Optimization of Pattern Layout Considering Multi- Set Pattern&Pieces Rotation

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Abstract

Packing problems arise in a wide variety of application Areas such as sheet metal, lumber, glass, leather, textile, and paper industries. Because of importance of minimizing scrap losses (cutting stock problem), many methods have been represented. One of the best methods is application of Genetic Algorithm. The main purpose in this case, is minimizing scrap losses without overlapping of pieces.

Many factors effects to achieve the qualified optimization .Two of the most important factors that we consider in this project are the number of sets and pieces' rotation. The results show that using penalty function to determine fitness of chromosomes and using dynamic fitness function are very important to achieve the qualified optimization.

The result of one non-fit set pattern with 500 initial population and 350 generation is 73.9% efficiency.

The result of two non-fit set pattern with 1000 initial population and 350 generation is 71.6 % efficiency.

Key words: Cutting Stock-Cutting-Optimization-Genetic Algorithm-Rotation

1-Introduction

Packing problems arise from a variety of situations including pallet loading, textile cutting, container stuffing and placement problems. Such problems are optimization problems that are concerned with finding a good arrangement of multiple objects (2-D or 3-D) in a larger containing region without overlap [1]. The usual objective of the allocation
process is to maximize the material utilization and hence to minimize the wasted area. The packing problem becomes much simpler when both objects and the containing region are rectangular in shape [1, 4]. Many research works have been done on two and three dimensional rectangular packing problems. However, in many practical applications, objects and containing regions may have irregular shapes [1, 5]. Due to the geometrical complexity introduced by irregular shapes, such problems are not as well studied as rectangular packing.[1]

2. Problem Representation

Figure (1) shows an example of an order book for 1 garment that could be a shirt [2]. If 2 shirts are required, the placement on a fixed width fabric is illustrated in figure (2). In each placement, the marker may be at 0 degrees or 180 degree orientations. In our experiment, each garment piece is modeled as a polygonal object. Objects that have smooth boundaries such as quadratic splines[7], must be approximated by a polygonal surface .

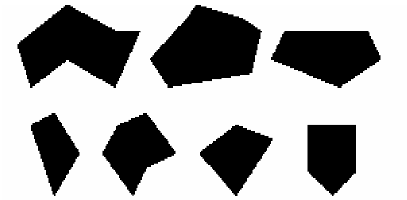


Figure (1) Sample pieces for 1 garment piece.[2]

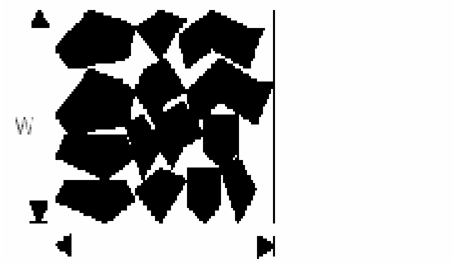


Figure (2) Placement on fabric of fixed width. [2]

For a given problem with N pieces illustrated in figure (1), each piece has a default initial orientation, but may be rotated 180 degrees. A solution or individual is a structure with the following format:

S=[(f1,x1,y1,O1),(f2,x2,y2,O2).(fn,xn,yn,on)]

where S is the solution from the order book, F represents each garment piece, O is the piece's orientation: 0 for 0 degrees or 1 for 180 degrees, x and y are the garment piece Position.

3-Genetic Algorithm

Genetic algorithms are search algorithms based on the principles of natural selection and survival of the fittest [3]. GA's were first introduced by John Holland [4]. [11], [10], [9], [1] and [5] provide good introductions. A GA attempts to evolve a solution using a population of potential solutions (or individuals). New individuals are created by promising genetic material from one individual being passed to another by a process of breeding. Each solution has a fitness value associated with it. Our fitness value is derived from the cost function presented in section 3.2. The fitness of a solution determines how likely it is to be chosen to breed with another solution. As GA's have their foundations in genetics, terms from this field are used to describe the various features of a GA[3]. It is usual to call a solution a chromosome and the individual parts that make up the chromosome, a gene. For this problem a chromosome is a set of patterns and a gene is an individual pattern breeding between chromosomes is carried by two operators[3,5]. Crossover is the most important. It takes two chromosomes (parents) and transfers genetic material from the parents to produce two new chromosomes (children).

3-1 Coding and initial population

At first the distance between surrounding pattern's points and center of pattern is calculated and then distance between center of pattern and coordinates is determined This work let rotation along center pattern point with least calculations.

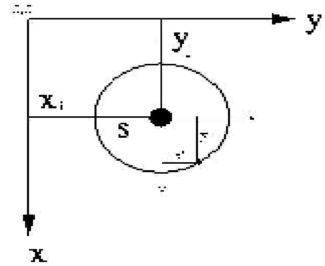


Fig (3) coding

at last the (θ_i ,x_i, y_i) is saved in three dimensional arrays by putting patterns randomly pattern position which contains random angle ,random x position an random y position , on layout a chromosome is made(fig(4)).

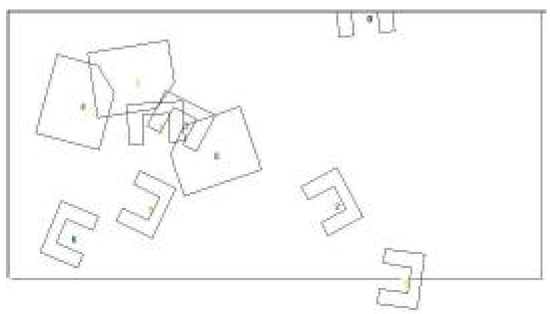


Fig (4) a chromosome sample

3-2 Fitness Function

The fitness function contains two parts:

a) Purpose functions

In which minimizing the wastage is desired and defines as blew:

$$o(s) = \sum_{j=1}^{n} (x_j . A_j + y_j)$$

and Y(j)and X(j) are the position of the patterns and A(j) is the area of them for each set of patterns the purpose functions is calculated considering to the left, up point of the visual fabric.

The index of the x position in the purpose function can be compare to accelerate of object in physical system .in fact by decreasing the purpose function big patterns tend more to pack in the left corner of the visual fabric.

b) Penalty function

only over lapping is considered as penalty function.

$$p(s) = \sum_{j=1}^{n-1} \sum_{i=j+1}^{n} OverlapArea(ij)$$

and at last the fitness function is defined :

$$fitnessfunction = \frac{k}{a.o(s) + b.p(s)}$$

a,b,k are constant value which are determine by experiments.

3-3 Generate New Population

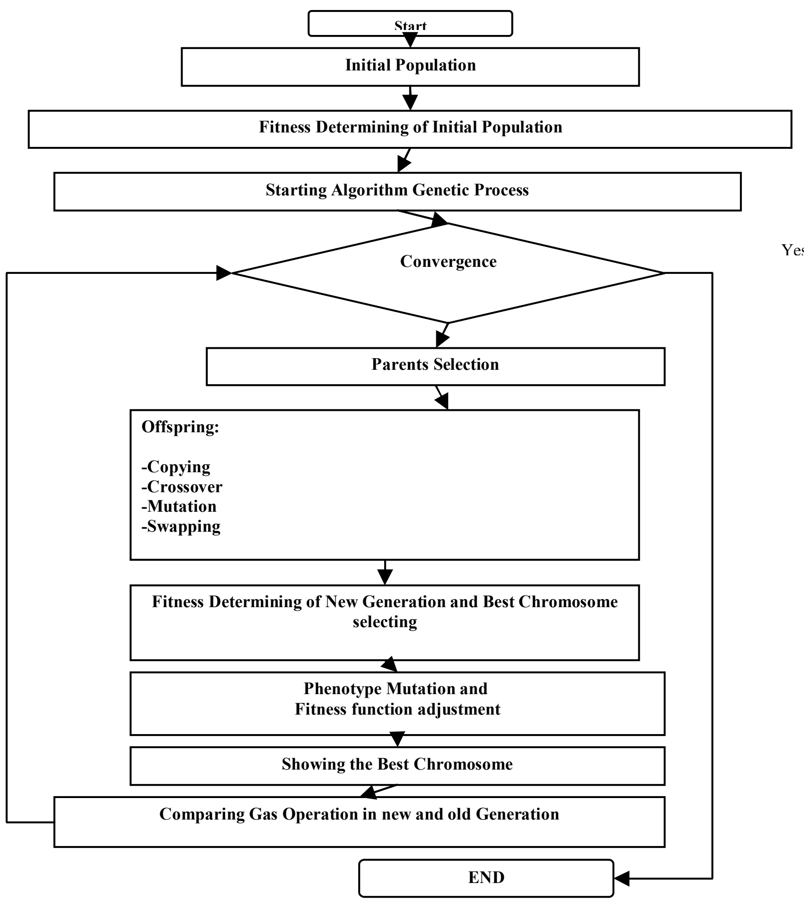
near 10 percent of new generation are directly selected from best chromosomes of past generation and for other genetic algorithm operation the chromosomes are selected by using Rolette round [8] .

for crossover operation two selected chromosomes are cut from same random point and two offspring are made. the mutation operator changes the position of random selected patterns randomly and make new chromosome. The swap operator changes the position of two randomly selected patterns in selected chromosome and make new chromosome.

Phenotype mutation operator just use on the best chromosome in the past population .the operator use for better space searching by little changing in each pattern position and calculating a fitness function ,if the change make a better fitness function the new change is kept else the last state will be kept .

This operator is very useful for space searching however increase the calculating hugely And therefore take a lot of time because of that this operator just use on the best chromosome of each generation.

The structure of program is illustrated in figure (5).



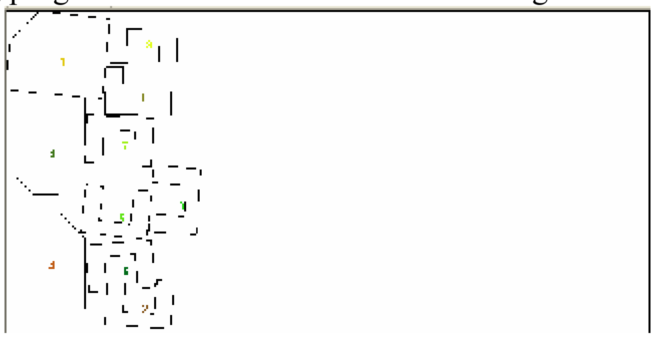
Figur(5) Program Structure

4-Expriments

4-1 Effect of Population in Initial Generation

Assume:
-number of patterns: 10 pieces
-number of generations: 350
-let all pieces rotate
-select initial population randomly

a) Running program with 50 chromosomes in initial generation



figure(6) best chromosome with 50 chromosomes in initial generation after 350 generations.

b) Running program with 500 chromosomes in initial generation

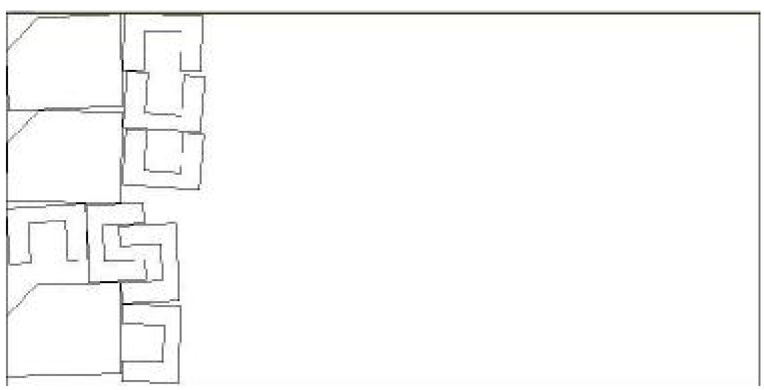


Figure (7) best chromosome with 500 chromosomes in initial generation after 350 generations.

As it is shown the operation of genetic algorithm strongly depends on the number of chromosomes in initial population[10] .If it's very low then the genetic algorithm lost it's proficiency. 500 chromosomes is used for initial population in this research consider to the number of chromosomes directly effects on time running.

4-2 Effect of Selecting Method for Initial Population

a) The initial population is selected from 100000 random produced chromosomes.

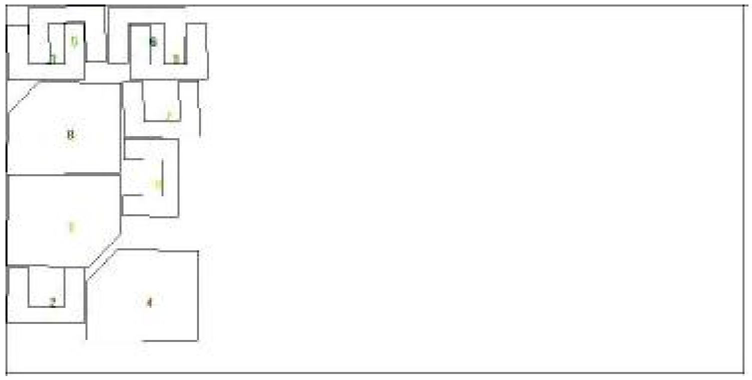


Figure (8) the result of initial population selecting from 100000 random produced chromosomes

b) The initial population is selected by random

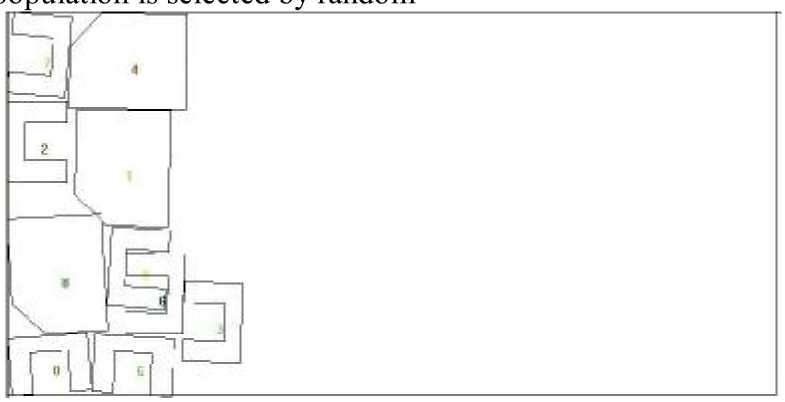
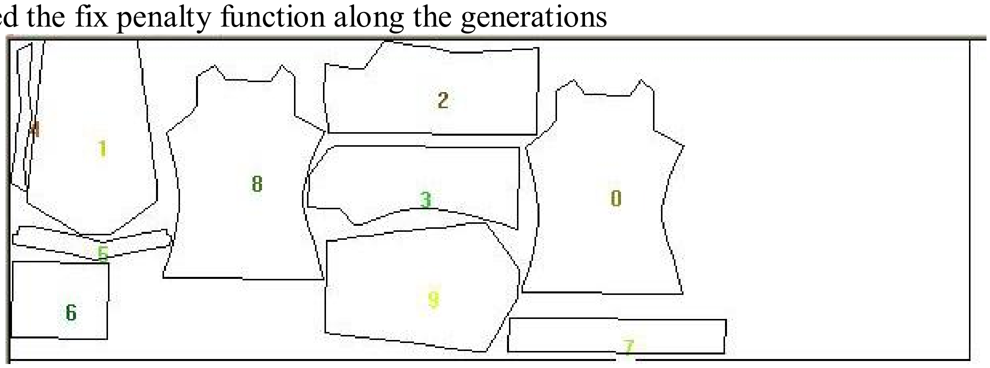


Figure (9) the result of initial population selecting by random

As it clears from figures selecting initial population from 100000 random produced chromosomes gives better result compare with random selecting. The effect of initial population selecting method clear in low generation number and by increasing the generation number the result difference between initial population selecting methods will vanish[11].

4-3 Effect of Penalty Function

a) Used the fix penalty function along the generations



Figure(10)result of fix penalty function

b) Dynamic penalty function

The penalty function increased by increasing the generation number.

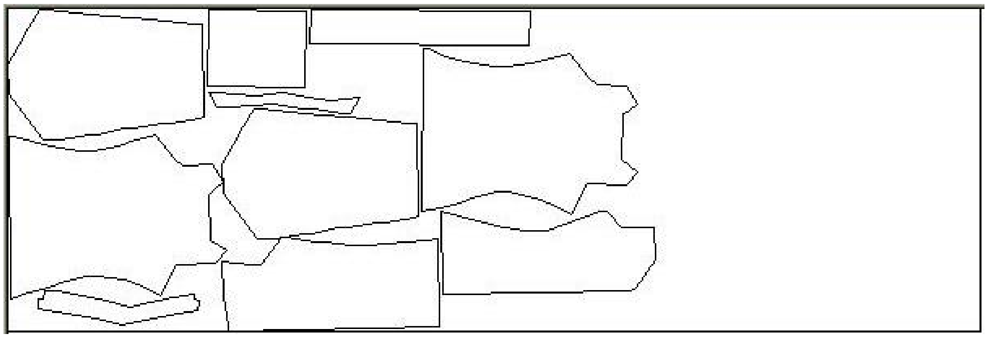


Figure (11) result of dynamic penalty function

Figures (10) and (11) represent the dynamic penalty function has better result consider to increasing penalty function along the generations omit the invalid chromosomes in higher generations when in the initiation generations gives more chance to the week chromosomes.

4-4 Effect of Using Dynamic or Fix Genetic Operators along the Generations

a) Dynamic genetic operators
The genetic operator's effective range is changed by increasing the generation's number as shown in blew table. and the result represents in fig (11)

Operators	Start	End
Copy	25%	10%
Crossover	50%	35%
Mutation	10%	20%
Angle mutation	5%	15%
Swapping	10%	20%

Table (12) dynamic rang genetic operators

b) Fix genetic operators
The genetic operator's effective range is fixed along the generations. The operators range is shown in table (13) and the result illustrate in fig (14).

Operators	rang
Copy	20%
Crossover	40%
Mutation	20%
Angle mutation	5%
Swapping	15%

Table (13) fix rang genetic operators

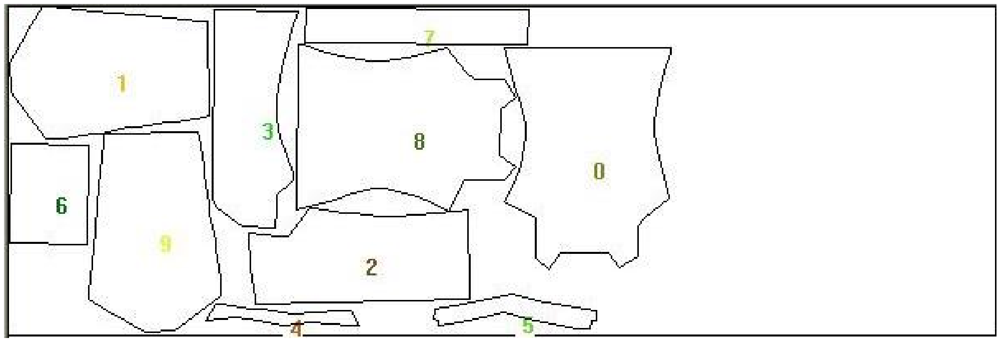


Figure (14) result of fix rang genetic operators with dynamic penalty function

Using Dynamic genetic operators gives73.9% optimization (fig 11) and by using Fix genetic operators gives 73.35% optimization (fig 14).

4-5 Optimizations of Multi-Set Patterns
Assume:
-number of patterns: 20 pieces
-number of generations: 350
-number of chromosomes in each generations: 1000
-let all pieces rotate
-select initial population randomly

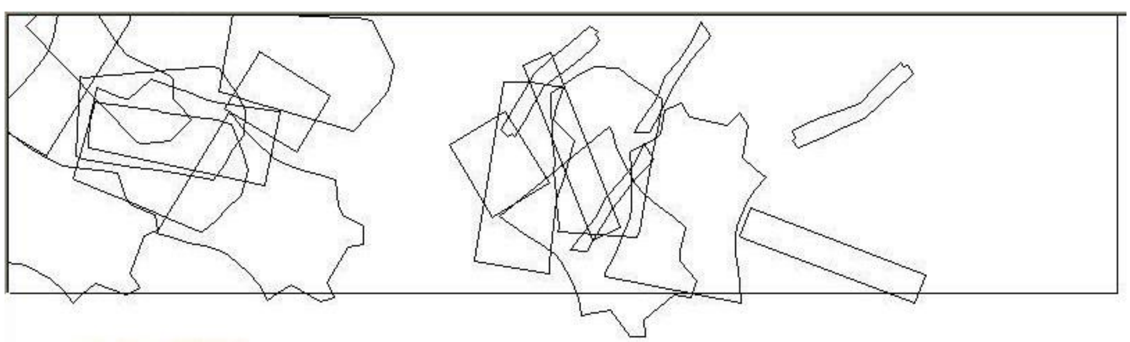


Figure (15) best chromosome with 500 chromosomes in initial generation after one generations.

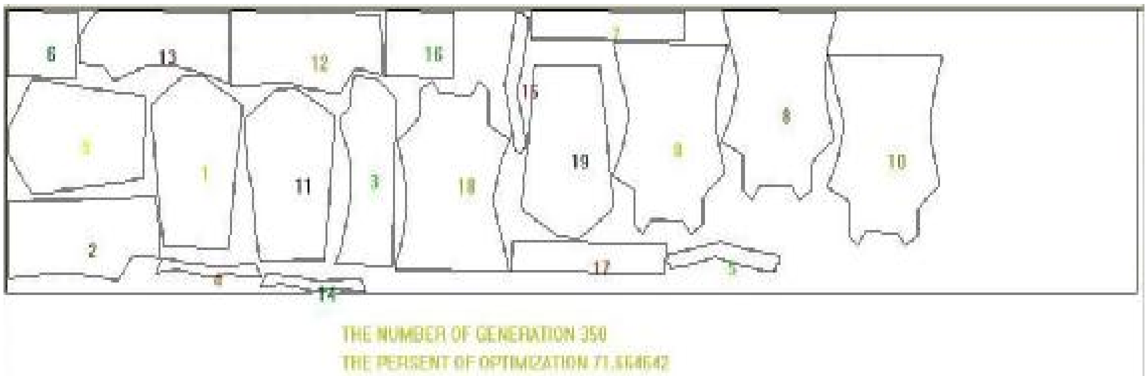


Figure (16) best chromosome with 1000 chromosomes in initial generation after 350 generations.

Result and conclusion

Experiments show that dynamic fitness function operate better than fix fitness function
In this paper we consider to pattern rotation which let us to have more compact packing however increase search space hugely .two effective factors to search space searching are The number of chromosomes in initial population and generation's number.[5,6]
In fact with low population and high generation we reach to the same result which achieved by high population and low generation .therefore the relation between these two factors should be optimized. in this research for one set pattern 500 chromosomes in population and 350 generation's number is used .the different experiments shows that by increasing the generation's number more than 350 didn't give much better results but takes much more times. the result illustrate that choosing initial population randomly or Selectively didn't have scientific difference.
For two-set layout packing the experiments denote that more initial population is needed. The result of one non-fit set pattern with 500 initial population and 350 generation is 73.9% efficiency. and for two non-fit set pattern with 1000 initial population and 350 generation is 71.6 % efficiency.

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