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On genetic algorithms for shoe making nesting – A Taiwan case

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Abstract

This paper proposes a methodology that integrates in-house placement heuristics with genetic algorithms to solve the nesting problems of shoe making. The problems are classified as placing a set of irregular patterns on a regular area and limited to at most two different types of patterns on the area. Because of the intractability of the nesting problem, our objective is to utilize genetic algorithms' fast convergence and solution quality to improve material utilization and reduce the calculation time of the pattern. Using the real-life data of two international brands of athletic shoes, the empirical results show that our proposed methodology can reduce average material requirements by 2.64% and average nesting time by 69.15% compared to those of current in-house software. The reduction of materials is becoming more important given that the industry is facing continuingly declining profit margins.

Keywords: Shoe making; Nesting; Genetic algorithms; Packing

1. Introduction

A general packing problem can be defined as follows. Given a set of small N patterns (parts, pieces), find the optimal non-overlapping layout of all patterns on a large containing area (surface, plate). Optimal packing can only be achieved when patterns are touching as tight as possible because any small gaps between two patterns are usually unusable. The gaps resulting from the spaces between and around the placed patterns are wasted materials and commonly referred to as trim loss. Traditionally, a trim loss problem generally refers to the case where the shapes of areas and patterns are regular. However, in industries such as shoe making the patterns are irregular shape and the area is also irregular in a handful of situations. The packing problems involving irregular patterns are known as nesting. Since the regular packing problems have been shown to be NP-complete (Fowler, Paterson, & Tatimoto, 1981) and the irregular packing problems only increase the complexity, the nesting problems can be regarded as NP-complete.

The shoe making process starts with the cutting of upper patterns from a hide with patterns nested together as tight as possible. To make a pair of shoes, the cost of raw materials is roughly 70% of the total making cost. Further, given this material cost, the ratio of upper patterns to sole is about 7 to 3. Normally, the material cost of upper patterns will not be available until the nesting is completed. Taiwan has a number of well-known original equipment manufactures/original design manufacturers (OEMs/ODMs) located worldwide for major international brand names such as *Nike*, *Adidas*, *Puma*, *New Balance*. With yearly production volumes of pairs of shoes being five billion, these OEMs/ODMs produce more than 35% of the world's shoes. Summarizing from the reports (http://www.footwear-assn.org.tw; http://www.shoenet.org.tw) as of 2004, we provide short profiles of Taiwan's major OEMs/ODMs in Table 1 that illustrates their important roles in the world's shoe making industry. For example, about every one out of six prestigious athletic shoes is made by Pouchen Group. Owing to the importance, major brand names of athletic shoes have selected Taiwan as the center of research and development (R&D), as shown in Table 2.

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Table 1
Short profiles of Taiwan's major OEMs/ODMs of shoe making

OEM/ODM	MP[a]	PL[b]	PV[c]	Remark
Pouchen Group	Athletic	309	167.2	17% of worlds' athletic shoes
Fengtay Ent.	Athletic	78	36.16	*Nike*'s customized shoes
Prime Success Int. Group Ltd.	Women shoes	24	30	Maker of *Daphne*, the most popular in China
Ever Rite International	Women shoes	92	100	Owner of *Miss Sofi*, *Sonia* & the largest maker of women shoes

[a] Major products.
[b] Production lines.
[c] Production volumes (in millions of pairs).

Table 2
Locations of R&D sites of popular athletic shoes in Taiwan

Brand	Taiwan's OEMs/ODMs	R&D sites
Nike	Pouchen, Fengtay	Taichung (Pouchen), Douliou (Fengtay)
Adidas	Pouchen, Chingluh, Dean Shoes	Taichung (Pouchen, Dean Shoes), Tainan (Chingluh)
Reebok	Pouchen, Chingluh, Dasheng	Taichung (Pouchen, Dasheng), Tainan (Chingluh)
New Balance	Dean Shoes	Taichung
Puma	Dasheng	Taichung

To see how the nesting can affect the material cost of shoes, consider the example that uses the cost structure and production quantities described earlier. According to the structure, if the nesting can reduce even as tiny as 0.1% of the upper's material cost given the average cost of a pair of shoes is \$13, then the cost reduced will be $\$13 \times 5{,}000{,}000{,}000 \times 70\% \times 70\% \times 0.1\% \cong \$32$ million, which is a significant number to the industry with decreasing gross profit margins.

To nest, Taiwan's OEMs/ODMs use in-house software or depend on experienced workers to do the nesting manually. Either way has challenges that are closely related. First, the in-house software RSPN (Rising Star Pattern Nesting), which was developed by Rising Star Technology Corporation (http://www.rising.com.tw/) and has been widely used by more than 200 Taiwan-based companies, fails to solve the intractable nesting problems efficiently. More specifically, RSPN is even extremely inefficient to solve the situation involving more than one pattern that we will describe below. This inefficiency initiates our motivation to consider an alternative. Second, the turnover rate of workers is so high that they are poor trained in most cases. Owing to the software's inefficiency, manual nesting is occasionally required to complement the nesting. Nesting inherently needs to deal with complex geometric problems. The complexity leaves workers exhausted easily, which mainly contributes to high turnover rate. Third, when using manual nesting, workers often fail to calculate the accurate material requirements. Under manual nesting, workers highly depend on using stock sheets to layout each pattern and then calculate the material requirements of patterns. The experience and training have a great impact on the final layout with fewer materials and less variability.

To understand how the calculation affects the material requirements, consider a generic type of the athletic shoe that possibly contains 40–50 types of upper patterns and accommodates 15–20 sizes. Given the types and sizes, the combination of the nesting is about 600–1000 patterns. Even by using common patterns as many as possible to reduce the combination, workers still have to deal with 300–500 patterns. Assume an experienced worker can finish calculating the nesting of a pattern in 2 min; the underlying generic type will approximately take 600–1000 min, or 10–17 h. Being infeasible given the amount of time in practice, the popular way is to select three representative sizes, i.e., large, medium, and small. On the basis of these three sizes, workers calculate the materials of other sizes according to the proportion relative to the representatives. Using representative sizes, however, cannot calculate accurate material requirements of other sizes due to the relationship between each pattern's material and each size is not perfectly linear. Miscalculation often leads to either material shortage or overstock that weakens the competitiveness.

Given the intractability to solve a nesting problem, in this paper we apply genetic algorithms (GAs), proposed by Holland (1975), to implement in-house placement heuristics derived from the experienced workers. Our objective is to improve material utilization and reduce calculation time by exploiting GAs' fast convergence and solution quality. A number of researchers have reported applying GAs to the problems related to packing or nesting. Cheng and Rao (2000) proposed an algorithm combining the compact neighborhood algorithm with GAs to optimize large-scale nesting processes considering multiple orientation constraints. Hopper and Turton (1999) used two GAs for a regular packing problem. Fischer and Dagli (2004) introduced a new GA to solve the irregular-shape, full-rotation nesting problem. Poshyanonda and Dagli (2004) integrated artificial neural networks and GAs to solve the stock cutting problem of regular and irregular shape. Crispin, Clay, and Taylor (2005) presented coding methodologies of GAs for the leather nesting problem involving cutting shoe upper components to maximize material utilization. Interested readers are referred to some reviews of solving nesting problems and applying GAs. For example, Dowsland and Dowsland (1995) reviewed a variety of approaches to the problems involving the nesting of irregularly shaped patterns. Hopper and Turton (2001) reviewed approaches developed to solve 2D packing problems with meta-heuristic algorithms, particularly GAs. Poshyanonda and Dagli (2004) discussed the solution approaches in length and classified them into three categories: optimization, heuristic and emerging. Gen and Cheng (1997) comprehensively introduced the applications of GAs and the design of the parameters.

The remainder of this paper is organized as follows. Section 2 provides the background of the shoe making nesting. Section 3 describes the proposed methodology that implements placement heuristics with GAs. Section 4 compares and discusses the empirical results of the proposed methodology using the real data of Puma and New Balance. Section 5 presents the conclusions and possible extensions.

2. Shoe making nesting

Depending on the shapes of patterns and the area, a nesting problem can be broadly classified into (1) placing regular patterns on a regular area, (2) placing irregular patterns on a regular area, (3) placing regular patterns on an irregular area, and (4) placing irregular patterns on an irregular area. In the shoe making industry, the area's shape depends highly on the types of raw materials used. Given the same type of the material, a nesting problem can be further classified into (1) only one type of pattern is placed, (2) two types of patterns are placed, and (3) multiple types of patterns are placed. These three different types are shown in Fig. 1.

The majority of patterns used in shoe making are irregular except in few cases. Common raw materials used for shoe making include natural leather and artificial materials such as polymer materials, where the former is mostly of irregular shape and the latter is regular. If artificial materials are used, the shoe nesting problem will deal with the cases such as Figs. 1(a) and (b), while Fig. 1(c) otherwise. Since the growing awareness to protect animals has led the shoe making industry to gradually reduce the use of natural leather, we focus on placing irregular patterns on a regular area in this paper.

As far as manual nesting is concerned, placing only one type of pattern eliminates frequent change of patterns and thus helps to calculate the material requirements more accurate and to generate fewer nesting errors. However, the accuracy and fewer errors are at the cost of wasted areas. If one of the wasted areas is large enough, then it should be reconsidered as a candidate area to accommodate another pattern. In theory, multiple types of patterns can be considered for the wasted areas. Considering the growing error rates and increasing time when more than two types of patterns are involved; however, limiting to only two types is a popular practice. We refer to the first placed pattern as a master pattern, and the succeeding one as a slave; the area using the master (slave) pattern is a master (slave) area, as shown in Fig. 2. In sum, we study placing irregular patterns on a regular area and at most two types of patterns are used for the same material. In the subsequence we will use the *master–slave* pair to mean two types of patterns, and use the *single* pattern to mean one type of pattern.

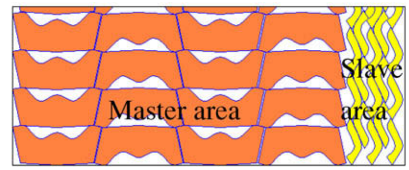

Fig. 2. An illustration of the master–slave pair.

3. Proposed methodology

In this section, we describe the foundations of in-house placement heuristics and the application of GAs.

3.1. In-house placement heuristics

To describe the heuristics, we briefly introduce a pattern's rotations, the moveable distance of a succeeding pattern relative to a previously placed pattern, and the manual nesting.

Different orientations of a pattern may produce different results. To describe a pattern's rotation, we need such parameters as x coordinate, y coordinate, and the angle of rotation. In this paper, four different orientations can be generated by rotating the pattern 0°, 90°, 180°, and 270° clockwise. Next, we describe the moveable distance of a succeeding pattern moving toward a specific direction that can be a single orientation or a combination of orientations. Such movement is constrained to the condition

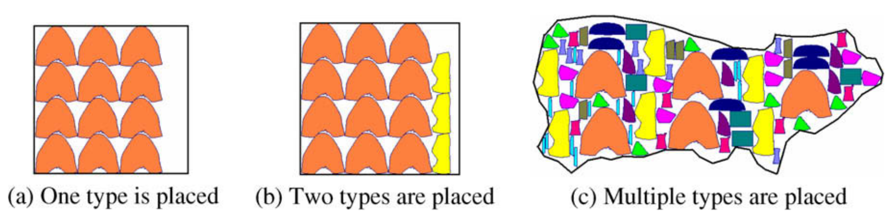

Fig. 1. Classifying shoe nesting according to the types of patterns given the same type of material.

that the pattern's locus can not overlap with the boundary of a placed pattern. In Fig. 3, let F, M, and B respectively denote a fixed (i.e., previously placed) pattern, a moving pattern, and the set of points on the material's boundary. Further, let o be the moving orientation and d the distance. Then the moveable distance of the B toward o (moving to the left in Fig. 3) can be computed as $d = \text{minimize}(D(M, F, o),\ D(F, M, -o),\ D(M, B, o))$, where $D(M, F, o)$ defines the minimal distance between M and F with respect to the orientation o.

On the basis of the preceding descriptions, workers commonly follow three categories of guidelines below.

(1) By the placing sequences of patterns: either from left to right, or from bottom to top.
(2) By the orientations of patterns: there are four cases as shown in Fig. 4.
(a)Consistent: each pattern has the same orientation (Fig. 4(a)).
(b)X-inverted: every other pattern rotates 180° with respect to only x coordinate (Fig. 4(b)).
(c)Y-inverted: every other pattern rotates 180° with respect to only y coordinate (Fig. 4(c)).
(d)XY-inverted: every other pattern rotates 180° with respect to both x coordinate and y coordinate (Fig. 4(d)).
(3) By the alignments of patterns: there are two cases as shown in Fig. 5.
(a) Line: two rows of patterns are aligned either vertically or horizontally (Fig. 5(a)).
(b)Zigzag: two rows of patterns are aligned to minimize the wasted areas (Fig. 5(b)).

Summing up the guidelines described above, we can obtain the combination of 16 nesting heuristics as shown

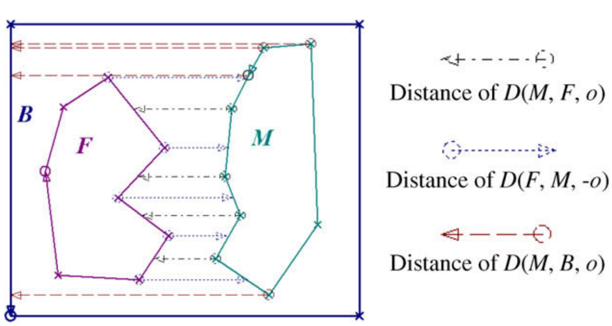

Fig. 3. Moveable distance of a pattern moving toward the left.

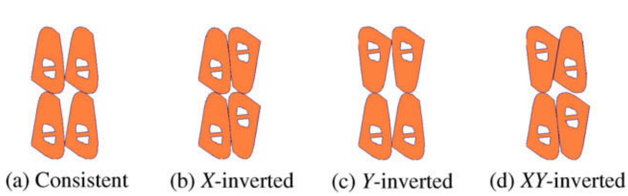

Fig. 4. Nesting by the orientations of patterns.

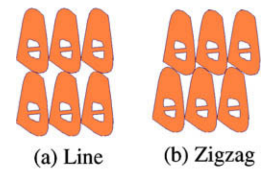

Fig. 5. Nesting by the alignments of patterns.

in Fig. 6, where the number in the parenthesis is referred to as the nesting serial number and will be mentioned later. One may raise the concern over whether other nesting approaches such as the bottom-left placement heuristic (Dowsland, Vaid, & Dowsland, 2002) can also be considered. In our case, the bottom-left heuristic is not appropriate for the zigzag arrangement.

Given a stock sheet, say j, and using the preceding heuristics, we can obtain the layout as shown in Fig. 7, where w_j, l_j, u_j, and t_{ij} represents the sheet's width, length, unit length, and the total number of patterns i used for this sheet. Since each pattern's length varies, a stock sheet's length may also vary from one to the other and complicate the material calculation. To tackle this variation, the unit length u_j is used to normalize the calculation and equals to 36 in. With u_j in place, the number of patterns in a unit-length sheet, say c_{ij}, can be expressed as the following.

$$c_{ij} = t_{ij} \times \frac{u_j}{l_j}$$

3.2. Application of genetic algorithms

Genetic algorithms include the following general steps:

- Generate an initial random population of potential solutions.
- Evaluate the population using a fitness function (objective function).
- Select the population with high fitness values as the parents to produce the offspring.
- Crossover the pair of parents at a chosen splice point(s) with some probability.
- Mutate a proportion of the offspring to avoid early trap in the local solutions.
- Reevaluate the fitness values of the offspring.
- Terminate the algorithm if the stopping criterion is satisfied.

To implement the preceding heuristics with GAs, recall that we use at most two types of patterns for a stock sheet, i.e., a master and possibly a slave. Moreover, we assume that each pattern will be given the opportunity to be a master for a stock sheet, i.e., the number of pattern is the number of stock sheets. Given a master, we are to find any feasible slave so that the material utilization can be improved. Under the circumstances, the coding of genes is the relationship between a stock sheet and a set of genes. The chromosome is composed of n genes, where n repre-

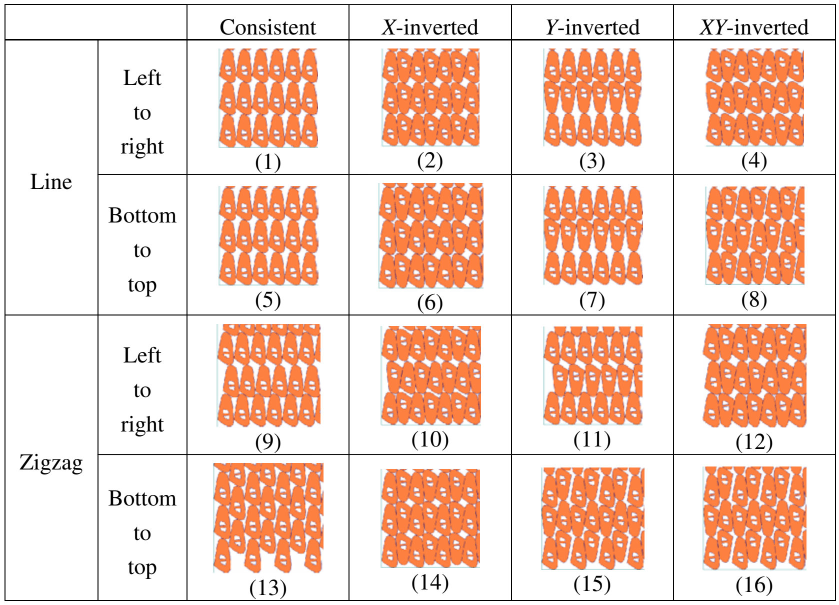

Fig. 6. The combination of 16 nesting heuristics.

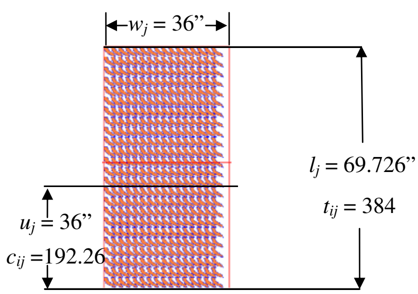

Fig. 7. An example of the stock sheet j with the pattern i.

sents the total number of patterns. Each gene consists of a triplet, where the first number represents the given master's serial number that is one of 16 in Fig. 6; the second and third numbers are the slave pattern and its serial number. Fig. 8 illustrates that given the master pattern being one, workers use serial number five; the slave pattern is four, and the serial number of the slave is seven.

To formulate the fitness function, let i and j represent the number of patterns and the number of stock sheets (recall that $1 \leqslant i = j \leqslant n$), x denote the length (i.e., the material requirement) of each sheet, and r be the number of patterns required. Then, the fitness function $f(x)$ is expressed as follows:

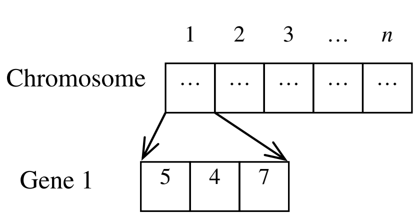

Fig. 8. An illustration of the coding of chromosome and gene.

$$\text{Min } f(x) = \sum_{j=1}^{n} x_j$$

$$\text{Subject to} \quad \sum_{j=1}^{n} c_{ij} x_j \geqslant r_i, \quad i = 1, 2, \ldots, n,$$

$$x_j \geqslant 0, \quad j = 1, 2, \ldots, n.$$

The parameters of GAs were determined in Lin (2006) by using the Taguchi method (Taguchi, Chowdhury, & Wu, 2004), where the crossover (one-point and two-point) rate is 40%, the mutation rate is 30%, and the number of population is 10. To form the parents for the succeeding generations, we use the *elitism strategy* preserving the best five chromosomes, and the ranking method selecting the remaining chromosomes. Further, we label the latest three pairs of parents as a list to prevent GAs from achieving a local solution at early generations. The value of three is determined by jointly considering the computational efficiency and the quality of solution. A higher value will reduce the likelihood to converge to a local solution at early stages, while will increase the time to search the list. The algorithm is terminated when the fitness function value improves less than 10^{-5} in consecutive 150 generations.

4. Empirical results

To validate our proposed methodology, we select New Balance (NB) and Puma (PUMA), where each of them provides two models (1 and 2) and each model uses two types (A for outsole and B for insole) of raw materials. In the subsequence, we refer to the name like NB1A01 as the pattern 01 used for the model NB1 with the material A; the material requirements in comparisons are the quantities (in yards) of 500 pairs of shoes; the calculation times of the patterns are measured by seconds. Note that the number of feasible patterns for each model with either type of material differs from one to the other; we refer readers to Lin (2006) for details. We use Visual C++ 6.0 to implement the heuristics on an AMD Athlon XP 2400+ with the capacity of one gigabyte memory. We compare our results to those by RSPN that is widely used to generate the nesting involving single pattern. Given the test data of two brands, two models, and two types of materials, we can obtain the combination of eight results where each of them shows the comparison of using all feasible patterns for a specific brand's model with either type of material. For brevity, we summarize those results in Table 3 and will give some of them when they are to be discussed in more details.

According to Table 3, with respect to the average considering all eight models, our proposed methodology outperforms RSPN in terms of material requirements by 2.64% and nesting time by 69.15%. In addition, with respect to the average considering all 80 patterns, each pattern's calculation time reduces to 2.23 s. Compared to 2 min mentioned in Introduction, the new calculation time appears to be a significant improvement. To understand how the material requirements are reduced given a master pattern on a stock sheet, consider three possible cases.

(1) Unchanged: no slave pattern is introduced and hence the material requirements remain unchanged.
(2) Different: the other slave pattern is introduced but the given master does not serve as a slave elsewhere, which leads to different requirements.
(3) Reduced: the other slave pattern is introduced and the given master also serves as a slave somewhere, which reduces material requirements.

These three cases are illustrated in Table 4 using NB1 with material A as the example, where the number of master pattern is 13.

According to Table 4, we have the following observations:

(1) If a master pattern (including NB1A03, Nb1A05, NB1A06, and NB1A07) is also introduced as a slave somewhere, its material requirements will be reduced. Among them, NB1A06 even reduces to zero because all of its requirements can be met by utilizing the wasted area of NB1A11. Given NB1A05 as the master, Fig. 9 illustrates introducing the slave NB1A03 (in yellow) to NB1A05 and shows that the material utilization is improved from 76.59% to 78.33%.
(2) If a master pattern such as NB1A02 (or NB1A13) is not introduced as a slave elsewhere, its material requirements by using the master–slave pair slightly increase, which seems to be contrary to the notion that a master–slave pair would be better. Further exploration reveals that the underlying nesting actually accommodates NB1A07 (or NB1A05) as a slave and improves the overall material utilization from 79.61% (or 60.26%) to 80.82% (or 67.36%).

Table 4
Comparisons between single and master–slave pair using NB1 with material A

Pattern	Material requirements		Case
	Single	Master–slave	
NB1A01	4.6877	4.6877	Unchanged
NB1A02	3.3354	3.3374	Different
NB1A03	1.1183	1.0173	Reduced: slave of NB1A05
NB1A04	3.1638	3.1638	Unchanged
NB1A05	11.1134	4.3219	Reduced: slave of NB1A13
NB1A06	0.9205	0.0000	Reduced: slave of NB1A11
NB1A07	0.7439	0.6198	Reduced: slave of NB1A02 & NB1A04
NB1A08	24.8982	24.8982	Unchanged
NB1A09	4.5119	4.5121	Different
NB1A10	6.2869	6.2869	Unchanged
NB1A11	25.1789	25.1789	Unchanged
NB1A12	4.8479	4.8479	Unchanged
NB1A13	46.4580	49.2816	Different
Total materials	137.2647	132.1534	Reduced by 3.72%
Total times	178.7500	46.1410	Reduced by 74.19%

Table 3
Comparisons between single (RSPN) and master–slave pair

Model	No. of Pattern	Single (RSPN)		Master–slave		Materials saved		Time saved	
		Material	Time	Material	Time	Yards	%	Seconds	%
NB1A	13	137.26	178.75	132.15	46.14	5.11	3.72	132.61	74.19
NB1B	11	217.04	44.33	210.02	18.99	7.017	3.23	25.34	57.17
NB2A	10	356.16	51.58	342.70	27.13	13.46	3.78	24.45	47.41
NB2B	8	282.26	38.00	272.80	11.06	9.47	3.35	26.94	70.89
PUMA1A	13	133.38	170.42	132.16	27.20	1.22	0.91	143.22	84.03
PUMA1B	10	140.00	55.33	139.46	15.81	0.55	0.39	39.52	71.42
PUMA2A	8	89.88	57.0	87.76	17.55	2.12	2.36	39.45	69.22
PUMA2B	7	50.93	66.688	49.21	14.09	1.71	3.37	52.59	78.87
Total	80	1406.92	662.09	1366.27	177.97	40.65	21.11	484.12	553.2
Average of all models		175.87	82.76	170.78	22.25	5.08	2.64	60.52	69.15
Average of all patterns		17.59	8.28	17.08	2.23	0.51	0.26	6.05	6.92

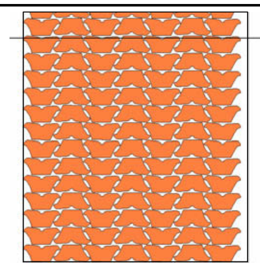	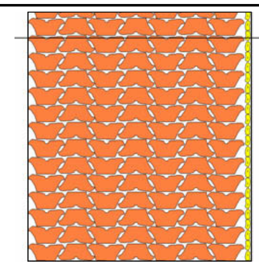
$w \times l$: 36" × 67.214"	$w \times l$: 36" × 67.214"
Material utilization: 76.59%	Material utilization: 78.33%
Number of master patterns used: 168	Number of master patterns used: 168
Number of slave patterns used: none	Number of slave patterns used: 39
(a) The master is NB1A05	(b) The slave NB1A03 is introduced

Fig. 9. An illustration of the master–salve pair in a stock sheet.

(3) Using the master–slave pair for NB1A09 marginally increases its material requirements too. The factor causing the increase is not the same as that of NB1A02 discussed earlier, but because GAs failed to produce genes of better solutions over the course of evolutions. The failure can be in part attributed to the marginally different fitness function value (0.0002 in this case) that is easily affected by some genes dominating the solution improvement.

(4) A chain of the master–slave pair is formed. For example, NB1A03 serves as the slave of NB1A05 that serves as the slave of NB1A13. Another example is that NB1A07 is the slave of NB1A02 and NB1A04. Without using GAs, discovering these chains is beyond the capability of manual nesting or RSPN. In other words, improving material utilization becomes a reality when GAs are implemented.

5. Conclusions

This paper presents a methodology that combines in-house heuristics with genetic algorithms to solve the nesting problems of shoe making industry in Taiwan. Largely determined by the raw materials, the problems in this paper are classified to be the placement of irregular patterns on a regular area. Considering the complexity, we limit the nesting problems to at most two types of patterns on the area and refer to the underlying nesting as the pair of master–slave.

To test our proposed methodology, we use real-life data of Puma and New Balance where each of them contains two models and uses two types of materials. According to Table 3, the results show that, for models tested, our methodology reduces their average material requirements by 2.64% and average nesting time by 69.15%. In addition, each pattern's average calculation time drastically reduces from 2 min to 2.23 s. Since OEMs/ODMs are exposed to the plight of high turnover rate in large attributed to the exhaustive calculation, the drastic reduction of calculation time may help to alleviate the plight. Finally, our methodology can produce the complex chain of patterns that helps improve the material utilization.

Despite the encouraging results, some issues remain. First, the heuristics summarized are far from exhaustive; a wider variety of in-house heuristics may improve solutions further. Second, as frequently discussed in the literature, different settings of GAs' parameters are highly likely to result in different solutions. Finally, the extensions to study placing more than two types of patterns, or placing irregular patterns on an irregular area appear to be more challenging.

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