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# Modified genetic algorithm for automated facility layout design

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## ABSTRACT

***The placement of facilities is a fundamental task in many industries, and the facility layout problem is frequently encountered. This paper describes the implementation of a modified genetic algorithm for solving the facility layout problem by minimizing the total material handling the cost. An isomer-based elitism is applied and the performance of the proposed algorithm is compared with previous results in the literature. An extended method for measuring the efficiency of the algorithm is proposed. The results suggest that the efficiency of the proposed methodology is competitive with prior work and that isomer-based elitism should be reviewed for application in a wider range of problems.***

***Keywords****— Facility layout problem, Genetic algorithm, Material handling cost, Sensitivity analysis, Isomer-based elitism*

## 1. INTRODUCTION

Facility layout is the arrangement of all the equipment, machinery and furnishings required in a production environment. Feasible arrangements often involve many potential permutations and combinations. Where the machines are placed efficiently, costs are reduced and the overall profit of the organization is improved. While there are several techniques which can be applied to solving the Facility Layout Problem (FLP), variations on the genetic algorithm have been widely used. One of the most common optimization functions used in this context is the material handling cost function. This paper considers the application of the Genetic Algorithm (GA) to the facility layout problem utilising a novel means of elitism, and extending the considerations of algorithm efficiency.

## 2. LITERATURE REVIEW

Several researchers have applied different algorithms to the solution of the facility layout problem (Chan and Tansri, 1994; El-Baz, 2004; Liu and Li, 2006; Misola and Navarro, 2013). It is a complex problem involving a range of overlapping and often conflicting issues. These include the shape of the layout, material handling systems design, the management of back-tracking and bypassing, and even more fundamentally, whether the layout should be static or dynamic. Attempting to integrate all these issues into a unified solution is a significant challenge, and a range of relatively standard problems have emerged in the literature, including the flow process layout, the multi-floor problem (Ahmadi, Pishvaee and Akbari Jokar, 2017), the single row problem and the multi-objective layout (Ripon, Glette, Hovin and Torresen, 2013; García-Hernández, Arauzo-Azofra, Salas-Morera, Pierreval, and Corchado, 2015). Minimizing the total flow cost is often seen as a useful start in approaching the best solution. The GA is frequently applied to this minimization problem and the total flow cost calculation provides the basis for a useful objective application.

In the literature, the GA is applied in a range of different ways, and with many of the conventional steps modified to some degree. There are many different types and rates of crossover and mutation applied, alongside a range of different elitism techniques. Since the GA is stochastic in nature it is important to identify the best parameters for a particular application.

Chan and Tansri (1994) applied their methodology with a PMX crossover operator and showed that it performed favorably when compared to order crossover and cycle crossover. El-Baz (2004) proposed a new crossover method and, using a crossover rate of 0.6 and a mutation rate of 0.001 showed better results than those obtained by Chan and Tansri (1994). Liu and Li (2006) showed the application of the GA for a supply chain oriented facility layout system. The broad applicability of the GA to a wide range of layout problems is illustrated.

While minimizing the total flow cost is a useful and effective approach to solving the FLP, it remains a single-objective function. Ripon, et al (2013) presented a genetic algorithm to solve the integrated job shop scheduling problem and facility layout problem considering multi-objectives. Aiello, La Scalia, and Enea (2012) developed a multi-objective genetic algorithm to solve the facility layout problem based on slicing structure encoding, using four objective functions of the block layout problem.

The FLP continues to challenge both researchers and practitioners. This paper addresses the flow process layout and attempts to minimize the total material handling the cost, using a single objective function with a novel method of elitism and a comprehensively evaluated algorithm efficiency.

## 3. METHODOLOGY

With this application of the genetic algorithm, the objective is to reduce the total material handling cost of the system. While this function is impacted by several factors in practice, there are three factors used here to develop the algorithm, which is: the volume of material handling (frequency of journeys); the cost of material handling, and the distance travelled. This is in agreement with the literature. These factors are tabulated and the sum of the product of the three tables used to develop a Total Flow Cost (TFC) for any potential layout. While it is assumed that the volume and cost tables remain fixed, the distance travelled between departments will change, depending on their specific locations within a given layout. These distances are assumed to be rectilinear. A sample of such a table can be seen in figure 1, while figures 2 and 3 represent the material handling cost and the volume of material flow among the facilities.

| From/To | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 2 | 1 | 2 | 3 | 2 | 3 | 4 |
| 2 | 1 | 0 | 1 | 2 | 1 | 2 | 3 | 2 | 3 |
| 3 | 2 | 1 | 0 | 3 | 2 | 1 | 4 | 3 | 2 |
| 4 | 1 | 2 | 3 | 0 | 1 | 2 | 1 | 2 | 3 |
| 5 | 2 | 1 | 2 | 1 | 0 | 1 | 2 | 1 | 2 |
| 6 | 3 | 2 | 1 | 2 | 1 | 0 | 3 | 2 | 1 |
| 7 | 2 | 3 | 4 | 1 | 2 | 3 | 0 | 1 | 2 |
| 8 | 3 | 2 | 3 | 2 | 1 | 2 | 1 | 0 | 1 |
| 9 | 4 | 3 | 2 | 3 | 2 | 1 | 2 | 1 | 0 |

**Fig. 1 Rectilinear distance**

The objective function thus obtained is:

$$\text{Min TC} = \sum\sum F_{ij} * C_{ij} * D_{ij}$$

Where:
$F_{ij}$ is the material flow among various equipment
$C_{ij}$ is the material handling cost among equipment
$D_{ij}$ is the distance between the facilities
TC is the total material handling the cost

| From/To | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 2 | 1 | 2 | 3 | 2 | 3 | 4 |
| 2 | 1 | 0 | 1 | 2 | 1 | 2 | 3 | 2 | 3 |
| 3 | 2 | 1 | 0 | 3 | 2 | 1 | 4 | 3 | 2 |
| 4 | 1 | 2 | 3 | 0 | 1 | 2 | 1 | 2 | 3 |
| 5 | 2 | 1 | 2 | 1 | 0 | 1 | 2 | 1 | 2 |
| 6 | 3 | 2 | 1 | 2 | 1 | 0 | 3 | 2 | 1 |
| 7 | 2 | 3 | 4 | 1 | 2 | 3 | 0 | 1 | 2 |
| 8 | 3 | 2 | 3 | 2 | 1 | 2 | 1 | 0 | 1 |
| 9 | 4 | 3 | 2 | 3 | 2 | 1 | 2 | 1 | 0 |

**Fig. 2: Unit material handling cost**

| From/To | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 2 | 3 | 3 | 4 | 2 | 6 | 7 |
| 2 | 0 | 0 | 12 | 7 | 4 | 5 | 8 | 6 | 5 |
| 3 | 0 | 0 | 0 | 5 | 9 | 1 | 1 | 1 | 1 |
| 4 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 4 | 6 |
| 5 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| 6 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 4 | 6 |
| 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 1 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Fig. 3: Material handling cost**

The genetic algorithm works by generating an initial random population, which is then passed to the objective function for a set of initial layout scores. Figure 4 gives a sample of these initial populations in the chromosome form and also lists associated values of the objective function in the right-hand column. The flow process problem considered is a standard problem from the literature, with nine departments, so there are 362,880 potential layouts. The initial population is a randomly selected sub-set of these.

| From/To | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 100 | 3 | 0 | 6 | 35 | 190 | 14 | 12 |
| 2 | 0 | 0 | 6 | 8 | 109 | 78 | 1 | 1 | 104 |
| 3 | 0 | 0 | 0 | 0 | 0 | 17 | 100 | 1 | 31 |
| 4 | 0 | 0 | 0 | 0 | 100 | 1 | 247 | 178 | 1 |
| 5 | 0 | 0 | 0 | 0 | 0 | 1 | 10 | 1 | 79 |
| 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Fig. 4: Material flow**

After the values of the objective function are calculated for this initial population, elitism must be applied, which involves specifying a replication rate and replacing the worst-performing potential solutions with several copies of the best-performing solution. The replication rate in the literature is frequently arbitrarily set to 5%. The objective of this replication is to allow the 'best' solution emerging from a given generation to be intensively considered for potential improvement while retaining sufficient diversity in the remaining 95% of solutions to avoid being trapped in local minima.

In this work, it is proposed that a 9-department solution, presented as a 3*3 layout, can be developed into eight 'isomers' through the application of matrix transformation and rotation. These isomers, while different from their source, will receive an identical objective function value. That is to say, they will be equally 'good,' but different layouts. It is proposed that by using these isomers in the replication stage instead of exact copies of the 'best' solution in a given generation that a more efficient algorithm will result. The population obtained was arranged in ascending order of the value of the objective function. Then the first chromosome was selected and its eight isomers were formed via matrix transformation and matrix rotation to get the eight isomers, as can be seen in figure 5.

```
array([[ 3, 6, 9, 7, 1, 2, 4, 8, 5, 4927],
       [ 3, 7, 4, 6, 1, 8, 9, 2, 5, 4927],
       [ 4, 7, 3, 8, 1, 6, 5, 2, 9, 4927],
       [ 4, 8, 5, 7, 1, 2, 3, 6, 9, 4927],
       [ 5, 2, 9, 8, 1, 6, 4, 7, 3, 4927],
       [ 5, 8, 4, 2, 1, 7, 9, 6, 3, 4927],
       [ 9, 2, 5, 6, 1, 8, 3, 7, 4, 4927],
       [ 9, 6, 3, 2, 1, 7, 5, 8, 4, 4927]])
```

**Fig. 5: Objective function values for a different layout**

After the isomers were created the next step was to replace the worst-performing chromosomes with the eight possible isomers in accordance to with the replication rate. With a population of 200 and a replication rate of 5%, the lowest-ranked ten solutions must be replaced. So eight were replaced with isomers, and then the ‘best’ solution was copied twice more. When the ten chromosomes are replaced, the crossover and mutation operations are applied.

**Table 1: modified GA**

| Experiment Number | Population size | Generation Size |
|---|---|---|
| 1 | 20 | 10 |
| 2 | 40 | 10 |
| 3 | 100 | 10 |
| 4 | 200 | 10 |
| 5 | 500 | 10 |
| 6 | 20 | 20 |
| 7 | 40 | 20 |
| 8 | 100 | 20 |
| 9 | 200 | 20 |
| 10 | 20 | 40 |
| 11 | 40 | 40 |
| 12 | 100 | 40 |
| 13 | 200 | 40 |
| 14 | 20 | 100 |
| 15 | 40 | 100 |
| 16 | 100 | 100 |
| 17 | 20 | 200 |
| 18 | 40 | 200 |
| 19 | 10 | 500 |

 

The crossover and mutation rates are decided beforehand. After elitism is implemented, a random number is generated between 0 and 1. If the number is less than the crossover rate, the process of crossover takes place. In the process of crossover, the 7th gene is replaced by the 4th gene and the 2nd gene is replaced by the 5th gene. Every chromosome is evaluated against the crossover rate. If the chromosome undergoes the crossover, the next step is a mutation. Again a random number is generated, and if it falls above the mutation rate the mutation takes place. To undergo the mutation, two random integers between 1 and 9 are selected. These numbers identify the position of the genes which are to be exchanged. In these experiments, the crossover and mutation rates were specified as 0.7 and 0.8, respectively, for the entire set of nineteen experiments listed in figure 6.

These operations generate a new population set, which is then passed through the objective function calculator. Again the processes of elitism, crossover and mutation are applied and in this way, a subsequent new population is generated. This work is done using the Python programming language utilizing the Spyder editor while the layouts are visualized using the IPython console. This sequence of steps is repeated for the population, until the stopping criteria for the algorithm, taken from the literature, is met.

## 4. DISCUSSION AND CONCLUSIONS

A sample of the results obtained by the implementation of the modified GA is shown in table 1. The minimum cost developed is 4818, which agrees with the literature. Thus it is concluded that this modified GA is effective and efficient in generating a solution to this optimization problem.

The modified GA illustrated here has used a specific approach for solving the facility layout problem, and it has been shown that the optimum solution (4818) is achieved. The efficiency of the algorithm is usually assessed in the literature by counting the number of trials in which the value 4818 occurred. This analysis is performed for this set of experiments and the outputs recorded in table 1. Ideally, the trial column should have a total sum of 19, provided that for each trial the value 4818 occurred in the first run of the experiment. The 'times' column in table 1 shows the total number of times the lowest value has occurred in ten runs of the experiment. This frequency of occurrence is interpreted as a proxy for algorithm effectiveness. Ideally, the column sum should be 190. In this way, the efficiency of the algorithm can be measured.

**Table 2: Results after application of Genetic Algorithm**

| Experiment | Population Size | Generation Size | Best | Average | Trial | Times |
|---|---|---|---|---|---|---|
| 1 | 20 | 10 | 4978 | 5261.6 | 0 | 0.00 |
| 2 | 40 | 10 | 5040 | 5265.9 | 0 | 0.00 |
| 3 | 100 | 10 | 4862 | 4893 | 0 | 0.00 |
| 4 | 200 | 10 | 4862 | 5053.6 | 0 | 0.00 |
| 5 | 500 | 10 | 4818 | 5917.1 | 4 | 5.00 |
| 6 | 20 | 20 | 4818 | 5298.7 | 3 | 1.00 |
| 7 | 40 | 20 | 4818 | 5110.4 | 7 | 1.00 |
| 8 | 100 | 20 | 4818 | 4994.3 | 7 | 2.00 |
| 9 | 200 | 20 | 4818 | 4893.8 | 2 | 4.00 |
| 10 | 20 | 40 | 4862 | 5103.7 | 0 | 0.00 |
| 11 | 40 | 40 | 4818 | 5065.7 | 8 | 1.00 |
| 12 | 100 | 40 | 4818 | 4942.9 | 3 | 3.00 |
| 13 | 200 | 40 | 4818 | 4827.8 | 1 | 7.00 |
| 14 | 20 | 100 | 4818 | 4984.6 | 2 | 2.00 |
| 15 | 40 | 100 | 4818 | 4951.6 | 2 | 2.00 |
| 16 | 100 | 100 | 4818 | 4827.8 | 1 | 8.00 |
| 17 | 20 | 200 | 4872 | 5179.7 | 0 | 0.00 |
| 18 | 40 | 200 | 4818 | 5073 | 1 | 5.00 |
| 19 | 10 | 500 | 4818 | 5061.37 | 2 | 4.00 |
| | | | | Total | 43 | 45 |

| | | | Proposed methodology 2018 | | | | Misola and Navarro 2013 | | | Mihajlović et al 2007 | | | El-Baz 2004 | | | Mak et al 1998 | | | Chan and Tansri 1994 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Experiment | Population Size | Generation Size | Best | Average | Trial | Times | Best | Average | Trial | Best | Average | Trial | Best | Average | Trial | Best | Average | Trial | Best | Average | Trial |
| 1 | 20 | 10 | 4978 | 5261.6 | 0 | 0 | 4862 | Not comparable | | 5119 | Not available | | 5039 | 5310.1 | 0 | 5233 | 5504.4 | 0 | 4938 | 5434.8 | 0 |
| 2 | 40 | 10 | 5040 | 5265.9 | 0 | 0 | 4818 | | | 5150 | | | 4818 | 5231.9 | 1 | 5040 | 5286.7 | 0 | 5039 | 5263.8 | 0 |
| 3 | 100 | 10 | 4862 | 4893 | 0 | 0 | 4818 | | | 4872 | | | 4818 | 4961 | 2 | 4818 | 5024.8 | 1 | 4938 | 5164.9 | 0 |
| 4 | 200 | 10 | 4862 | 5053.6 | 0 | 0 | 4818 | | | 4818 | | | 4818 | 4895.9 | 5 | 4818 | 4891.4 | 2 | 4818 | 4966.8 | 2 |
| 5 | 500 | 10 | 4818 | 5917.1 | 4 | 5 | 4818 | | | 4818 | | | 4818 | 4822 | 9 | 4818 | 4833.2 | 7 | 4818 | 4892.3 | 5 |
| 6 | 20 | 20 | 4818 | 5298.7 | 3 | 1 | 4818 | | | 4818 | | | 4872 | 5172.9 | 0 | 5225 | 5481.2 | 0 | 4938 | 5402.1 | 0 |
| 7 | 40 | 20 | 4818 | 5110.4 | 7 | 1 | 4818 | | | 4939 | | | 4818 | 5052 | 1 | 4927 | 5174.6 | 0 | 4992 | 5184.6 | 0 |
| 8 | 100 | 20 | 4818 | 4994.3 | 7 | 2 | 4818 | | | 4990 | | | 4818 | 4855.2 | 4 | 4818 | 4889.1 | 4 | 4818 | 4991.7 | 2 |
| 9 | 200 | 20 | 4818 | 4893.8 | 2 | 4 | 4818 | | | 4818 | | | 4818 | 4842.1 | 6 | 4818 | 4846.5 | 5 | 4818 | 4919.8 | 2 |
| 10 | 20 | 40 | 4862 | 5103.7 | 0 | 0 | 4818 | | | 4818 | | | 4862 | 5074.1 | 2 | 5225 | 5462.2 | 0 | 4938 | 5402.1 | 0 |
| 11 | 40 | 40 | 4818 | 5065.7 | 8 | 1 | 4818 | | | 4818 | | | 4818 | 4979.5 | 2 | 4927 | 5163.8 | 0 | 4992 | 5180.7 | 0 |
| 12 | 100 | 40 | 4818 | 4942.9 | 3 | 3 | 4818 | | | 4818 | | | 4818 | 4842.8 | 7 | 4818 | 4871.4 | 4 | 4818 | 4919.5 | 3 |
| 13 | 200 | 40 | 4818 | 4827.8 | 1 | 7 | 4818 | | | 4818 | | | 4818 | 4842.1 | 6 | 4818 | 8440 | 5 | 4818 | 4887.9 | 4 |
| 14 | 20 | 100 | 4818 | 4984.6 | 2 | 2 | 4818 | | | 4818 | | | 4818 | 4940.9 | 5 | 5225 | 5453 | 0 | 4938 | 5337 | 0 |
| 15 | 40 | 100 | 4818 | 4951.6 | 2 | 2 | 4818 | | | 4818 | | | 4818 | 4862.7 | 6 | 4818 | 5141.6 | 1 | 4927 | 5122.4 | 0 |
| 16 | 100 | 100 | 4818 | 4827.8 | 1 | 8 | 4818 | | | 4818 | | | 4818 | 4826.8 | 8 | 4818 | 4866 | 5 | 4818 | 4863.9 | 4 |
| 17 | 20 | 200 | 4872 | 5179.7 | 0 | 0 | 4818 | | | 4818 | | | 4818 | 4893.6 | 6 | 4818 | 5303.9 | 1 | 4938 | 5224.6 | 0 |
| 18 | 40 | 200 | 4818 | 5073 | 1 | 5 | 4818 | | | 4818 | | | 4818 | 4858.3 | 7 | 4818 | 5441.4 | 1 | 4862 | 5088.4 | 0 |
| 19 | 10 | 500 | 4818 | 5061.37 | 2 | 4 | 4818 | | | 4818 | | | 4818 | 4983.7 | 4 | 4818 | 5184.3 | 1 | 4818 | 5166.1 | 1 |
| | | | 4847.9 | Total | 43 | 45 | 4820.3 | | | 4869.6 | | | 4834.8 | Total | 81 | 4927.3 | Total | 37 | 4893.9 | Total | 23 |

**Fig. 6: Comparison of Results to the previous results**

 

In figure 6, the results obtained by employing different applications of the GA to solve the 9-department FLP in the literature are shown. The sum of trials ('total' of trial columns) is done to compare the algorithms. In the application presented here, the sum of trials for the methodology presented in this paper is 43, which is better than almost all the methods. This shows that the implemented methodology performs competitively against many others.

It would be helpful to perform a larger, more demanding set of tests to more comprehensively evaluate the methodology. It would be interesting to evaluate the applicability of the isomer-based elitism to a wider set of facility layout problems. The transferability of the isomer concept to problems in different disciplines might also be usefully investigated.

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