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OPTIMIZATION OF FACILITY LAYOUT PROBLEMS USING GENETIC ALGORITHM

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Abstract

The facility layout problem (FLP) is one of the most important classic industrial engineering and production management problems that have attracted the attention of many researchers over the last few decades. Poor production facility layout planning can result in additional operational costs; one of them is the cost of material handling. Although crucial, FLP is a challenging issue to resolve. A unique method is needed depending on the constraint, case study, and layout type. This research was conducted in order to improve the existing layout of PT. XYZ to minimize material handling costs. The layout type in this case is the Open-field layout problem (OFLP). A genetic algorithm is proposed to optimize the layout. The result is 18.1% material handling costs can be reduced.

Keywords: Facility layout problem (FLP), Open-field layout problem (OFLP), Material Handling Cost, Genetic Algorithm, facility layout planning

Introduction

The facility layout problem (FLP) is one of the most important classic industrial engineering and production management problems that has attracted the attention of many researchers over the last few decades. To operate production and service systems efficiently, companies must not only operate with optimal operational planning and policies but must also have a well-designed facility layout. The facility layout problem (FLP) is defined as an attempt to find the most efficient arrangement of elements on the factory floor subject to different constraints to fulfill one or more objectives. Effective facility layout design improves throughput, overall productivity and efficiency. Conversely, poor facility layout results in increased work-in processes and manufacturing lead times.

The most significant indicator of layout efficiency is material handling cost (MHC) (Emami & S. Nookabadi, 2013). Since 20–50% of a manufacturing company's total operating costs and 15–70% of a product's total production costs are attributed to MHC (Mohamadghasemi & Hadi-Vencheh, 2012), companies can reduce these costs by

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at least 10–30% (Madhusudanan Pillai et al., 2011), and increase their productivity if their facilities are managed effectively. In contrast, an ineffective layout can increase MHC by as much as 36%(Ripon et al., 2013). In addition, another research shows that more than 35% of system efficiency is likely to be lost by applying the wrong location layout and design(Izadinia & Eshghi, 2016).

Several model studies based on area and proximity of facilities have been conducted since the 1960s to 1990s, Muther (1973) which includes Systematic Layout Planning (SLP) and Heragu & Kusiak, (1990) using the Quadratic Assignment Problem (QAP) to solve equal area . Also, many improvements have been made to the models to increase their adaptability. Meanwhile, with the wide application of computer-aided technology, a large number of related software and technologies have also been developed such as CORELAP, ALDEP, graphic theory, CRAFT, MultiPLE and so on. Since the 1990s, optimization algorithms have been introduced to the field of FLP (Liu & Sun, 2012).

In the literature review (Hosseini-Nasab et al., 2018) classify facility layouts based on material handling systems as follows, Single-row layout problem (SRLP), This problem is concerned with arranging a number of adjacent rectangular facilities along a line to minimize the total arrangement cost of the total product flow and facility-to-facility distance. Several shapes of SRLP can be detected, such as straight line, semicircular, or U shape.

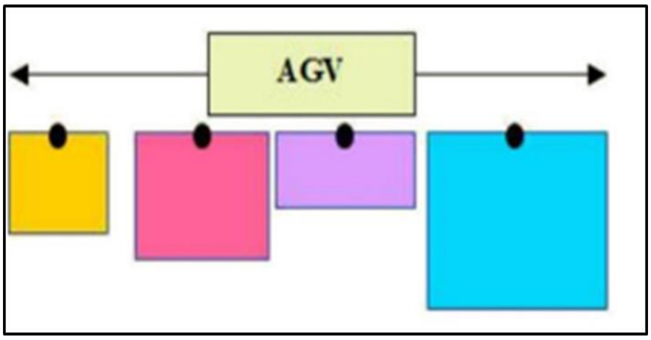

Figure 1. Single-row layout problem (SRLP)

Multi-row layout problem (MRLP) locates a set of rectangular facilities on a fixed number of lines in two-dimensional space, so that the weighted sum total center-to-center distance between all pairs of facilities is minimized. In this type of configuration, each resource can be assigned to any of the given rows. All of these rows are the same height, and the spacing between adjacent rows is all the same

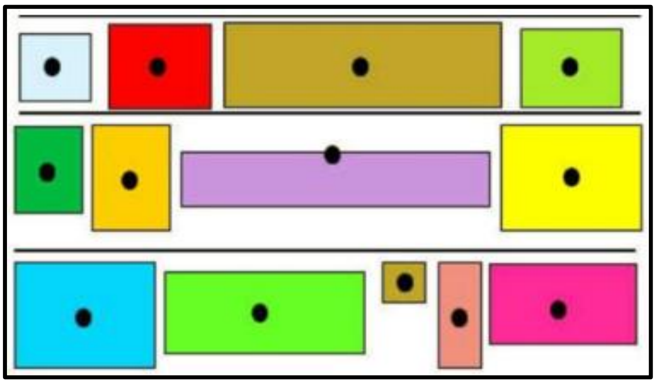

Figure 2. Multi-row layout problem (MRLP)

Double-row layout problem (DRLP) involves setting up a number of rectangular facilities of varying widths on both sides of a straight-line corridor to minimize the total cost of material handling between facilities. AGV systems operate along aisles to move materials from one facility to another.

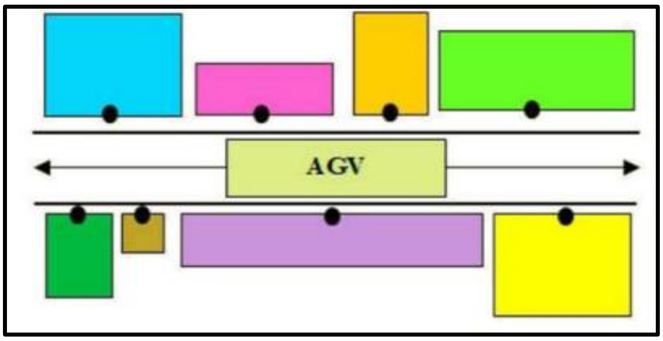

Figure 3. Double-row layout problem (DRLP)

Parallel-row ordering problem (PROP)

In PROP, the sub-facilities with several characteristics in common are arranged in one row, while the remaining facilities are left in parallel rows. DRLP and PROP differ in that PROP assumes that the settings in both lines start from the same point and no space is allowed between two adjacent facilities, whereas DRLP makes no such assumption. Also, DRLP assumes that the distance between two parallel lines is zero, while PROP does not

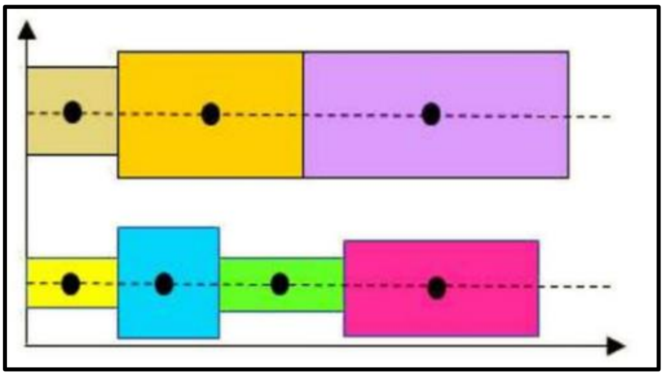

Figure 4. Parallel-row ordering problem (PROP)

Loop Layout Problem (LLP)

This type of layout aims to find n facility assignments to n predefined candidate locations in a closed loop, so that the total handling cost can be minimized. LLP incorporates loading/unloading stations, i.e. locations from which a section enters and exits the loop. This station is unique, and is assumed to lie between positions n and 1.

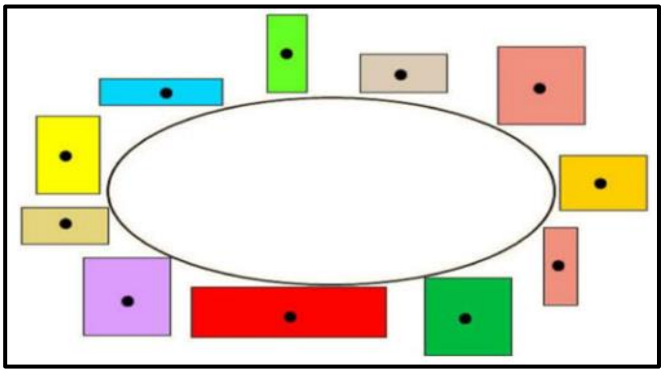

Figure 5. Loop layout problem (LLP)

Open-Field Layout Problem (OFLP)

Open-field layouts (OFLP) correspond to situations where facilities can be located without restrictive arrangements such as single-row, double-row, parallel-row, multi-row, or loop layouts. The most prominent limitations of Open-field layouts (OFLP) are the non-overlapping constraints that force the facility to lie on the ground without overlapping.

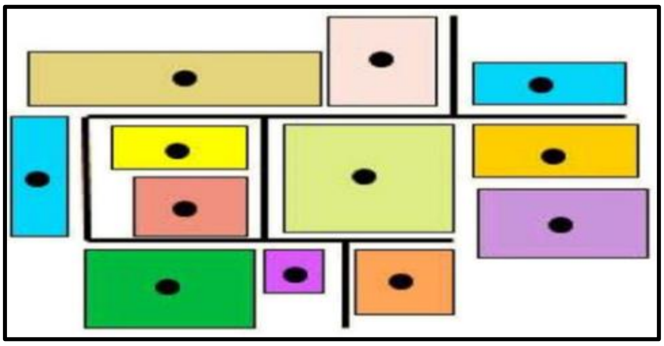

Figure 6. Open-field layout problem (OFLP)

Multi-Floor Layout Problem (MFLP)

Insufficient space in cities and the very high cost of providing living space, especially in metropolitan cities, makes designers and engineers consider the Multi-floor layout problem (MFLP) instead of a single-floor layout. Also, in rural areas where land can be provided more cheaply than in urban areas, multi-storey factories are preferred to store land for future expansion. Figure 7 shows that sections can move not only horizontally on a given floor (ie in the horizontal flow direction) but also from one floor to another which is located at a different level (ie in the vertical flow direction).

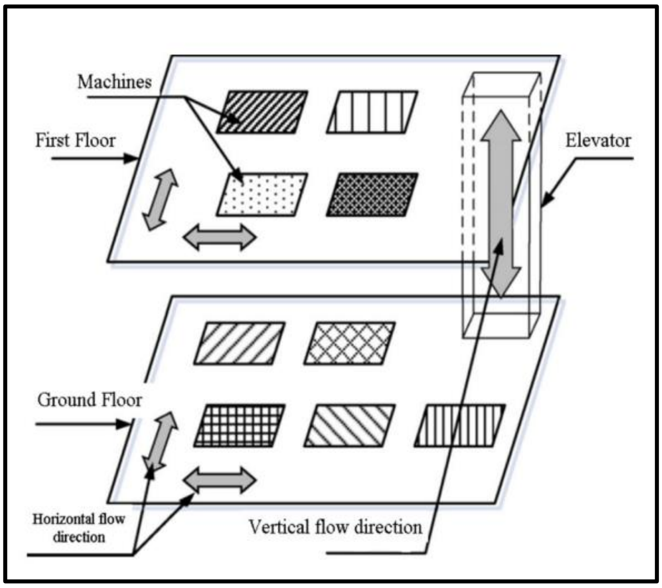

Figure 7. Multi-floor layout problem (MFLP)

Genetic Algorithm

The genetic algorithm was first developed in the 1970s by John Holland (a professor from the University of Michigan, USA). At the time, Holland aimed to create software whose underlying principles mimicked natural evolutionary processes. To do this, he wanted to abstract the processes that occur in nature over the course of evolution. Genetic algorithms can therefore genuinely resolve issues that cannot be resolved by doing regular mathematical operations.

A genetic algorithm is a search technique and optimization technique that mimics the process of evolution and changes in the genetic structure of living things. The main principle of how the genetic algorithm works is inspired by the process of natural selection and the principles of the science of genetics. In natural selection, individuals compete to survive and reproduce. Individuals who are more fit will have the opportunity to continue to survive and reproduce (produce offspring). Conversely, individuals who are less fit will die and become extinct (this principle is also used as "survival of the fittest". Crossover) and mutation. Both of these processes occur in the chromosomes of individuals who reproduce. This process of selection and reproduction (crossover and mutation) takes place repeatedly, until the most fit individual is produced. This most suitable solution is the solution to the problem faced.

the problems that can be solved with the genetic algorithm are as follows (Al-Tabtabai & Alex, 1999):

1) The range of the ideal answer is enormous.
2) Inadequate conventional statistical & mathematical methods.
3) Solutions to these problems can be encoded in the form of strings or characters.
4) The difference between optimal and near optimal solutions can be considered.

5) Some of the advantages of using GA are as follows:
6) Simultaneous search of various cost surface samples
7) Can solve cases with wide variables
8) Is well suited for parallel computers
9) Optimizing variables with very complex surface costs
10) Can encode variables

According to the explanation above, GA is considered as a very effective method to solve the temporary facility location problem.

The fitness function is used to test the optimality of the chromosomes. Chromosomes that are proven to be more optimal are allowed to multiply and produce new, better generation chromosomes. The Fitness function must be developed for each problem to be solved.

Related Works

One of the commonly used optimization algorithms to solve several FLPs is the Genetic Algorithm. Several studies using genetic algorithms have been carried out, but not many researchers have optimized the open-field layout problem (OFLP). In fact, many cases of FLP in the field are of the open-field layout type. Some of the latest research on the Facility Layout Problem including (Datta et al., 2011) optimized the Single Row Facility Layout Problem (SRFLP) case using a permutation-based genetic algorithm, then (Kothari & Ghosh, 2014; Lenin et al., 2013) also optimized the case of the Single row facility layout problem (SRFLP) using a genetic algorithm, then

(Khaksar-Haghani et al., 2013; Kia et al., 2014)also used a genetic algorithm to optimize the Multi-floor layout problem (MFLP) case. Next (Aiello et al., 2013; Gonçalves & Resende, 2015; Paes et al., 2017; Palomo-Romero et al., 2017) used a genetic algorithm to solve the Unequal-Area Facility-Layout Problem (UA-FLP) case.

Problem Formulation

The problem presented in this study can be modeled as a Quadratic Assignment Problem (QAP) which is the same as the number of existing facilities and locations. If the number of locations exceeds facilities, dummy facilities can be added to the model (with zero distance or frequency to existing real facilities so as not to affect layout planning). The model incorporates the following decision parameters that contribute to the total cost to be minimized.

The proposed mathematical model for distance optimization and movement costs is as follows:

Objective

Minimize Z

$$Z=\sum_{i=1}^{n}\sum_{j=1}^{n} F_{ij}D_{ij} \quad (1)$$

Then D_{ij} defined as follows:

$$D_{ij}=\left|x_i-x_j\right|+\left|y_i-y_j\right| \quad (2)$$

where,

Z	: moment of movement from station i to Station (Meters/month)
Fij	: frequency of movement from station i to station j(times/month)
Dij	: the distance between station i and station j (meter)
n	: the number of machines used for each product
Xi,Yi	: the orthogonal coordinates of the centre of facility i

Subject to

The constraints for this research is adopted from (Said & El-Rayes, 2013) as follow:

Boundaries Constraint

Boundary restrictions are put in place to ensure that all temporary facilities are located within the site boundaries. As shown in the fig. 8. Facility 3 and Facility 4 are violating the constraints.

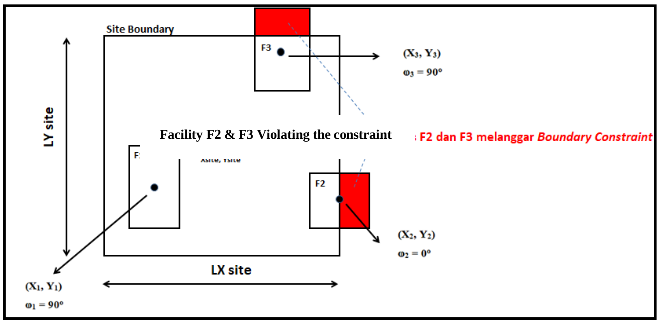

Figure 8. Boundaries constraint

$$|X_{site} - X_i| \leq (LX_{site} - (Lx_i\, COS\varphi_i + Ly_i SIN\varphi_i))/2; And$$
$$|Y_{site} - Y_i| \leq (LY_{site} - (Ly_i\, COS\varphi_i + Lx_i SIN\varphi_i))/2 \quad (3)$$

Overlap Constraint

Overlap constraints are imposed to prevent overlap between each pair of facilities. As shown in the fig. 9. Facility 3 and Facility 4 are violating the constraints.

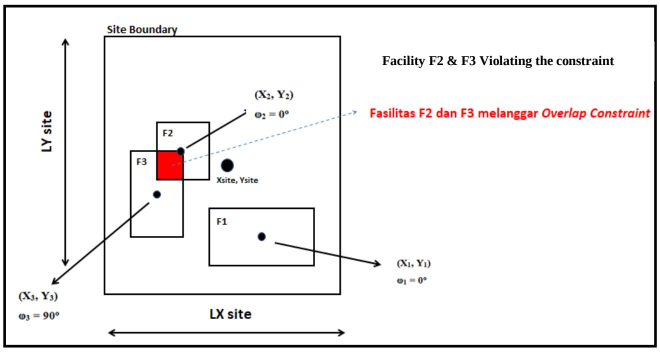

Figure 9. Overlap constraint

$$|X_i - X_j| \geq (Lx_i COS\varphi_i + Ly_i SIN\varphi_i)/2 + \left(Lx_j COS\varphi_j + Ly_j SIN\varphi_j\right)/2\, ; Or$$
$$|Y_i - Y_j| \geq (Ly_i COS\varphi_i + Lx_i SIN\varphi_i)/2 + \left(Ly_j COS\varphi_j + Lx_j SIN\varphi_j\right)/2 \quad (4)$$

Where,

X_i, Y_i : the orthogonal coordinates of the centre of facility i

X_{site} Y_{site} : the orthogonal coordinates of the center of the construction site

LXi LYi : the definedwidth and length offacility i with zero orientation angle (φ_i)

LX_{site}, LY_{site} : the defined width and length of the construction site

φ_i φ_j : orientation angle of facilities i and j

$D_{ij}^{min}, D_{ij}^{max}$: the minimum/maximum distance allowed between facili- ties (i,j)

Min-Distance Constraints

Minimum & maximum Distance Constraints can be used to provide a safe buffer distance around. As shown in the fig. 10. Facility 2 is violating the constraints.

maximum Distance Constraints also implement as shown in fig. 10. Facility 2 is violating the constraints

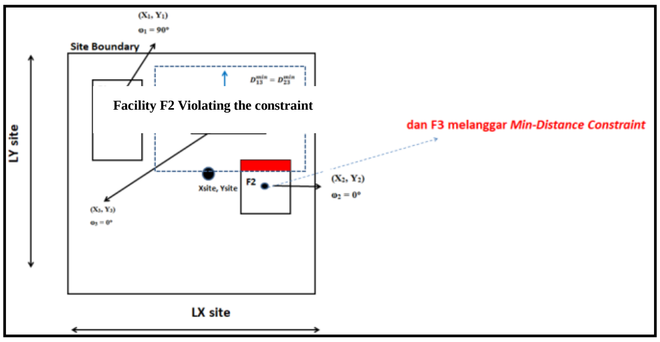

Figure 10. Min-Distance Constraints

$$|X_i - X_j| \geq (Lx_i COS\varphi_i + Ly_i SIN\varphi_i)/2 + \left(Lx_j COS\varphi_j + Ly_j SIN\varphi_j\right)/2 + D_{ij}^{min}\ ; Or$$
$$|Y_i - Y_j| \geq (Ly_i COS\varphi_i + Lx_i SIN\varphi_i)/2 + \left(Ly_j COS\varphi_j + Lx_j SIN\varphi_j\right)/2 + D_{ij}^{min} \quad (5)$$

- Max-Distance Constraints

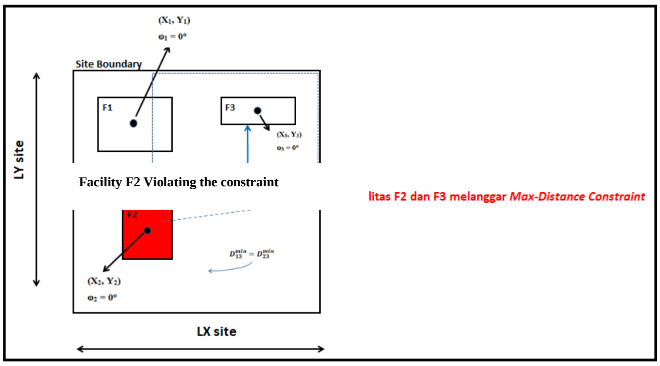

Fig. 11 Max-Distance Constraints

$$|X_i - X_j| \geq (Lx_i COS\varphi_i + Ly_i SIN\varphi_i)/2 + \left(Lx_j COS\varphi_j + Ly_j SIN\varphi_j\right)/2 + D_{ij}^{max}\ ; Or$$
$$|Y_i - Y_j| \geq (Lx_i COS\varphi_i + Ly_i SIN\varphi_i)/2 + \left(Lx_j COS\varphi_j + Ly_j SIN\varphi_j\right)/2 + D_{ij}^{max}$$
(6)

Results and Discussion

A. *Chromosome Representation*

Before carrying out the chromosomal arrangement, it is necessary to have data on the facilities used on the production floor, including coordinates. Then code the facilities as shown in Table 1.

Table 1
Station List & Coordinate

Stations	Coordinates		Codes
	X	Y	

Stations	Coordinates		Codes
	X	Y	
Warehouse 1	19,72	10,19	A
Warehouse 2	17,37	10,86	B
Warehouse 3	25,40	7,93	C
Warehouse 4	24,05	13,00	D
Block Cutter 1	13,18	10,56	E
Block Cutter 2	19,66	4,38	F
Block Cutter 3	25,40	7,17	G
Machine Brush Hammer 1	21,36	4,38	H
Machine Brush Hammer 2	25,54	4,94	I
Polish Machine 1	17,13	6,89	J
Polish Machine 2	12,04	6,65	K
Burning Machine 1	17,12	13,27	L
Burning Machine 2	20,76	13,27	M
Burning Machine 3	16,97	3,99	N
elbow cut Machine 1	23,05	3,87	O
elbow cut Machine 1	22,22	6,89	P
elbow cut Machine 1	17,37	9,14	Q
elbow cut Machine 1	21,48	6,89	R
elbow cut Machine 1	25,40	8,81	S
elbow cut Machine 1	24,40	4,10	T
Storage	25,77	21,50	U

In this study the number of products is 4 namely; Granit Poles, Granit Bakar, Granit Brush Hammer, dan Granit Honned. Each product almost all uses the same machines. Differences in the use of machines for the production of each product. The machines used on the production floor are presented in Table 2.

Table 2
Machine Used

No	Product Name	Machine Used
1	Granit Poles	Block cutter elbow cut Machine Polish Machine
2	Granit Bakar	Block cutter elbow cut Machine Burning Machine
3	Granit Brush Hammer	Block cutter Mesin brush hammer elbow cut Machine
4	Granit Honned	Block cutter

No	Product Name	Machine Used
		elbow cut Machine

The operations process chart in this study was made separately for each product to make it easier to understand each production operation for each product. In Fig. 12 Granit Poles products went through a process from the raw material warehouse, block cutter machine, polishing machine 1, polishing machine 2, to the storage warehouse with a total time of 57 minutes per product.

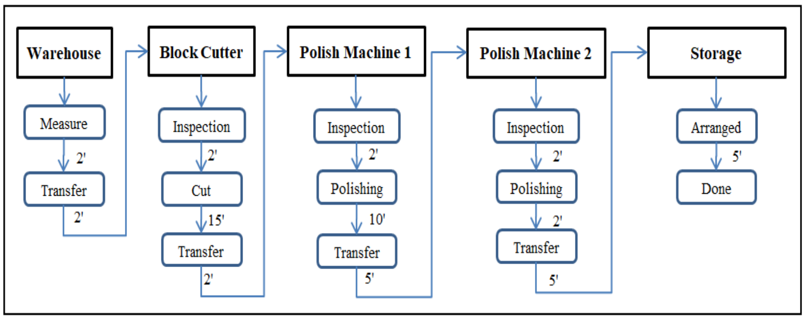

Figure 12. Operations Process Chart Granit Poles

In the figure Fig. 13 Granit Bakar products went through a process from raw materials, block cutter machines, angle cutting machines, Burning machines, to storage warehouses with a total time of 16 minutes per product.

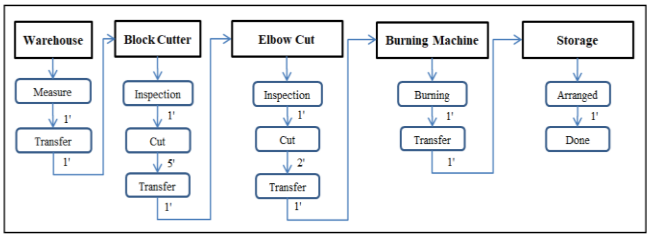

Figure 13. Operations Process Chart Granit Bakar

In Figure 14 Granit Brush Hammer products went through a process from raw materials, block cutter machines, bush hammer machines, angle cutting machines, to warehouse storage with a total time of 29 minutes per product.

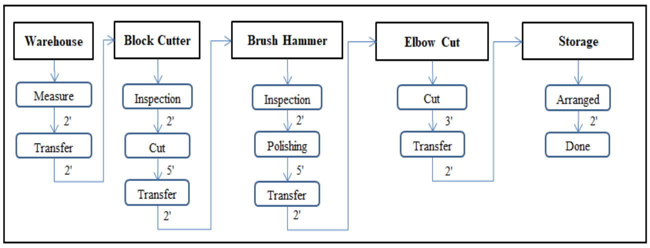

Figure 14. Operations Process Chart Granit Brush Hammer

In Figure 15 Granit Honned products went through a process from raw materials, block cutter machines, angle cutting machines, to warehouse storage with a total time of 14 minutes per product.

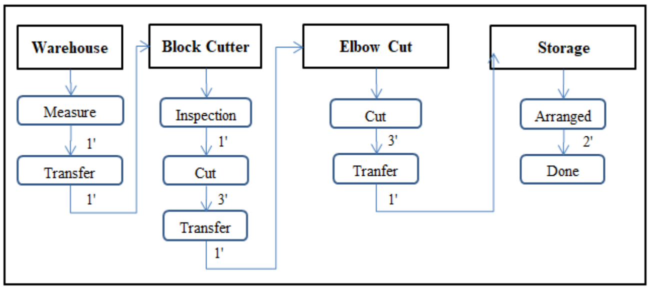

Figure 15. Operations Process Chart Granit Honned

Based on the Operations Process Chart, the standard time per unit for each product is; Granit Poles 57 minutes / Product, Granit Bakar 16 minutes / Product, Granit Brush Hammer 29 minutes / Product, Granit Honned 14 minutes / Product. Standard time and production capacity are presented in Table 3.

Table 3
Standard Time & Capacity per Unit

No	Product	Production Capacity (unit)	Standard time per Unit (menit)
1	Granit Poles	176	57
2	Granit Bakar	648	16
3	Granit Brush Hammer	336	29
4	Granit Honned	808	14

After the production capacity is known, material handling costs can also be known by knowing the Distance of Movement. Movement Distance & Material Handling Cost can be seen in Table 4.

Table 4
Movement Distance & Material Handling Cost

No	Product	Distance of Movement (meter)	Material Handling Cost (Rp.)
1	Granit Poles	4151,31	Rp.155,674.13
2	Granit Bakar	4993,34	Rp.187,250.25
3	Granit Brush Hammer	1866,68	Rp.70,000.50
4	Granit Honned	5415,84	Rp.203,094.00

Total	**16427,20**	**Rp.616,018.88**

The number of work stations to be arranged is n. Machines are coded according to facility layout in Fig.16. The number of workstations allowed per column is p, and each row is q. So that the layout of the work station can be represented in a line.

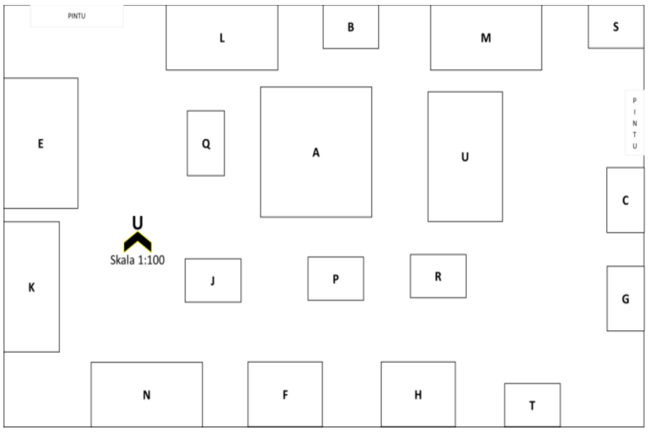

Figure 16. Initial Layout

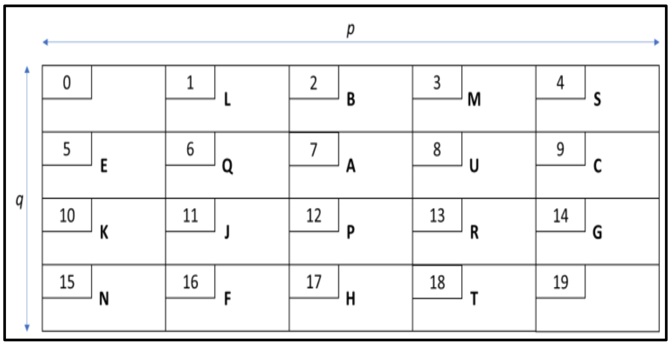

Figure 17. Chromosome Arrangement

Based on Fig.17, the chromosome arrangement is represented as a sequence: M_L M_B M_M M_S M_E M_Q M_A M_U M_C M_K M_J M_P M_R M_G M_N M_F M_H M_T

Then the row is changed to a positive integer number so that the chromosomes are obtained:

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17

Testing Scenario with Code Python

The test scenario is carried out to find out the parameters in determining the best fitness value. Parameters used include iteration, mutation probability, and crossover probability. Determination of parameter values is based on previous research, including (Umam et al., 2022) using 1000 iterations and a mutation probability of 0.1 in completing flow shop scheduling using a genetic algorithm. Research by (Saputro et al., 2015) used a genetic algorithm with 400 iterations and a mutation probability of 0.5 to solve agricultural land optimization problems. Whereas (Nasution, 2015) in his research used a crossover probability of 80% and 90% to overcome the problem of traveling salesmen using a genetic algorithm. Based on previous research, the test scenario parameters in this study are as follows in Table 5.

Table 5
Testing Scenario with Code Python

No	Scenarios	Iterat-ions	mutation probability	crossover probability
1	Skenario 1	400	0,1	80%
2	Skenario 2	400	0,1	99%
3	Scenario 3	400	0,5	80%
4	Scenario 4	400	0,5	99%
5	Scenario 5	1000	0,1	80%
6	Scenario 6	1000	0,1	99%
7	Scenario 7	1000	0,5	80%
8	Scenario 8	1000	0,5	99%

The Results Of The Test Scenarios Using Code Python

Based on the results of the test scenarios using Code Python, the fitness, cost, and chromosome values for each scenario are presented in Table 6:

Table 6
Test Scenario Results Using Python

No	Skenario	Cost	*Fitness*	New Chromosome
1	Scenario 1	98887.5	753825.0	17 1 14 12 10 2 8 15 4 0 7 11 5 16 9 13 6 3
2	Scenario 2	100987.5	761550.0	0 2 17 6 15 12 9 14 7 1 16 4 5 11 3 8 10 13
3	Scenario 3	104737.5	797250.0	9 8 15 13 6 12 2 4 11 5 3 14 1 17 16 7 0 10
4	Scenario 4	95700.0	747712.5	16 5 8 14 3 0 15 9 4 13 17 6 11 1 7 12 10 2
5	Scenario 5	100650.0	784575.0	8 2 12 10 11 15 13 4 3 5 0 1 14 17 16 9 7 6
6	Scenario 6	90112.5	774337.5	1 2 16 6 9 17 13 8 14 3 7 12 10 4 0 15 5 11
7	Scenario 7	95437.5	737887.5	7 6 1 2 10 9 12 15 13 16 8 3 4 5 14 17 11 0
8	Scenario 8	91612.5	706612.5	13 10 4 2 6 7 5 17 14 1 16 8 11 9 0 15 3 12

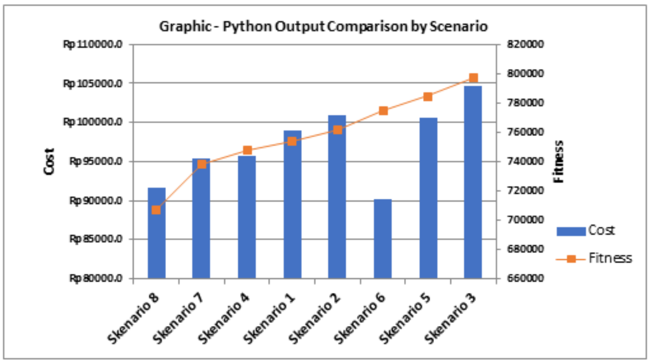

Figure 18. The Results Of The Test Scenarios Using Code Python

Based on Table 3 and the graph in Fig. 18 it can be seen that the smallest cost value is in scenario 6 while the highest cost value is in scenario 3. The highest fitness value is obtained in scenario 3 while the lowest fitness value is obtained in scenario 6. The best solution in the genetic algorithm is generally use the highest fitness value, but for layout optimization problems the smallest cost value is needed. Therefore, scenario 6 and scenario 3 will be compared to find out the results of layout optimization as the best solution.

For scenario 3, the chromosome sequence is (9 8 15 13 6 12 2 4 11 5 3 14 1 17 16 7 0 10) So the sequence of work stations based on the chromosome sequence is as follows:

M_K M_C M_F M_G M_A M_R M_M M_E M_P M_Q M_S M_N M_B M_T M_H M_U M_L M_J

Fig. 19 Shows the new Layout for Scenario 3 that repsent the New Chromosome.

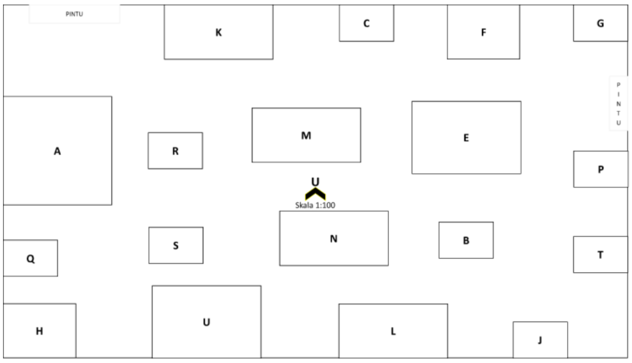

Figure 19. Layout Scenario 3

For scenario 6, the chromosome sequence is (2 16 6 9 17 13 8 14 3 7 12 10 4 0 15 5 11 For scenario 6, the chromosome sequence is as follows:

M_B M_M M_H M_A M_K M_T M_G M_C M_N M_S M_U M_R M_J M_E M_L M_F M_Q M_P

Fig. 20 Shows the new Layout for Scenario 3 that repsent the New Chromosome.

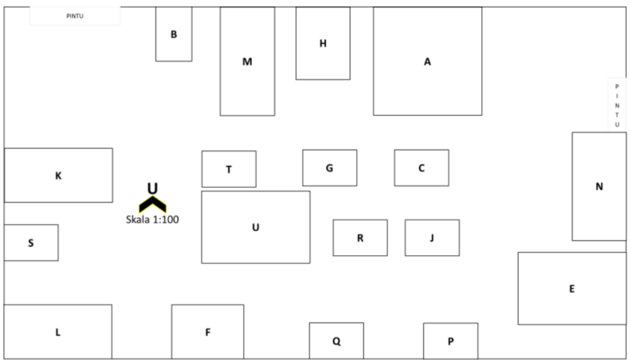

Figure 20. Layout Scenario 6

Table 7
Total Distance Movement & Material Handling Cost for Scenario 3

No	Product	Distance of Movements	*Material handling*

		(meter)	Cost(Rp.)
1	Granit Poles	5925,57	223394
2	Granit Bakar	3047,41	114277,9
3	Granit Brush Hammer	1334,26	50034,75
4	Granit Honned	7225,54	270957,8
	Total	**17532,78**	**658664,4**

Table 8
Total Distance Movement & Material Handling Cost for Scenario 6

No	Product	Distance of Movements (meter)	*Material handling* Cost(Rp.)
1	Granit Poles	4514,03	170178,9
2	Granit Bakar	3537,55	132658,1
3	Granit Brush Hammer	1087,51	40781,63
4	Granit Honned	4285,5	160706,3
Total		13424,59	504324,9

Table 9
Comparison of Material Movement Distance Between Initial Layout and Proposed Layout

No	Layout	Distance of Movement in Scenario [A]	Initial Distance of Movement [B]	Variance [A-B]	Percentage
1	Scenario 3	17532,78	16427,17	1105,61 m	6,7%
2	Scenario 6	13424,59	16427,17	- 3002,58 m	- 18,3%

Table 9 shows that the difference in material movement distance between the initial layout and the proposed layout in accordance with scenario 3 is 1105.61 m or 6.7%, where the displacement distance in scenario 3 layout is larger than the displacement distance in the initial layout. Meanwhile, the difference between the displacement distance of the initial layout and the proposed layout in accordance with scenario 6 is 3002.58 m or 18.3% where the displacement distance in scenario 6 layout is smaller than the displacement distance in the initial layout. This shows that the best results for optimizing the layout of production machines using genetic algorithms are in accordance with scenario 6 which can reduce the material movement distance by 3002.58 m or 18.3%.

Table 10
Comparison of Material Handling Cost Between Initial Layout and Proposed Layout

No	Layout	Material Handling Cost in Scenario [A]	Initial Material Handling Cost [B]	Variance [A-B]	Percent age
1	Scenario 3	Rp.658,665	Rp.616,019	Rp.42,645.49	6,9 %
2	Scenario 6	Rp.504,325	Rp.616,019	Rp.- 111,693.94	- 18,1 %

Table 10 shows that the difference in material handling costs between the initial layout and the proposed layout according to scenario 3 is Rp.42,645.49 rupiah or 6.9%, where the material handling costs in scenario 3 layout are greater than the material handling costs in the initial layout. Meanwhile, the difference in material handling costs for the initial layout and the proposed layout according to scenario 6 is Rp.111,693.94 or 18.1% where the material handling costs in scenario 6 layout are smaller than the material handling costs in the initial layout. This shows that the best results for optimizing the layout of production machines using genetic algorithms are in accordance with scenario 6 which can reduce material handling costs by Rp.111,693.94 rupiah or 18.1%.

Conclusion

Optimization of production machine layout at PT. XYZ is carried out on 18 work stations. The optimization results using a genetic algorithm with the help of the python program produce a new layout arrangement that can reduce material movement distances and reduce material handling costs. The difference in material movement distance between the initial layout and the new layout resulting from optimization according to the best proposal is 3002.58 m or 18.3%, where the displacement distance in the new layout is smaller than the displacement distance in the initial layout. The optimization results can also reduce the cost of material handling by Rp.111,693.94 or 18.1% lower than the initial layout. Layout optimization using genetic algorithms is able to shorten material movement distances and reduce material handling costs.

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