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A tool for generating optimum facilities layouts under demand uncertainty with/without machine breakdown

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Abstract

Manufacturing systems are subject to many uncertainties including variability in demand and machine breakdown. The layout of manufacturing facilities has a large impact on lead-times, inventory, costs and delivery performance. The distance travelled by materials is a commonly used proxy for the efficiency of layouts. It is common for planners to avoid production interruptions by adopting alternative routings if machines are unavailable due to breakdown or maintenance. Demand uncertainty and rerouting both have an impact on material flow.

The objective of layout design is to produce a block plan that shows the relative positioning of resources. A block plan can then be translated into a detailed layout drawing. The facility layout problem is an NP complete combinatorial optimisation problem, which means that the time taken to solve problems using enumerative search increases exponentially with problem size.

This paper presents the development of the Genetic Algorithm (GA) based layout design tool for generating robust layouts that minimises the distance travelled by materials and costs taking into account demand uncertainty and machine maintenance. The experimental programme used eight datasets with/without machine breakdown. It identified the relationship between the GA parameters, distance travelled and the cost of relocating equipment. There is a trade-off between minimising material travel distance and costs; the results provide a framework for evaluating investments in layout redesign.

Keywords: Machine layout, Machine breakdown, Stochastic demand, Genetic Algorithm.

1. Introduction

Changes to the manufacturing environment may be caused by internal and external forces (Kulturel-Konak 2007; Wahab and Stoyan 2008). Internal disturbances, such as breakdown maintenance (BM), reduce the number of available machines and can cause delays. This can disturb the flow of materials which can cause other resources to run out of input work-in-process and it may cause excessive workload, longer flow time, lower productivity and higher production costs. External uncertainties include variations in the level of customer demand, product prices and product mix. Other factors include alterations in product design, shorter product life cycles, elimination of existing products and the introduction of new products. Variations in customer demand can disrupt the efficient flow of materials between machines in the manufacturing area. Material handling distance can be considered as a performance index for internal logistics activities within a chain of supply (Sabóia et al. 2006). Between 20% and 50% of the total operating expenses within manufacturing is attributed to material handling (Tompkins et al. 2010).

Manelbaum (1978) defined flexibility as “the ability to respond effectively to changing circumstances”. Flexibility is a means of addressing problems caused by uncertainty. Flexibility in manufacturing systems relates to the reconfiguration of resources to efficiently produce products of the required quality in changing circumstances. Flexibility helps address internal disturbances arising from machine breakdowns, variable task times, queuing delays, rejects and rework (Sethi and Sethi 1990). There are 11 different types of flexibility: machine, material handling, operation, process, product, routing, volume, expansion, program and market (Sethi and Sethi 1990). The flexibility to use alternative machines or routings helps mitigate problems with material flow that can arise when a particular machine becomes unavailable. Byrne (1997) considered alternative machines to be those that could perform the same operations; whilst alternative routings could perform the same sequence of operations. A system with alternative production routes (flexible routes) can maintain high production performance when some machines have broken down or are under maintenance (Chang 2007). Routing flexibility has been recognised as a fundamental characteristic of a manufacturing system's overall flexibility, as it enhances a system's ability to produce a given set of part types or part families without interruption. When routings are changed, material flow time and distances may also be changed. The time taken to transport material is another crucial factor that needs to be recognised in flexible manufacturing system design. Transportation time can be minimised by reducing transportation distance to a minimum (Byrne and Chutima 1997).

Machine layout design (MLD) involves arranging machines within the manufacturing facility. The MLD usually has a large effect on production cost and time (Ficko et al. 2004). An effective facility layout can reduce material handling costs by at least 10-30% (Tompkins et al. 2010). Reduced material flow between machines leads to quicker transfer times, which leads to better productivity and lower production costs, which increases competitiveness. MLD frequently assumes that machines are available throughout the planning horizon. In reality, reorganization, breakdown and planned maintenance all cause disruption, which causes machines to become unavailable.

Frequently, MLD does not consider volatile customer demand, which may lead to excessive material travel. There is the option to redesign the layout, but in many cases machine repositioning is costly and impractical within a short period of time. The costs associated with rearrangement include labour, equipment cost and lost capacity costs (McKendall et al. 2006; Moslemipour and Lee 2012). Cost is a function of the number of machines moved and the distance that they are moved (Yang and Brett 1998). A robust design that can accommodate stochastic demand can avoid the need for the rearrangement of facilities. The design of robust layouts aims to minimise the total material flow distance through multi-period planning horizons based upon predicted demand.

The objectives of this paper were to describe the application of a Genetic Algorithm (GA) for designing non-identical machine layouts that are subject to stochastic demand and to investigate the effect of breakdown maintenance on the material flow distance.

The paper is organised as follows. Section 2 describes the uncertainties in production environments, which is followed by a outlines the development of a Genetic Algorithm for solving MLD problems. The experiment results are presented in section 4. Section 5 highlights the conclusions of the work.

2. Uncertainties in production environment

There are many uncertainties that can effect production arisen from external or internal sources.

2.1 Breakdown maintenance

Machine breakdown is a stochastic event that is a major concern in industry. If operations are interrupted it may be necessary to revise the schedule to re-optimise the remaining operations taking into account the machine downtime. The easiest solution is often to apply some dispatching rule to sequence operations immediately after the breakdown occurs (Blackstone et al. 1982). A number of parameters have been used to model machine maintenance problems, for example machine failure rate has often been represented by the Poisson distribution (Safari and Sadjadi 2011; Lin and Chiu 2012; Schemeleva et al. 2012) or generated randomly (Kenne and Nkeungoue 2008; Nodema et al. 2011). Machine lifetime is commonly modelled using the Weibull distribution (Fitouhi and Nourelfath 2012). Mean time to failure (MTTF) has been represented by the normal distribution (Guo et al. 2007) or the exponential distribution (Schemeleva et al. 2012). Breakdown maintenance has also considered in the context of robust scheduling for a flexible job-shop scheduling problem (Xiong et al. 2013).

2.2 Demand uncertainties

Variability in product demand can be either deterministic or stochastic. Deterministic demand is known in advance (Pillai et al. 2011). Stochastic demand may be considered in terms of various scenarios with different probabilities (Dunker et al. 2005; McKendall and Hakobyan 2010). The demand profiles for each time period can be forecasted (Ertay et al. 2006) or determined using statistical distribution functions such as the uniform distribution (Krishnan et al. 2009; Jithavech and Krishnan 2010), the normal distribution (Tavakkoli-Moghaddam et al. 2007) or the exponential distribution (Chan and Malmborg 2010). Fuzzy numbers have also been used to consider the stochastic flow between facilities and fuzzy costs have been represented by a triangular membership function (Enea et al. 2005).

The evaluation function (Z) for the efficiency of robust layout design can be used to minimise total material flow distance as defined by Eq. (1) or to minimise total material flow cost as shown in Eq. (2).

$$Minimise\ Z = \sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{g=1}^{N}\sum_{k=1}^{P} d_{ij}\, f_{ijgk}\, D_{gk}\ , \tag{1}$$

$$Minimise\ Z = C_{MF}\left(\sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{g=1}^{N}\sum_{k=1}^{P} d_{ij}\, f_{ijgk}\, D_{gk}\right), \tag{2}$$

M is the number of machines, i and j are machine indexes (i and $j = 1, 2, 3, \ldots, M$). N is the number of product types, g is a product index ($g = 1, 2, 3, \ldots, N$) and P is the number of time periods, k is a time period index ($k = 1, 2, 3, \ldots, P$). d_{ij} is the distance from machines i to j ($i \neq j$), f_{ijgk} is the frequency of material flow of product g from machines i to j on period k, D_{gk} is the customer demand of product g on period k, and C_{MF} is the material flow cost per distance unit.

3. Genetic Algorithm for solving layout design problem

Machine Layout Design (MLD) problems are NP-hard problems (Loiola et al. 2007), which means that the amount of computation required to find solutions increases exponentially with problem size. If there are m machines, there are $m!$ possible solutions. For ten machines, the number of possible solutions can be upto 3,628,800 (10!). In consequence efficient metaheuristics have been widely applied for solving the MLD problem, including Genetic

Algorithm (Balakrishnan et al. 2003; Jithavech and Krishnan 2010), Simulated Annealing (Balakrishnan 1992), Tabu Search (Wangta and Pongcharoen 2010), Ant Colony Optimisation (Corry and Kozan 2004) and the Artificial Bee Colony (Soimart and Pongcharoen 2011).

The Genetic Algorithm (GA) (Goldberg 2002; Gen et al. 2008) is a population-based, nature-inspired algorithm (Yang 2008). A set of candidate solutions is generated as an initial set of solutions, which then undergoes an evolutionary search process. Exploitation and exploration processes are carried out simultaneously via crossover and mutation operations, respectively. GA have been widely applied (Aytug et al. 2003; Chaudhry and Luo 2005). The selection of GA parameters has a large impact on performance (Pongcharoen et al. 2007). The appropriate setting of GA parameters for machine layout problems was considered by Vitayasak (2011). She suggested that the probability of crossover (P_c) and mutation (P_m) should be set at 0.9 and 0.5, respectively, with 50 chromosomes and 50 generations. The genetic operators adopted in this work were the Two-point Centre Crossover (2PCX) and Two Operation Random Swap (2ORS) (Vitayasak and Pongcharoen 2011).

The pseudo-code for the proposed MLD GA is shown in Figure 1. It comprises the following steps: i) problem encoding, which produces a list of genes using a numeric string (see Figure 2). Each chromosome contains a number of genes, each representing a machine number, so that the length of each chromosome is equal to the total number of machines needed to be arranged; ii) input data: the number of machines (M), the dimensions of machines (width: M_W x length: M_L), the number of products (N) and the machine sequences (M_S); iii) specify parameters: the population size (*Pop*), the number of generations (*Gen*), the probability of crossover (P_c), the probability of mutation (P_m), floor length (F_L), floor width (F_W), the gap between machines (G), the number of periods (P) and the percentage of machines with breakdown maintenance (*%BMM*); iv) identify the demand levels for each product in each period (D_{gk}); v) randomly generate a list of machines for breakdown maintenance according to the *%BMM*; vi) randomly generate an initial population based on the defined *Pop*; vii) apply crossover and mutation operators to generate new offspring considering P_c and P_m respectively; viii) arrange machines row by row based on F_L and F_W; ix) evaluate the fitness function value; x) select the best chromosome having the shortest material flow distance using the elitist selection mechanism; xi) choose chromosomes for next generation by using the roulette wheel selection; and xii) stop the GA process according to the number of generations. When the GA process is terminated, the best-so-far solution is reported.

```
Input problem dataset (M, M_W, M_L, M_S, N)
    Set parameters (Pop, Gen, P_c, P_m, F_L, F_W, G, W, P, %BMM)
    Create demand level (D_gkl) for each product associated with demand distribution
    Randomly create a list of machines for breakdown maintenance according to %BMM
    Randomly create initial population (Pop)
    Set i  = 1 (first generation)
    While i ≤ Gen do
        For j = 1 to cross (cross = round ((P_C x Pop)/2))), perform crossover operation
        For k = 1 to mute (mute = round(P_m x Pop)), perform mutation operation
        Arrange machines row by row based on F_L , F_W and G
        Calculate material flow distance based on either re-layout or robust layout
        Elitist selection
        Chromosome selection using roulette wheel method
        i = i + 1
    End loop while
Output the best solution
```

Figure 1. Pseudo code of GA for MLD.

4	8	2	9	5	7	6	3	1	10

Figure 2. Chromosome representation.

Rectangular machine layout design is concerned with the placement of machines into a limited shop floor area (Length: F_L and width: F_w) having gap (G) between machines. Machines are sequentially arranged row by row, from left to right, starting at the first row and respecting F_L and the gap (G). When there is not enough area for placing the next machine at the end of the row, it is placed in the next row. Vehicles moving between rows move to the left or the right side of the row and then up or down to the destination row.

In this work, the following assumptions were made in order to simplify and formulate the problem: i) the material flow distance between machines was determined from the machines' centroids; ii) machines were arranged in multiple rows; iii) each machine had either one alternative machine or a set of alternative machines; iv) there was enough space for machine arrangement; v) the movement of AGV was a straight line; vi) the gap between machines was similar; and vii) the processing time and moving time were not taken into consideration.

4. Experimental design and analysis

The combination of population size and the number of generations ($P*G$) determines the amount of search and the computational time required. In this work $P*G$ was set to 2500 solutions. Two-point centre crossover and Two-operations random swap with probabilities of crossover and mutation of 0.9 and 0.5 were adopted (Vitayasak and Pongcharoen 2011).

The computational experiments were conducted using eight testing datasets, all of which had different numbers of non-identical machines with various product types as shown in Table 1. Each type of product had different demand profiles and machine sequences as shown in Table 2. Demand profiles can be obtained from empirical data (in which the demand value is known in advance and changes over time periods) or by using different types of distributions (exponential, normal distribution, or uniform). The program was developed and coded in modular style using the Tool Command Language and Tool Kit (Tcl/Tk) programming language (Ousterhout 2010). The experiments were conducted on a personal computer with an Intel Core i5 2.8 GHz CPU and 4 GB DDR3 RAM.

Datasets	Number of machines (M)	Number of products (N)
10M5N	10	5
20M10N	20	10
20M20N	20	20
20M40N	20	40
30M15N	30	15
40M20N	40	20
40M40N	40	40
50M25N	50	25

Table 1. Testing datasets.

Product	Product demand distribution	Machine sequence
1	Uniform (100, 200)	2-1-6-5-8-9-3-4
2	Uniform (50, 100)	10-8-7-5-9-6-1
3	Normal (180, 50)	9-2-7-4
4	Normal (300, 120)	8-10-5-9-6
5	Exponential (1/200)	2-4-8-10-7

Table 2. Summary of product demand distributions and machine sequence for 10M5N.

Two scenarios were considered: robust design, with no relocation when demand changed; and re-layout after demand changes. These were considered with/without breakdown maintenance. The distance travelled without maintenance was termed MFD and the values with maintenance were termed MFD*. Ten time periods were considered. In each period, the percentage of machines with breakdown maintenance (%BMM) was considered at 10%, 20% and 30%. During periods of maintenance alternative machines were used, which required changes to the routings. Each experiment was replicated thirty times using different random seeds. There were eight datasets, thirty replications, three values of %BMM and two types of layout, which gave a total of 8x30x3x2 = 1,440 runs. Each solution was evaluated in terms of the distance travelled with/without maintenance (MFD/MFD*).

4.1 Material flow distance based on re-layout and robust layout

The first experiment aimed to minimise the material flow distance (MFD) based on either re-layout or robust layout design. The minimum, maximum, mean and standard deviations (SD) of the distances travelled are shown in Table 3. They were analysed using an analysis of variance (ANOVA) to calculate *P* values. The number of machines moved by re-layout (NNM) and the distances machines were moved (MMD) between the periods are included in Table 3.

The total material flow distances are shown in Table 3, where the lowest mean value of MFD for each dataset is indicated in bold. The average total distance for re-layout was shorter than with the robust layout in almost all datasets. With re-layout the layout was redesigned according to the production flow over the previous time period. The Student's t-test was applied to compare the differences in material flow distance means. There were statistically significant differences between re-layout and robust layout with a 95% confidence interval except for 40M20N and 40M40N. Comparing the minimum MFD, the robust layout produced a lower distance than re-layout with some datasets. However, the degree of demand variability was not investigated in this work. The process of re-layout can generate movement of machines between the periods which effects the machine movement distance (MMD) and number of machines moved (NMM). Over ten periods, the machines could be repositioned nine times, so the possible number of machines moved in 10M5N was 90. It can be seen from Table 3 that the maximum number of machines moved was eighty-one, which generated a maximum machine movement distances of 960.7 metres. These costs of movements are considered in the next section.

Performing breakdown maintenance increases the flow distance (MFD*) (see Table 3). In most datasets, the distance (MFD*) for re-layout was shorter than for the robust layout. The ANOVA showed that the %BMM ratios significantly affected the material flow distance with a 95% confidence interval (since the *P* values were less than 0.05 for all datasets). An increase in the number of BM machines caused more changes in machine sequences, so MFD* increased. However, the machine sequences depended upon the alternative machines defined.

Dataset	Value	Robust layout				P-value of ANOVA	Re-layout						P-value of ANOVA	P-value of Student's t-test
		MFD	MFD* based on %BMM (metre)				MFD	MMD	NMM	MFD* based on %BMM (metre)				
		(metre)	10%	20%	30%		(metre)	(metre)	(machines)	10%	20%	30%		
10M5N	Mean	531,623.4	595,992.6	648,008.0	718,537.9	0.000	**523,545.7**	589.3	62.6	587,690.4	642,451.2	701,071.5	0.000	0.001
	SD	11,023.7	18,962.6	22,179.8	19,694.1		6,716.8	202.0	10.4	12,336.1	12,828.6	16,117.7		
	Min	523,969.5	578,595.5	629,746.0	703,029.4		515,607.4	188.2	35.0	569,744.6	624,781.7	679,311.9		
	Max	565,028.6	649,594.9	701,533.4	774,072.3		542,662.9	960.7	81.0	623,345.7	675,020.9	737,729.3		
20M10N	Mean	3,375,077.5	3,542,104.0	3,628,745.5	3,941,721.4	0.000	**3,291,791.1**	2,128.8	178.4	3,480,769.7	3,590,226.8	3,943,083.0	0.000	0.000
	SD	66,940.2	70,083.5	90,727.4	93,797.2		31,598.7	141.0	1.4	44,159.4	62,496.9	88,685.8		
	Min	3,246,870.4	3,405,568.5	3,491,732.5	3,751,832.7		3,222,192.6	1,863.7	175.0	3,393,370.5	3,484,739.5	3,804,493.3		
	Max	3,525,702.9	3,697,350.4	3,825,789.1	4,136,080.9		3,354,304.0	2,490.0	180.0	3,593,512.0	3,738,508.9	4,135,547.0		
20M20N	Mean	10,258,008.5	10,886,407.5	11,491,341.5	10,040,630.5	0.000	**10,040,630.52**	1,987.2	177.3	10,235,922.3	10,665,973.00	11,374,110.73	0.000	0.000
	SD	174,047.6	377,961.7	379,507.2	64,521.2		64,521.22	178.5	2.3	147,267.5	244,816.87	206,137.12		
	Min	9,849,434.2	10,135,672.5	10,873,095.3	9,911,473.3		9,911,473.34	1,623.0	172.0	9,987,599.7	10,141,010.20	10,940,283.42		
	Max	10,614,291.9	11,917,048.8	12,629,320.2	10,145,030.9		10,145,030.94	2,266.9	180.0	10,548,10856	11,224,764.25	11,741,392.68		
20M40N	Mean	19,594,343.6	20,347,121.1	21,261,068.2	20,815,688.1	0.000	**19,344,232.0**	1,922.1	177.4	20,139,726.0	21,155,152.9	20,714,559.3	0.000	0.000
	SD	231,398.2	318,814.4	355,670.7	361,285.2		86,578.0	192.8	2.7	162,503.9	285,552.8	212,577.9		
	Min	19,246,235.6	19,887,820.5	20,614,947.8	20,049,924.7		19,196,354.8	1,441.9	166.0	19,776,615.4	20,599,823.7	20,343,304.6		
	Max	20,141,262.1	21,181,869.2	22,179,471.9	21,493,810.5		19,559,491.6	2,321.7	180.0	20,451,603.2	21,706,222.8	21,159,455.8		
30M15N	Mean	7,895,278.6	8,276,170.0	8,489,326.7	9,056,617.6	0.000	**7,751,286.3**	3,445.4	268.2	8,171,360.7	8,413,654.6	8,989,992.9	0.000	0.001
	SD	190,541.8	213,714.2	209,076.6	197,351.2		84,920.4	304.2	3.1	101,229.6	116,774.8	149,437.6		
	Min	7,477,879.1	7,915,148.6	8,041,397.4	8,663,135.8		7,602,228.3	2,608.1	253.0	7,997,155.8	8,170,185.6	8,740,363.1		
	Max	8,205,071.8	8,642,410.7	8,884,425.3	9,448,623.8		7,908,281.0	3,985.0	270.0	8,361,727.9	8,675,979.0	9,276,844.5		
40M20N	Mean	15,209,235.0	17,166,328.0	17,680,469.6	19,807,215.4	0.000	**15,009,095.03**	5,386.4	358.2	16,976,417.6	17,412,457.8	16,976,417.5	0.000	0.093
	SD	604,071.8	596,320.1	711,828.6	628,823.9		197,095.41	230.8	1.4	231,094.9	249,105.6	231,094.9		
	Min	14,168,156.5	16,275,826.0	16,382,959.9	18,444,970.6		14,526,384.17	4,899.7	355.0	16,516,726.2	16,862,780.6	16,516,726.2		
	Max	16,423,379.4	18,793,575.0	19,249,222.1	20,954,182.8		15,415,321.48	5,791.1	360.0	17,584,220.7	17,824,532.5	17,584,220.7		
40M40N	Mean	**27,952,468.5**	30,354,735.4	32,107,292.1	34,014,129.5	0.000	28,081,365.5	5,389.3	358.5	30,461,892.5	32,183,090.3	33,912,727.2	0.000	0.393
	SD	665,215.8	710,209.0	732,868.0	913,114.6		478,026.0	225.2	1.3	540,129.6	476,920.7	536,309.0		
	Min	26,735,184.2	28,861,378.3	30,625,120.7	32,160,002.9		27,262,325.6	4,911.6	355.0	29,295,863.1	30,959,845.3	32,852,483.2		
	Max	29,016,247.4	31,531,345.4	33,591,573.4	36,340,903.2		29,379,487.2	5,871.5	360.0	31,606,931.3	33,303,980.1	35,149,160.4		
50M25N	Mean	25,216,694.2	27,178,003.2	30,270,244.4	30,870,860.1	0.000	**24,834,671.4**	7,446.8	448.5	26,918,721.8	29,659,717.6	30,636,330.6	0.000	0.017
	SD	789,782.7	668,805.8	1,470,163.5	1,062,502.1		279,895.3	312.5	2.0	456,708.4	507,280.9	598,307.5		
	Min	23,928,776.0	25,890,014.3	28,608,583.1	29,248,548.6		23,883,084.6	6,891.8	443.0	25,888,161.1	28,725,879.4	29,174,212.3		
	Max	26,950,652.2	28,643,707.9	34,650,791.3	33,655,833.1		25,311,940.1	8,248.3	450.0	27,726,425.7	30,672,417.1	32,139,498.5		

Table 3. Values of total material flow distance.

Dataset	Value	Robust layout				Re-layout							
		MFC	MFC* based on %BMM (currency unit)			TC (MMD)	TC* (MMD) based on %BMM (currency unit)			TC (NMM)	TC* (NMM) based on %BMM (currency unit)		
		(currency unit)	10	20	30	(currency unit)	10	20	30	(currency unit)	10	20	30
10M5N	Mean	531,623.4	595,992.6	648,008.0	718,537.9	553,009.4	617,154.1	671,914.9	730,535.2	586,145.7	650,290.4	705,051.2	763,671.5
	SD	11,023.7	18,962.6	22,179.8	19,694.1	14,336.7	19,091.1	19,243.6	21,080.1	15,286.6	19,789.0	20,922.9	22,120.9
	Min	523,969.5	578,595.5	629,746.0	703,029.4	526,644.5	584,482.9	634,191.7	695,406.9	552,234.5	610,072.9	659,781.7	727,311.9
	Max	565,028.6	649,594.9	701,533.4	774,072.3	588,964.2	662,230.7	720,037.3	775,130.1	622,662.9	703,345.7	755,020.9	816,245.1
20M10N	Mean	3,375,077.5	3,542,104.0	3,628,745.5	3,941,721.4	3,397,598.8	3,586,577.4	3,696,034.5	4,048,890.7	3,470,191.1	3,659,169.7	3,768,626.8	4,121,483.0
	SD	66,940.2	70,083.5	90,727.4	93,797.2	31,005.2	44,299.4	61,865.7	88,405.8	31,228.0	44,107.5	62,585.4	88,702.6
	Min	3,246,870.4	3,405,568.5	3,491,732.5	3,751,832.7	3,331,036.6	3,496,907.5	3,588,321.5	3,908,075.3	3,401,192.6	3,569,370.5	3,660,739.5	3,980,493.3
	Max	3,525,702.9	3,697,350.4	3,825,789.1	4,136,080.9	3,463,198.0	3,703,134.0	3,848,130.9	4,244,894.5	3,533,304.0	3,772,512.0	3,917,508.9	4,314,547.0
20M20N	Mean	10,258,008.5	10,886,407.5	11,491,341.5	10,040,630.5	10,139,991.7	10,335,283.5	10,765,334.2	11,473,471.9	10,217,897.2	10,413,189.0	10,843,239.7	11,551,377.4
	SD	174,047.6	377,961.7	379,507.2	64,521.2	68,532.2	149,103.1	245,520.8	206,918.0	64,320.5	147,020.8	244,641.4	205,679.7
	Min	9,849,434.2	10,135,672.5	10,873,095.3	9,911,473.3	10,012,763.3	10,091,920.2	10,231,535.7	11,023,521.9	10,090,473.3	10,164,599.7	10,318,010.2	11,120,283.4
	Max	10,614,291.9	11,917,048.8	12,629,320.2	10,145,030.9	10,254,087.9	10,647,773.1	11,305,913.8	11,852,185.2	10,324,030.9	10,722,108.6	11,398,764.3	11,919,392.7
20M40N	Mean	19,594,343.6	20,347,121.1	21,261,068.2	20,815,688.1	19,440,338.1	20,235,832.1	21,251,259.0	20,810,665.4	19,521,665.4	20,317,159.4	21,332,586.3	20,891,992.7
	SD	231,398.2	318,814.4	355,670.7	361,285.2	88,273.5	165,232.7	286,826.0	212,576.5	86,839.1	162,608.5	286,568.2	212,810.9
	Min	19,246,235.6	19,887,820.5	20,614,947.8	20,049,924.7	19,284,193.3	19,864,453.9	20,696,530.7	20,447,300.6	19,373,354.8	19,953,615.4	20,773,823.7	20,522,304.6
	Max	20,141,262.1	21,181,869.2	22,179,471.9	21,493,810.5	19,655,657.1	20,537,783.2	21,799,237.3	21,255,621.3	19,738,491.6	20,627,603.2	21,886,222.8	21,338,455.8
30M15N	Mean	7,895,278.6	8,276,170.0	8,489,326.7	9,056,617.6	7,923,556.1	8,343,630.4	8,585,924.3	9,162,262.6	8,019,453.0	8,439,527.3	8,681,821.3	9,258,159.5
	SD	190,541.8	213,714.2	209,076.6	197,351.2	89,296.9	101,249.5	120,358.7	144,596.4	84,689.9	101,180.5	115,640.4	148,779.8
	Min	7,477,879.1	7,915,148.6	8,041,397.4	8,663,135.8	7,772,775.7	8,177,523.4	8,343,097.6	8,912,985.1	7,870,228.3	8,265,155.8	8,439,185.6	9,008,363.1
	Max	8,205,071.8	8,642,410.7	8,884,425.3	9,448,623.8	8,079,591.0	8,545,580.9	8,866,431.5	9,468,480.5	8,176,281.0	8,631,727.9	8,942,979.0	9,545,844.5
40M20N	Mean	15,209,235.0	17,166,328.0	17,680,469.6	19,807,215.4	15,278,413.5	17,245,736.0	17,681,776.2	17,245,735.9	15,367,295.0	17,334,617.6	17,770,657.8	17,334,617.5
	SD	604,071.8	596,320.1	711,828.6	628,823.9	203,181.5	237,005.0	254,929.8	237,005.0	197,200.6	231,222.1	249,132.9	231,222.1
	Min	14,168,156.5	16,275,826.0	16,382,959.9	18,444,970.6	14,777,255.2	16,767,597.2	17,127,857.6	16,767,597.2	14,885,384.2	16,875,726.2	17,222,780.6	16,875,726.2
	Max	16,423,379.4	18,793,575.0	19,249,222.1	20,954,182.8	15,693,211.5	17,862,110.7	18,107,170.5	17,862,110.7	15,774,321.5	17,943,220.7	18,181,532.5	17,943,220.7
40M40N	Mean	27,952,468.5	30,354,735.4	32,107,292.1	34,014,129.5	28,350,828.1	30,731,355.1	32,452,552.9	34,182,189.7	28,439,832.2	30,820,359.2	32,541,557.0	34,271,193.9
	SD	665,215.8	710,209.0	732,868.0	913,114.6	482,626.3	544,456.3	479,500.9	540,295.4	477,948.1	540,169.0	476,529.2	536,438.5
	Min	26,735,184.2	28,861,378.3	30,625,120.7	32,160,002.9	27,532,346.1	29,541,444.1	31,231,225.3	33,114,762.2	27,621,325.6	29,652,863.1	31,319,845.3	33,210,483.2
	Max	29,016,247.4	31,531,345.4	33,591,573.4	36,340,903.2	29,651,844.7	31,895,652.8	33,576,337.6	35,442,737.4	29,738,487.2	31,964,931.3	33,662,980.1	35,508,160.4
50M25N	Mean	25,216,694.2	27,178,003.2	30,270,244.4	30,870,860.1	25,207,009.7	27,291,060.2	30,032,056.0	31,008,669.0	25,283,171.4	27,367,221.8	30,108,217.6	31,084,830.6
	SD	789,782.7	668,805.8	1,470,163.5	1,062,502.1	281,574.1	459,718.3	504,468.1	603,017.6	280,087.1	456,842.0	507,530.8	598,949.3
	Min	23,928,776.0	25,890,014.3	28,608,583.1	29,248,548.6	24,237,851.6	26,242,928.1	29,081,217.4	29,529,550.3	24,330,084.6	26,335,161.1	29,168,879.4	29,617,212.3
	Max	26,950,652.2	28,643,707.9	34,650,791.3	33,655,833.1	25,724,355.6	28,071,017.2	31,055,738.6	32,509,922.5	25,761,940.1	28,172,425.7	31,122,417.1	32,589,498.5

Table 4. Values of total cost.

4.2 Total cost for robust layout and re-layout

The results obtained for the total costs of robust and re-layout were presented in the previous section. For robust layout, the total cost was the total of the material flow cost. It was assumed that the material flow cost (C_{MF}) was one currency unit per metre. The total cost of re-layout included material flow cost and machine shifting costs as shown in Eq. (3) and (4). The shifting costs were related to the number of machines moved (U) and the distance of machine movement (V). The average shifting cost based on the number of machines moved (C_{MV}) and the distance of machines moved (C_{MD}) was set at 1,000 currency units per machine moved (Moslemipour and Lee 2012) and 50 currency units per metre, respectively. Total costs were calculated based on the results obtained from the previous experiment shown in Table 4.

$$\text{Total cost of re-layout} = C_{MF}\left(\sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{g=1}^{N}\sum_{k=1}^{P}\sum_{l=1}^{W} d_{ij}\, f_{ijgkl} D_{gkl}\right) + \sum_{k=1}^{P} C_{MD} V_{k+1} \,, \tag{3}$$

(Shifting cost based on no. of moved machines)

$$\text{Total cost of re-layout} = C_{MF}\left(\sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{g=1}^{N}\sum_{k=1}^{P}\sum_{l=1}^{W} d_{ij}\, f_{ijgkl} D_{gkl}\right) + \sum_{k=1}^{P} C_{MV} U_{k+1} \,, \tag{4}$$

(Shifting cost based on the moving distance)

Table 4 shows that the total cost of robust layout was lower than for re-layout both in terms of the number of machines moved and the distance moved except for 20M20N, 20M40N and 50M25N. A Student's t-test showed there were statistically significant differences in the mean of total cost between robust layout and re-layout in terms of some types of shifting cost. The mean total cost had no statistically significant difference between the layout designs for the 40M20N and 50M25N cases, so the layout was robustly designed or redesigned. However, the re-layout approach consumed time repositioning machines and required shifting costs which increased the total cost. For re-layout, the total cost in terms of the number of machines moved was lower than the moving distance cost. Whether the layout was robustly designed or redesigned to another layout in the next period depended on the shifting cost and number of machines and product types (datasets). However, it should be noted that the shifting costs considered in this work were excluded and other costs related to the shutting down of the manufacturing line were also omitted.

With breakdown maintenance, the lowest mean total cost for each %BMM is highlighted in Table 4. The total cost of robust layout was lower than re-layout based on both types of shifting cost for 10M5N, 20M10N, 30M15N and 40M40N. For all %BMM, the difference in mean total cost between robust layout and re-layout for 10M5N and 20M10N were statistically significant with a 95% confidence interval (since the P values obtained from the Student's t-test were less than 0.05 as shown in Table 5). The total cost of re-layout in terms of moving distance was higher than for robust layout for 20M20N and 20M40N but there were no statistically significant differences.

The robust layout was more effective than re-layout for some datasets and some types of shifting costs. Within both types of shifting cost for re-layout, the total cost in terms of the number of machines moved was lower than in terms of moving distance. This confirmed that the shifting cost and number of machines and product types (datasets) have an influence on machine layout design. However, the appropriate %BMM determined whether the layout should be robust or re-laid out.

Dataset	MMD			NMM		
	%BMM			%BMM:		
	10%	20%	30%	10%	20%	30%
10M5N	0.000	0.000	0.027	0.000	0.000	0.000
20M10N	0.000	0.000	0.000	0.000	0.000	0.000
20M20N	0.611	0.148	0.822	0.082	0.602	0.450
20M40N	0.097	0.907	0.948	0.649	0.395	0.324
30M15N	0.126	0.033	0.022	0.000	0.000	0.000
40M20N	0.502	0.993	0.000	0.158	0.517	0.000
40M40N	0.025	0.036	0.390	0.006	0.009	0.190
50M25N	0.040	0.407	0.540	0.052	0.572	0.342

Table 5. P-value of the student's t-test between MFC and TC* in terms of MMD and NMM.*

5. Discussions and conclusions

This paper has presented the development of a Genetic Algorithm that designs non-identical machine layouts for stochastic demand environments. The GA aims to minimise the total material flow distance. The computational experiments were carried out using eight datasets with different demand distributions. The analysis considered scenarios where 10%, 20% and 30% of machines had breakdown maintenance. The material flow distances for both re-layout and robust layout increased when some machines were maintained during each period. This was caused by changes in routings due to the use of alternative machines. The experimental results indicated that the material flow distance for re-layout was shorter than for robust layout. However, redesigning the machine layout according to demand levels generated shifting costs.

The total cost of the robust layout designs that did not consider maintenance were lower than those that involved re-layout for almost all the datasets. Robust layout designs also produced lower cost in breakdown maintenance situations. This was because re-layout caused machines to be moved which caused shifting costs. However, shifting costs may have according to the machine movements, which has an influence on total cost for re-layout designs. It can be beneficial for companies to consider both demand and machine uncertainty when designing layouts, providing that the future demand and availability of machines are properly forecast and planned. Investors should make decisions based on a trade-off between rearrangement cost and material flow cost. Future research should be focused on designing the machine layout without considering preventive machine maintenance and both of preventive and breakdown maintenance.

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7. References

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