therefore, it can be concluded that the proposed heuristic can perform superior to the MGA1 in this experiment.

Table 16 computational results of an experiment 1-3.

Case	30 plies		40 plies		50 plies	
	Heuristic	MGA1	Heuristic	MGA1	Heuristic	MGA1
1	*548*	760	*1105*	1400	*1558*	1623
2	*746*	826	*354*	497	*1065*	1426
3	*841*	1200	*992*	1207	*1569*	1992
4	*1184*	1281	*1321*	1348	*1546*	1761
5	1428	*1171*	*1348*	2117	*1247*	1425
6	*1031*	1053	*1764*	2245	*1275*	1685
7	*1369*	1754	*1406*	1908	*1095*	1270
8	*1802*	2015	*1214*	1926	*1424*	1562
9	*472*	1129	*1913*	2170	*1135*	1171
10	*1625*	1793	*695*	1005	*1008*	1295
11	*821*	1443	*975*	1385	*1403*	2023
12	*1392*	1450	*1505*	1675	2294	2313
13	*750*	1017	*1507*	1635	*1954*	2090
14	*456*	1069	1267	*1107*	*1782*	1893
15	1126	*1040*	*862*	1011	*1632*	1785
16	*1578*	1610	*565*	611	*1839*	2007
17	*1432*	1517	*939*	1042	*1525*	1574
18	*1127*	1200	*1807*	2330	1034	*510*
19	*1247*	1498	*1155*	1665	*1672*	1675
20	*1051*	1320	*526*	615	*1562*	1640

From these three experiments, it is obvious that the proposed heuristic is superior to MGA1. Although, values of major parameters are changed, the proposed heuristic still performs better than MGA1.

4.3.3 Analysis of computational results.

From this experiment, it can be concluded that the proposed heuristic can perform better than the MGA1 in a situation summarized as follows.

- There are a lot of markers that have the same ply height. In this situation, step 1 of the heuristic will have a great chance of rearranging marker patterns among markers that have equal ply height. This situation usually occurs when a demand pattern of a considered customer order is relatively smooth.
- There are a large amount of remaining areas. As described previously, a remaining area is an unused area which is equal to a difference between the maximum allowable area and a total assigned stencil area. In both heuristic step, this area can facilitate an exchanging of stacks between markers. However, too many remaining area can cause a difficulty with respect to a number of alternative solutions. Consequently, a solution space and a computation time will also increase proportionally.
- There are a lot of excess units occurred in many sizes. In step 2 of the heuristic, excess units will help stacks move to lower ply height markers. In some sense, these units can be seen as flexibility in moving stacks. Hence, it can be implied that there are a higher chance of improving marker pattern when these numbers are higher.

4.4 Conclusion

This Section focuses on marker planning problem with lean manufacturing concept which is extended from a marker planning problem presented in Section 3. In Section 3, a marker planning problem which is affected from applying a mass customization production strategy is studied. In this Section, a lean manufacturing concept which helps support the use of a mass customization strategy is implemented to a garment manufacturer. The core idea of this concept is to identify and eliminate waste from a production line. Generally, waste is identified as a non-value added activity or workload. In an interested production line which composes of three major processes, i.e. a marker planning, a cutting, and a sub-assembly and assembly process, a work-in-process inventory workload can be occurred. Furthermore, this inventory workload is placed on an inventory area in front of a sub-assembly and assembly line.

To reduce this work-in-process inventory, a sewing schedule in terms of a due date of each size is incorporated into consideration. This due date is used to represent a sewing start date of that size. Hence, stencils arriving at a sewing line on their due dates are incurred no workload while stencils arriving at a sewing line before their due dates are certainly incurred inventory workloads.

The purpose of this Section is to develop a marker planning heuristic used to improve a marking plan derived from a proposed heuristic presented in Section 3. Hence, an input to this heuristic is a marking plan which a number of markers used is minimum and a number of excesses occurred is already improved. The aim of a heuristic is to reduce an amount of work-in-process inventory which is kept in an inventory area in front of a sub-assembly and assembly line.

The major concept used to tackle this problem is to rearrange a marker pattern of each marker. A marker pattern is a combination of sizes which also a combination of due dates. Obviously, a different marker pattern can result in a different inventory workload. From this concept, a heuristic which composes of two major steps is constructed. The first step which is a marker pattern rearrangement is divided into two sub-steps, i.e. a marker pattern rearrangement and a remaining area allocation. The second step, stack rearrangement, in this step, special-structure stacks will be exploited. These stacks will be moved to more appropriated markers which result in an inventory workload reduction.

To evaluate performance of the proposed heuristic,140 problem instances are generated based on characteristics of a mass customization. These 140 problem instances are classified into three computational experiments which in each experiment, a different parameter is varied. Moreover, the MGA1 (the modified genetic algorithm version 1) which is a modification of a genetic based approach presented in [11] is constructed and used to compare with the proposed heuristic. All 140 generated problem instances are solved with both methods and the results are compared. The compared results show that the proposed heuristic can perform better in 132 problem instances which are equal to 94.3%of all problem instances.

The reason why the proposed heuristic can perform superior to the MGA1 is related to a structure of the problem. The proposed heuristic can perform better when 1.there are a lot of markers that have the same ply height, 2.there are a large amount of remaining areas, and 3.there are many number of excess units occurred in many sizes.

Finally, a future research can be done in many ways. The first idea is to incorporate a capacity constraint or a resource constraint of each process into consideration. For example, a number of cutting machines in a cutting process, a number of cutting equipments, a number of markers that can be cut per cutting machine per period, a number of units that can be operated per period in a sub-assembly and assembly process, and etc. These constraints will make a problem more realistic and, importantly, a solution will be closer to a real-life situation. The second idea is to include a cutting schedule together with a sewing schedule into a marker planning process. Apparently, with consideration of these two schedules, a problem is more complex and hard to solve. However, inclusion of these schedules will reflect an amount of inventory workload that is very close to an actual amount. The third idea is related with an inventory area limitation. With this limitation, a number of stencils that can be cut out and sent to a work-in-process inventory are limited. Therefore, some markers must be delay in order to wait for an available inventory area.

Chapter 5
Thesis conclusion

5.1 Conclusion

Over the last decade, there have been three changes occurred in garment industry which directly affect all garment manufacturers [18]. Firstly, an occurrence of new information technologies which enable an accurate, efficient, and effective collection of customer requirements. Secondly, a rapid change in customer requirements which make product life cycles shorter than ever. To correspond with a rapid changing, a more flexible production strategy is needed. Finally, due to a progress in logistics system, high fashion and premium brand garment manufacturers shift their attention from a local market to a global market. Therefore, their production amounts are substantially increased which makes current planning methods do not work.

As described in Section 1, using only one of the two current production strategies, i.e. a mass production and a custom production, doesn't agree with these three changes. Apparently, a mass production does not satisfy the three major changes described previously because of its inflexibility. The mass strategy is not suitable for a rapid changed demand. On the other hand, a custom production also does not satisfy these changes because of its production cost which reflects in expensive products. The custom strategy cannot fulfill a cost dimension of garment manufacturers.

Therefore, a mass customization production strategy which is a combination of a mass production and a custom production is applied. With mass customization production strategy, manufacturers still produce high value garment products which compose of high price fabrics and accessories but in larger lot size and smoother demand pattern. As a demand is higher, a set up cost which is directly related to number of markers used should be still in consideration and to agree with a production of high value products, an excess cost is also still included in consideration. Moreover, to successfully use a mass customization strategy which is relatively flexible, a concept of lean manufacturing should be applied. With this concept, garment manufacturers should reduce their non-value-added workload from their production lines. In this research, a work-in-process inventory is seen as an important non-value added workload that should be reduced first. To reduce this work-in-process inventory, a sewing schedule in terms of a due date of each size is incorporated into consideration.

In an application of mass customization and lean manufacturing concept, three objective components are incurred in an objective function, i.e. set up cost, excess cost, and work-in-process inventory workload. Minimization of these three objective components simultaneously is very difficult. Thus, the interested problem is separated into two problems which each problem is laid on a different level.

In the first level, only effect of a mass customization to marker planning process is considered. In this level, two objective components which are set up cost and excess cost are incurred. To develop the heuristic, three major concepts are applied. The first concept is an improvement heuristic concept. With this concept, the proposed heuristic will begin with an initial solution and, subsequently, this initial solution will be improved through all later processes. The second concept is randomization which is used to escape from a local optimum by randomly generate initial solutions to the heuristic. The third concept is to decompose the original marker planning problem into five related sub-problems, i.e., an initial solution generation, ply height determination, stack relocation, ply height reduction, and marker pattern randomization.

To evaluate performance of this heuristic, two types of experiment are conducted. The first type is to verify that the proposed heuristic is able to solve small- and medium-sized problem instances from [7, 8, 11]. The second experiment is to evaluate performance of the proposed heuristic in solving large-sized marker planning problems which are often occurred in a mass customization garments.

The numerical results show that the proposed heuristic can reach to the optimal solutions for all small instances. For medium instances, the heuristic can reach to the optimal solutions in 3 out of 8 instances. Compare to GA1 and GA2, the heuristic can perform equally as GA1 but superior to GA2 in most instances. With large-sized problem instances, the optimal solutions are unknown because of high complexity. Therefore, solutions from a modification of GA1 [11] which is called MGA1 is used to compare with solutions from the proposed heuristic. In summary, the heuristic can perform superior to MGA1 in 30 out of 35 problem instances while the solutions are equal in 5 problem instances.

In the second level, a lean manufacturing concept is applied addition to a mass customization. In this level, only a work-in-process inventory workload is incurred. A marking plan derived from a heuristic proposed in the first level is further improved with respect to only a work-in-process inventory workload. To reduce a work-in-process inventory workload, a marker pattern of each marker should be rearranged in the way that a difference among due dates on each marker is lower. Two key concepts are used as a framework for developing the heuristic. The first concept is to create new marker patterns by rearranging stencils on markers with respect to due date differences. The second concept is to adjust marker patterns by relocating some special-structure stacks.

To evaluate performance of the proposed heuristic, 140 problem instances are generated based on characteristics of a mass customization. Moreover, the MGA1 which is a modification of a genetic based approach presented in [11] is further modified and used. The compared results show that the proposed heuristic can perform better in 132 problem instances which are equal to 94.3%. Therefore, it can be concluded that the proposed heuristic can perform superior to MGA1.

5.2 Research limitation

In the first level problem, a marker planning problem with the objective to minimize a set up cost plus an excess cost, it can be observed from the experiment that in some problem instances, MGA1 can perform equal to the proposed heuristic. The reason of this phenomenon is related with characteristics of the problem. From the experiment, it can be concluded that the heuristic can perform well when an amount of demand area together with a degree of smoothness are high. These two parameters are briefly described as follows.

1. An amount of demand area – this area is an actual required fabric area per customer order which is equal to total number of demand units multiply by their required areas. When an amount of this area is large, it means that an amount of remaining area is small which directly affect an ability to exchange stacks of the proposed heuristic. Apparently, when an amount of remaining area is small, a number of possible solutions tend to be low which can shorten a computation time.

2. A degree of smoothness – this parameter is used to present a fluctuation of demand among required sizes. It shows how large of a degree of smoothness of a considered customer order. As explained previously, customer demands in a mass customization garment which are an emphasis of this research are usually smoother than customer demands in fashion garment. When this degree is high, it means that differences of demands between sizes in a customer order are low. Moreover, when this degree is high, an actual demand of each stack tend to be equal which make the problem more easier to improve with respect to an excess unit occurred.

Additionally, the reason why the heuristic can perform well with large-sized problems is related with a decomposition concept which is a key concept of the heuristic. A decomposition concept which decomposes the original mark planning problem into many related sub-problems helps reduce an original search space to only a set of important search areas. These search areas are hoped to contain good or even the best solutions. Subsequently, the heuristic will search through only these important areas of a search space.

In the second level problem, a marker planning problem with the objective to minimize a work-in-process inventory workload, it can be concluded from the experiment that the proposed heuristic can perform better than the MGA1 in a situation summarized as follows.

- There are a lot of markers that have the same ply height. In this situation, step 1 of the heuristic will have a great chance of rearranging marker patterns among markers that have equal ply height. This situation usually occurs when a demand pattern of a considered customer order is relatively smooth.

- There are a large amount of remaining areas. As described previously, a remaining area is an unused area which is equal to a difference between the maximum allowable area and a total assigned stencil area. In both heuristic step, this area can facilitate an exchanging of stacks between markers. However, too many remaining area can cause a difficulty with respect to a number of alternative solutions. Consequently, a solution space and a computation time will also increase proportionally.

- There are a lot of excess units occurred in many sizes. In step 2 of the heuristic, excess units will help stacks move to lower ply height markers. In some sense, these units can be seen as flexibility in moving stacks. Hence, it can be implied that there are a higher chance of improving marker pattern when these numbers are higher.

5.3 Future researches

Finally, future researches should emphasize on the integration between marker planning process and other relevant processes. The integration can be done with either previously processes, e.g., product design, purchasing, etc., or later processes, e.g., marker making, sewing, etc. Moreover, the levels of integration are relatively varied depending on planner's decisions. For example, in some cases, only data from other relevant processes are included whereas, in some cases, marker planning is combined with other processes to form a new larger problem that can cover a wider range of production decision. In case of time information, e.g. due date, production start date, from downstream processes are included into marker planning process, a single objective function will become a multi-objective function. Moreover, this problem is more complex when a capacity constraint or a resource constraint of each process is incorporated into consideration. For example, a number of cutting machines in a cutting process, a number of cutting equipments, a number of markers that can be cut per cutting machine per period, a number of units that can be operated per period in a sub-assembly and assembly process, and etc. These constraints will make a problem more realistic and, importantly, a solution will be closer to a real-life situation. The second idea is to include a cutting schedule together with a sewing schedule into a marker planning process. Apparently, with consideration of these two schedules, a problem is more complex and hard to solve. However, inclusion of these schedules will reflect an amount of inventory workload that is very close to an actual amount. The third idea is related with an inventory area limitation. With this limitation, a number of stencils that can be cut out and sent to a work-in-process inventory are limited. Therefore, some markers must be delay in order to wait for an available inventory area.

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APPENDIX

In this appendix, small-, medium-, and large-sized problem instances used in computational experiments of Section 3 are shown as follows.

1. Demand data of small-sized problem instances set 1.

In Table 17, 12 small-sized problem instances from [7, 8] are presented. A number of sizes of these instances are fixed at five sizes whereas the maximum allowable number of stacks per marker is fixed at four stacks. The amount of total demand is ranged from 200 to 400 units per customer order. The minimum and maximum allowable ply heights are set at 1 and 35 plies, respectively. Moreover, a number of markers used for each customer order are set at the minimum number of markers which is equal to three markers for all instances.

Table 17 Small-sized problem instances set 1.

Case	Demand data					Total	Case	Demand data					Total
	1	2	3	4	5			1	2	3	4	5	
a	54	84	91	60	29	318	g	57	81	96	42	35	311
b	30	61	89	76	45	301	h	29	58	87	72	34	280
c	25	70	63	54	39	251	i	51	76	87	64	46	324
d	33	82	77	62	34	288	j	36	59	84	76	40	295
e	62	69	94	81	55	361	k	74	64	28	34	59	259
f	49	72	89	66	34	310	l	23	78	56	89	41	287

2. Demand data of small-sized problem instances set 2.

In Table 18, 22 small-sized problem instances from [11] are presented. A number of sizes of these instances are either 4 or 6 sizes while the maximum allowable numbers of stacks per marker are either 3 or 5 stacks. The amount of total demand is ranged from 40 to 880 units per customer order. The maximum allowable ply heights are set at 10 and 50 plies. Furthermore, a number of markers used for each customer order are set at the minimum number of markers which are equal to 2, 3, and 4 markers.

Table 18 Small-sized problem instances set 2.

Case	Demand data						Total	Case	Demand data						Total
	1	2	3	4	5	6			1	2	3	4	5	6	
a	8	12	11	9			40	l	26	46	49	67	72	38	298
b	4	5	8	10	9	7	43	m	18	27	39	26			110
c	33	42	73	54			202	n	8	12	14	23	16	6	79
d	18	23	37	46	33	25	182	o	78	133	176	96			483
e	15	21	25	16			77	p	44	58	68	119	78	34	401
f	10	14	19	18	16	9	86	q	17	23	27	19			86
g	65	84	163	98			410	r	6	9	12	14	10	5	56
h	49	72	94	97	78	43	433	s	63	112	136	74			385
i	8	17	29	16			70	u	25	32	49	37			143
j	5	8	9	13	15	6	56	v	19	25	40	43	31	17	175
k	66	79	123	72			340	x	98	145	180	207	167	83	880

3. Demand data of medium-sized problem instances.

In Table 19, eight medium-sized problem instances from [11] are presented. A numbers of sizes of these instances are between 13 to 20 sizes whereas the maximum allowable numbers of stacks per marker are varied between 3 to 7 stacks. The amount of total demand is ranged from 200 to 600 units per customer order. The maximum allowable ply heights are set at 20, 25, and 30 plies. Additionally, a number of markers used for each customer order are set at the minimum number of markers which are equal to 3, 4, 5, 6, and 7 markers.

Table 19 A set of medium-sized problem instances

Case	Demand data																				Total
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
8	4	13	20	24	14	5	20	53	70	53	32	31	30								369
10	4	10	16	16	16	16	14	8	4	6	26	36	26	10							208
14	6	18	28	40	26	14	4	30	66	100	76	40	40	38	7	7					540
15	34	8	34	29	15	21	25	3	23	10	30	7	7	11	11	12					280
17	13	20	1	1	4	23	26	15	4	14	46	32	19	39	23	2	2	12			296
18	25	2	19	1	6	6	24	17	8	15	26	16	40	49	40	1	2	1	2		300
19	18	15	6	5	2	12	1	22	14	53	40	59	30	20	1	1	41	12	1		353
20	1	15	1	37	5	37	28	48	1	7	33	6	7	61	22	96	55	30	77	10	577

4. Demand data of large-sized problem instances.

In this problem, a number of sizes of these instances are fixed at 10 sizes per customer order. The amount of total demand is ranged from 1100-2700 units per customer order while in a fashion garment, total demand is no more than 1000 units. Additionally, this total demand is randomly distributed to all 10 sizes. The maximum allowable ply height is set at 40 plies per marker while the minimum allowable ply height is set at 1 ply per marker. A number of markers used for each customer order are set at the minimum number of markers which are between 8 and 18 markers. Especially in this research, areas of stencil of different sizes are unequal which makes the problem more realistic. These areas are set between 0.8 to 1 m^2. In Table 20, 35 generated problem instances are displayed. All 10 columns under demand data display amount of demand for size 1 to size 10. The last column named total shows a total demand of all 10 sizes in each problem instances.

Table 20 Large-sized generated problem instances.

	Demand data												Demand data										
Case	1	2	3	4	5	6	7	8	9	10	Total	Case	1	2	3	4	5	6	7	8	9	10	Total
1	143	108	152	83	202	155	65	257	59	94	1318	19	272	199	317	115	330	208	78	299	130	166	2114
2	143	122	234	83	281	155	65	275	59	100	1517	20	300	169	425	136	390	234	126	318	75	237	2410
3	171	144	288	105	300	155	85	275	59	135	1717	21	393	169	478	134	405	199	96	315	75	237	2501
4	268	152	326	105	295	177	78	275	59	130	1865	22	418	199	470	181	363	235	90	270	72	160	2458
5	264	152	345	105	327	208	78	275	55	121	1930	23	438	190	480	158	395	265	96	312	80	222	2636
6	272	152	367	115	330	208	78	299	55	146	2022	24	358	190	440	198	395	265	136	312	160	222	2676
7	300	169	450	136	405	234	96	336	75	217	2418	25	171	124	288	102	293	155	82	277	59	168	1719
8	393	169	512	134	405	234	96	335	75	217	2570	26	274	153	372	113	326	208	73	303	55	145	2022
9	458	169	520	141	392	265	90	315	72	220	2642	27	194	140	318	119	285	157	85	276	59	156	1789
10	468	169	525	154	405	265	96	335	75	222	2714	28	247	140	230	155	279	168	64	228	59	96	1666
11	300	169	450	136	405	234	96	336	75	217	2418	29	152	141	348	117	318	150	81	277	63	133	1780
12	191	144	318	115	285	162	85	275	59	155	1789	30	191	147	316	114	291	263	80	276	55	158	1891
13	246	138	234	153	281	170	65	225	59	95	1666	31	230	183	319	271	118	153	81	239	58	135	1787
14	157	144	328	108	325	175	75	299	59	135	1805	32	390	171	482	135	401	195	96	319	78	234	2501
15	287	159	408	125	375	294	88	303	68	199	2306	33	159	144	326	108	325	171	79	299	58	136	1805
16	152	144	348	115	315	152	85	275	59	135	1780	34	191	143	318	117	283	162	85	276	61	154	1790
17	306	169	410	125	348	198	88	277	68	158	2147	35	141	123	235	83	280	156	65	269	63	104	1519
18	228	184	319	275	115	152	85	235	59	135	1787												

In this appendix, large-sized problem instances used in computational experiments of Section 4 are shown as follows.

5. Demand data of large-sized problem instances used in experiment 1-1.

In Table 21, 20 large-sized problem instances generated based on major characteristics of a mass customization production are shown. A number of sizes of these instances are fixed at 10 sizes whereas the maximum allowable area per marker is fixed at 4 m^2. The amount of total demand is ranged from 1,000 to 3,000 units per customer order. The minimum and maximum allowable ply heights are set at 1 and 40 plies, respectively. Moreover, a number of markers used for each customer order are set at the minimum number of markers which is varied depending on amount of total demand.

In Table 22, 20 large-sized problem instances generated based on major characteristics of a mass customization production are displayed. All parameters are set as in Table 20 except a number of sizes which is set at 5 sizes.

In Table 23, 20 large-sized problem instances generated based on major characteristics of a mass customization production are displayed. All parameters are set as in Table 20 except a number of sizes which is set at 15 sizes.

Table 21 Demand data of problem instances with 10 sizes.

Case	Demand data										Total
	1	2	3	4	5	6	7	8	9	10	
1	103	94	140	83	183	155	43	177	59	78	1115
2	143	108	152	83	202	155	65	257	59	100	1324
3	143	122	234	83	281	155	65	275	59	100	1517
4	171	144	288	105	300	155	85	275	59	135	1717
5	268	152	326	105	295	177	78	275	59	130	1865
6	264	152	345	105	327	208	78	275	55	121	1930
7	272	152	367	115	330	208	78	299	55	146	2022
8	272	169	400	125	375	234	88	303	68	199	2233
9	300	169	450	136	405	234	96	336	75	217	2418
10	393	169	512	134	405	234	96	335	75	217	2570
11	393	169	478	134	405	199	96	315	75	237	2501
12	133	118	184	83	242	155	65	275	96	109	1460
13	155	93	142	88	192	181	47	177	54	76	1205
14	125	151	248	81	281	199	64	275	59	120	1603
15	282	152	335	115	302	160	78	275	63	127	1889
16	117	99	166	80	183	151	48	178	59	36	1117
17	203	135	322	115	300	162	85	275	59	140	1796
18	335	159	462	152	405	234	96	382	75	220	2520
19	364	181	440	198	407	265	145	338	160	245	2743
20	299	175	476	140	450	234	100	336	108	223	2541

Table 22 Demand data of problem instances with five sizes.

Case	Demand data					Total
	1	2	3	4	5	
1	205	196	242	186	285	1114
2	269	234	278	209	328	1318
3	274	253	365	214	412	1518
4	313	286	390	247	375	1611
5	411	296	469	249	438	1863
6	411	300	492	252	473	1928
7	429	309	524	272	487	2021
8	450	347	578	305	553	2233
9	492	360	642	328	597	2419
10	584	360	703	325	596	2568
11	650	361	712	333	584	2640
12	667	368	724	353	604	2716
13	443	340	546	296	519	2144
14	492	361	642	328	597	2420
15	211	195	251	179	279	1115
16	583	364	635	346	528	2456
17	338	291	465	262	432	1788
18	369	261	357	276	404	1667
19	564	364	605	346	523	2402
20	633	385	675	353	590	2636

Table 23 Demand data of problem instances with 15 sizes.

Case	Demand data															Total
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
1	94	70	126	75	105	105	43	132	59	78	40	43	58	37	50	887
2	103	88	122	78	142	115	65	137	59	94	96	49	68	47	55	1003
3	133	112	172	83	141	155	65	99	59	90	115	110	72	60	51	1109
4	161	124	108	105	160	135	85	152	59	115	145	58	110	134	66	1204
5	188	132	126	105	221	177	78	105	59	130	138	155	113	82	56	1321
6	148	112	129	105	187	208	78	204	55	121	206	81	132	94	70	1347
7	158	152	202	95	172	188	77	229	55	136	141	101	108	83	125	1464
8	208	139	154	122	235	195	88	203	69	189	149	105	84	130	163	1602
9	185	139	250	136	215	242	96	153	85	227	161	118	145	94	172	1728
10	242	169	262	134	205	174	96	235	75	217	171	134	186	108	162	1809
11	226	169	238	141	284	260	90	267	72	207	176	118	134	155	105	1954
12	228	169	325	154	205	265	96	200	75	226	181	125	198	154	113	1943
13	96	139	125	112	185	201	88	150	68	179	143	185	104	162	208	1343
14	223	169	230	136	200	175	96	181	75	137	161	174	122	186	153	1622
15	100	52	75	68	93	92	48	85	59	55	55	108	72	89	64	727
16	218	159	208	181	133	215	90	205	72	120	154	195	192	146	170	1601
17	131	124	88	115	94	142	85	193	59	120	108	99	145	136	150	1151
18	176	98	140	133	108	127	65	168	59	95	111	135	94	72	85	1169
19	199	149	240	181	158	225	90	170	72	152	140	175	165	110	178	1636
20	205	190	280	149	195	225	96	194	80	222	176	202	148	170	104	1836

6. Demand data of large-sized problem instances used in experiment 1-2.

In Table 24, 20 large-sized problem instances generated based on major characteristics of a mass customization production are presented. A number of sizes of these instances are fixed at 10 sizes whereas the maximum allowable area per marker is varied which are 3.3, 4, and 4.9 m^2. The amount of total demand is ranged from 1,000 to 3,000 units per customer order. The minimum and maximum allowable ply heights are set at 1 and 40 plies, respectively. Moreover, a number of markers used for each customer order are set at the minimum number of markers which is varied depending on amount of total demand.

Table 24 Demand data of problem instances with 3.3, 4, and 4.9 m^2.

Case	Demand data										Total
	1	2	3	4	5	6	7	8	9	10	
1	103	94	140	83	183	155	43	177	59	78	1115
2	143	108	152	83	202	155	65	257	59	100	1324
3	143	122	234	83	281	155	65	275	59	100	1517
4	171	144	288	105	300	155	85	275	59	135	1717
5	268	152	326	105	295	177	78	275	59	130	1865
6	264	152	345	105	327	208	78	275	55	121	1930
7	272	152	367	115	330	208	78	299	55	146	2022
8	272	169	400	125	375	234	88	303	68	199	2233
9	300	169	450	136	405	234	96	336	75	217	2418
10	393	169	512	134	405	234	96	335	75	217	2570
11	393	169	478	134	405	199	96	315	75	237	2501
12	133	118	184	83	242	155	65	275	96	109	1460
13	155	93	142	88	192	181	47	177	54	76	1205
14	125	151	248	81	281	199	64	275	59	120	1603
15	282	152	335	115	302	160	78	275	63	127	1889
16	117	99	166	80	183	151	48	178	59	36	1117
17	203	135	322	115	300	162	85	275	59	140	1796
18	335	159	462	152	405	234	96	382	75	220	2520
19	364	181	440	198	407	265	145	338	160	245	2743
20	299	175	476	140	450	234	100	336	108	223	2541

7. Demand data of large-sized problem instances used in experiment 1-3.

In Table 25, 20 large-sized problem instances generated based on major characteristics of a mass customization production are presented. A number of sizes of these instances are fixed at 10 sizes whereas the maximum allowable area per marker is fixed at 4 m^2. The amount of total demand is ranged from 1,000 to 3,000 units per customer order. The minimum allowable ply height is set at 1 ply while the maximum allowable ply height is varied which are 30, 40, and 50 plies. Moreover, a number of markers used for each customer order are set at the minimum number of markers which is varied depending on amount of total demand.

Table 25 Demand data of problem instances with 30, 40, and 50 plies.

Case	Demand data										Total
	1	2	3	4	5	6	7	8	9	10	
1	103	94	140	83	183	155	43	177	59	78	1115
2	143	108	152	83	202	155	65	257	59	100	1324
3	143	122	234	83	281	155	65	275	59	100	1517
4	171	144	288	105	300	155	85	275	59	135	1717
5	268	152	326	105	295	177	78	275	59	130	1865
6	264	152	345	105	327	208	78	275	55	121	1930
7	272	152	367	115	330	208	78	299	55	146	2022
8	272	169	400	125	375	234	88	303	68	199	2233
9	300	169	450	136	405	234	96	336	75	217	2418
10	393	169	512	134	405	234	96	335	75	217	2570
11	393	169	478	134	405	199	96	315	75	237	2501
12	133	118	184	83	242	155	65	275	96	109	1460
13	155	93	142	88	192	181	47	177	54	76	1205
14	125	151	248	81	281	199	64	275	59	120	1603
15	282	152	335	115	302	160	78	275	63	127	1889
16	117	99	166	80	183	151	48	178	59	36	1117
17	203	135	322	115	300	162	85	275	59	140	1796
18	335	159	462	152	405	234	96	382	75	220	2520
19	364	181	440	198	407	265	145	338	160	245	2743
20	299	175	476	140	450	234	100	336	108	223	2541

VITA

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