APPLICATION OF GROUP GENETIC ALGORITHM FOR GENERATION OF CELLS TO SOLVE A MACHINE LAYOUT PROBLEM

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Abstract

This paper explains the improvement of a layout arrangement as a result of application of Group Genetic Algorithm (GGA) on an excel platform for generaation of cells, in celluar manufacturing to minimize distance travelled and materials handling between workstations. It is based on a case study of ABC (Pvt) Ltd, a privately owned manufacturing company in Zimbabwe. The main objective of the study is to come up with manufacturing cells of machine part matrix generated from chromosomes using GGA. The researchers use the GGA to come up with a machine part matrix which reduces distances between machines which processes related parts. Excel is used in calculating fitness function values and the analysis of the best chromosome is done using the radar and line plots. From the study the first offspring in the second generation (chrom 4) is chosen as the best chromosome which enables best machine layout with 83% machine-part movement minimization and 62% machine utilization and 73% effectiveness.

Keywords: Group Genetic algorithm, Chromosome, Material handling, Cells

Introduction

Genetic Algorithms are very effective search techniques that actually replicate natural phenomena. They have shown effectiveness in solving a number of combinatorial optimization problems. Many researchers have used genetic algorithms in cell formation for part matrix problems. Venugopal and Narendran (1992), applied GA to the cell formation problem with the objective of considering variations in cell load and minimization of the total number of intercellular moves. Al-Sultan and Fedjki (1997), formed part families by using the combination of quadratic integer programming model with GA and then later on found corresponding machine groups. The cell formation problem was initially developed as a 0-1 integer programming model with the objective of maximizing the total number of intracell moves while considering the cell size constraint by Moon and Kim (1999). Zhao & Wu (2000) presented a GA based approach for the machine grouping problem considering multiple objectives such as minimizing cost involved in intracell part movements, cell load variation, and number of intercell movements. The approach is an effective one as the work of some of the previous researchers, have been further improved. Onwubolu & Mutingi (2001) used a GA based approach is to solve the cell formation problem by taking into account the cell load variation. Murugan et al. (2007) implemented cellular manufacturing system using cell formation algorithms namely ROC, ROC-2 and DCA and validated the better performance of DCA. Geonwook and Herman (2006) presented a two-phase mathematical approach for the cell formation problem.Xiadon and Chu (2007) developed a hierachical genetic algorithm to simultaneously form manufacturing cells and determine the group layout of a Cellular Manufacturing System.

Even all this swork has been carried out, very little has been done in terms of measuring the effectiveness of the cells formed and the machine utilization. It is in this purview that the researchers have researched on solving machine part matrix problem using GGA, then evaluated the effectiveness of cells formed and machine utilization using excell. The rest of the paper is structured as follows: Background of the problem, Literature review, Case study audit, Methodology, Modeling and simulation, Results and analysis, lastly conclusions and recommendations.

Problem Definition

Machines at ABC Engineering (not its real name), are under utilized due to the ineffective machine layout. The machines are arranged considering only the available space and not taking major considerations of the sequencing operations. Many machines are new and operate with minimum machine breakdown but production time is lost in moving parts to be processed from one machine to the other. The movements' results in increased waiting time which adds up to about 2.5 hrs per shift as machines have to wait for parts to be delivered from one department by a forklift or a trolley; this has resulted in increased throughput time. Parts to be processed are normally heavy and bulky thus they cannot be easily moved from one point to another. One of the major objectives in process layout is to minimize transportation cost, distance, and time. (Stevenson 2007). Other concerns include initial costs in setting up the layout, expected operating costs, the amount of effective capacity created, and the ease of modifying the system like the costs of relocating any work center.

The distances moved by workers cause worker fatigue, reduce the workers' level of concentration thus resulting in reduced worker productivity. It is argued that an effective layout design reduces manufacturing lead time, increases throughput and overall efficiency and productivity of the plant (M.Adel 2004). At ABC Engineering the available material handling equipment is inadequate and a forklift is normally hired or additional labour force of about 5 people per shift is hired to assist in the movement of material and this increases the materials handling cost which adds on the production cost thus reducing profits. Data from daily log sheets shows that about 2 hours of every 9 hour shift is lost due to material movement. The ineffective arrangement of machines has reduced production output to 30 agro-processing units a day instead of the expected 45 units.

GA starts with an initial set of random solutions for the problem under consideration. This set of solutions is known as the population. The individuals of the population are called 'chromosomes'

Case study audit

The current machine layout at ABC Engineering

Machines at the ABC Engineering workshop are arranged according to the available space therefore resulting in high material handling cost about 8% of daily production cost. Material handling and plant layout are inter-dependent and their relationship has a bearing on the optimization of material flow in any manufacturing plant. ABC Engineering has 8 departments, with some which are 35, 40 or 50metres far apart and this increases the time to move material between departments. The inter-departmental distances were determined using Euclidean distance and Manhattan distance, (Weisstein, 2008).

Euclidean distance moved: $\boldsymbol{d(x,y) = (\sum_{i=1}^{n} \sqrt{(xi - yi)^2}}$ (1)

Manhattan distance/ Rectilinear distance: $\boldsymbol{d(x,y) = \sum_{i=1}^{n} (/ \, xi - yi \, /)}$ (2)

The measured distances are shown in Table 1. The total times have been calculated using the given distances and average speed. It was observed that a worker moves at an average speed of 1.2m/s when pushing a trolley with raw materials and a forklift moves at an average speed 5m/s. the total time taken to move between workstations is shown in Table 1.

Table 1: Showing distances moved and time taken

Material flow	**Distance (m)**	**Material handling**	**Time(s)**	**Frequency per shift**	**Total time (m)**
Drilling to grinding	50	Forklift	41.6	25	17.3
Grinding to painting	30	Trolleys + operators	25	20	8.3
Cutting to machining	40	Trolleys+ operators	33.3	30	16.6
Machining to assembling	80	Trolleys + operators	66.6	45	50
Machining to grinding	70	Trolleys	58.3	20	19.4
Fabrication to assembling	50	Trolleys	41.6	25	17.3
Fabrication to grinding	70	Forklifts	58.3	15	14.6
Fabrication to drilling	20	Forklifts+trolleys	16.6	20	5.5
Total					**149mins**

Total time taken between workstation movement

The total time taken by an operator to move material between departments is contributing to production lateness, from summations of time on the log sheet it is found that almost 2 hrs of production time is lost in manual material handling movements. The material handling process is an additional cost of production thus it has to be minimized. This problem of material movement and ineffective arrangement of machines has initiated the need to develop a method to solve the problem. The bulkiness of the raw materials to be assembled makes it difficult to move material to be processed between workstations, thus this initiates the need to reduce distances between work stations to optimize productivity.

Methodology

The researchers used the group genetic algorithm to group machines which perform subsequent operations together so as to minimize distances between work stations. A Genetic algorithm is a heuristic search technique that is analogous to the concept of natural selection and survival of the fittest. The technique employs a population of solutions, combining those solutions in specific ways in an attempt to form better solutions. Genetic algorithms have become a popular solution methodology for a variety of complex problems (Brown 1996). The population of solutions with which a genetic algorithm (GA) works is comprised of encodings, known as chromosomes.

Individual elements of the chromosomes are called genes. Based on the objective function of the problem at hand, each chromosome is evaluated and given a fitness score. The generation of chromosomes is summarized and shown in Figure 2.

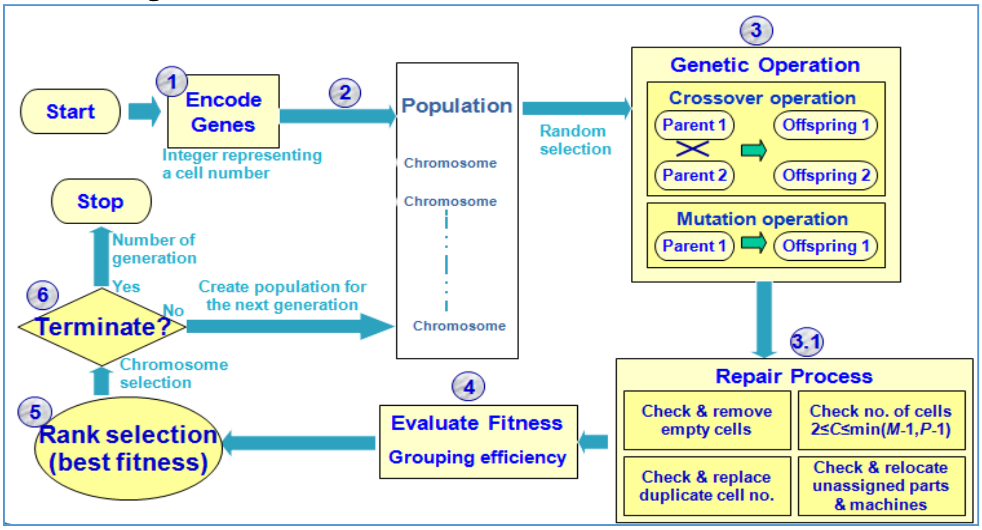


Fig 2: Flowchart of the Grouping Genetic Algorithm

Machine-part (MP) index matrix for a machine layout

The researchers considered the problem of grouping 12 parts and 16 machines into cells.. Machines and parts are shown on Table 3. The Machine Part (MP) matrix shown in Table 2 reflects the conditions for the sample programme, with a 1 in position a_{ij} indicating that **machine (*i*)** is required by **component (*j*).**

Table 2: Machines and parts at ABC engineering

No	Machines at ABC *(i)*	Parts to be processed (j)
1	Lathe machine	Shaft
2	Milling machine	Disk
3	Electrical guillotine	Frame parts
4	Hydraulic press	Cyclone holder bars
5	Manual press	Mill plates
6	cropper	Beaters
7	Electrical bending	Spacers
8	Arch welding machine	Studs
9	Electrical pressing machine	Bosses
10	Grinding machine	Pins
11	Spraying machine	Cyclone plates
12	Drilling machine	Guard plates
13	Bar cutting machine	
14	Manual bending machine	
15	Rolling machine	
16	Oxy-acetylene cutting	

The machines have been numbered from 1 to 16 whilst the parts have been numbered from 1 to 12. These numbers are used in the machine part matrix were the machines and parts are represented in binary form in Table 3. The numbers are also used to generated chromosomes and off springs for the Group Genetic Algorithm

Table 3: Machine-part index matrix for a machine layout problem

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}
M_1	1	1							1			
M_2	1	1							1			
M_3		1			1	1					1	1
M_4												1
M_5				1	1							1
M_6			1		1	1						1
M_7			1	1	1						1	1
M_8		1	1	1	1				1		1	1
M_9			1	1	1						1	1
M_{10}		1	1	1	1						1	1
M_{11}			1	1	1						1	1
M_{12}	1	1	1	1	1	1			1	1	1	1
M_{13}	1			1			1	1	1	1		
M_{14}			1	1	1						1	1
M_{15}				1	1						1	
M_{16}		1	1		1						1	

The MP matrix enables clear visualization of parts that need to be processed at a particular machine, thus making it easier to group machines closer to each other. Population of chromosomes is generated randomly using a replacement strategy. In this project, the initial population was created randomly using a machine part incident matrix.

Selection and crossover

By random creation and random selection, the parents selected for cross over are **223155422155/1142212334354515/12543** & **121242334144/3214121144233424/1432** from the machine part incident matrix in Table 3 above. The randomly generated cross-points for parent 1 and 2 are shown below with parent 1 showing cross section of group 2,5 and 4 only while parent 2 shows groups1and 4.

Parent 1: 1/254/3
Parent 2: /14/32

First generation:
Offspring 1: 1/14254/3
Offspring 2: 2541432.
For Offspring 1: 1/14254/3

(Note that 1 and 4 are underlined to signify that it is part of the inserted section, not part of the original parent). Now the composition of each group of offspring one is listed, with braces used to separate the components listing from the machines listing. For example, group 1 includes parts 1, 3, and 10, as well as machines 3, 5, 7 and 8.

Group 1 {1, 3, 10}**,** {3, 5, 7, 8}
Group 4 {9, 11, 12}, {4, 9, 10, 16}
Group 2 {1, 2, 8, 9}, {4, 5, 7}
Group 5 {5, 6, 11, 12}, {12, 14, 16}
Group 4{7}, {3, 10, 13}
Group 3 {5, 6, 11, 12}, {12, 14, 16}

Note that five items now occur twice: component 1, machine 3, machine 5, machine 10 and machine 7. Machines 1, 2, 6, 11 have no group therefore there are assigned to any group looking at the machine part index matrix. Following the steps for crossover, we now remove the duplicates from the groups they were in as a part of parent one. Thus, the injected section remains intact and the other groups are subject to alteration. Results of this step are as follows:

Group 1 {1, 3, 10}**,** {1, 2, 3, 5, 7, 8} [unaltered][Adding machine 1 and 2]
Group 4 {9, 11, 12}, {4, 9, 10, 16} [unaltered]
Group 2 {2, 4, 8} [component 1, 9 removed adding component 4][machines 4, 5 & 7 removed]
Group 5 {5, 6, 12}, {6, 9, 11, 12, 14, 15} [removing component 11, 12, removing machine 16 and adding machine15]
Group 4{7}, {13} [machine 3 and 10 removed]

Now there are no machines in group 2. A replacement method for machine utilization is used to assign parts or components to remaining groups using machine part incident matrix in Table 3

The remaining groups become:

Group 1 {1, 2, 3, 10}**,** {1, 2, 3, 5, 7, 8} [unaltered] [Adding component 2]
Group 4 {9, 11, 12}, {4, 9, 10, 16} [unaltered]
Group 5 {4, 5, 6}, {6, 11, 12, 14, 15} [adding component 4]
Group 4{7, 8}, {13} [adding component 8]

Therefore **offspring 1**= 1 1 1 5 5 5 4 4 4 1 4 4/1 1 1 4 1 51 1 4 4 5 5 4 5 5 4/1 4 5

The procedure for generating offsprings is repeated for offspring number 2 of the first generation, parent offspring 1 and 2 for second generation and parent offspring 1 and 2 for the third generation. The offsprings generated from each generation are shown below

Offspring 2= 2 2 1 2 5 5 4 2 2 1 5 5/2 2 4 2 2 2 2 1 5 4 2 5 4 5 2 5/2 5 4 1 2

Second generation

Offspring 1= 1 1 5 5 5 5 4 4 1 5 5 5/1 1 4 5 1 5 5 5 5 4 5 5 4 5 5 5/5 4

Offspring 2= 1 1 1 5 5 5 4 4 1 1 4 5 /1 1 1 4 1 5 5 1 4 4 5 5 4 5 5 1/ 1 4 5 4

Third generation

Offspring 1= 1 1 5 5 5 5 4 4 1 5 4 5 /1 1 4 4 1 5 5 5 4 4 5 5 4 5 5 5/ 4 5 5 4 1

Offspring 2 = 5 5 5 5 5 5 4 4 5 5 5 5 /5 5 4 5 5 5 5 5 5 4 5 5 4 5 5 5/ 5 4

The offsprings generated makes up the chromosomes. The offsprings 1 and 2 of the first generation are regarded as chromosome 6 and 5 respectively, offsprings 1 and 2 from second generation are chromosomes 4 and 3 respectively, and lastly 1 and 2 from the 3rd generation are chromosomes 1 and 2 respectively. The 6 chromosomes generated form the 6 possible layout designs for the machine part matrix.

Modeling and simulation

The possible layout designs from the chromosomes are modeled and simulated using Microsoft Excel programming so as to relate to the initial objective of minimization of movement and increased machine utilization.

Measurement of layout performance

The researchers used the formula below to calculate the efficiency of each layout to determine the layout which has maximum machine utilization. The efficiency of the layout is determined using the number of 1's and 0's in each block diagonal for all the 6 chromosomes.

$$\boldsymbol{eff = [qy + (1 - q)x]100}$$

Where

$\boldsymbol{y}$ **=** is ratio of the number of 1's in the diagonal blocks to the total number of elements in the diagonal blocks of the final matrix;

$\boldsymbol{x}$ = is ratio of the number of 0's in the off-diagonal blocks to the total number of elements in the off-diagonal blocks of the final matrix;

$\boldsymbol{q}$ = weight factor. *(0≤ q ≤ 1)*

$$\boldsymbol{y = \frac{ed}{\sum_{r=1}^{k} \mathrm{MrNr}}} \qquad \boldsymbol{x = 1 - \left[\frac{eo}{\mathrm{mn} - \sum_{r=1}^{k} \mathrm{MrNr}}\right]}$$

***e*d =** total number of ones in the diagonal blocks,

***e*o**= total number of ones in the off diagonal blocks,

$\boldsymbol{k}$ **=** limiting number of groups,

$\boldsymbol{m}$ = number of machines (rows),

$\boldsymbol{n}$ **=** number of parts (columns),

Mr **=** number of machines in the r^{th} cell,

Nr = number of parts in the r^{th} cell.

The formula for the objective function was used in the excel platform and the block diagonal for all the chromosomes were also generated in excel. From the block diagram it is observed that the closer the value of ***(x)*** to 1, the more the increase in efficiency. If you change the value of ***(x)*** you will automatically change the value of efficiency using excel. The same effect when you change the values of ***(y)***

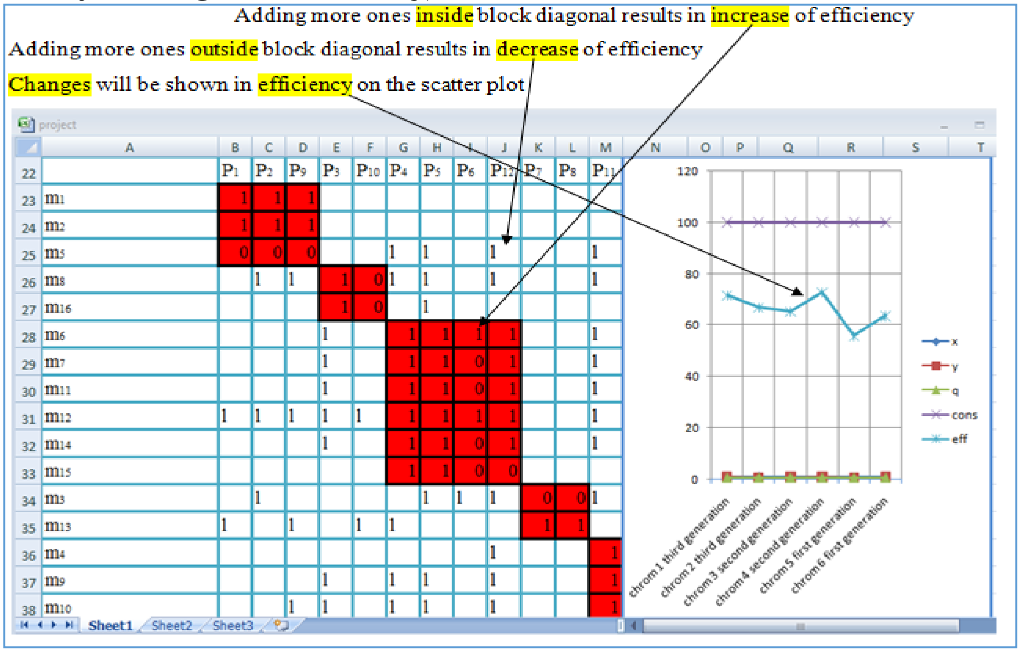


Figure 3: Increase or decrease in efficiency with "1"outside the block diagram

Results

The block diagrams for all the chromosomes were generated in excel and the formula of the objective function was applied to the machine part matrix for all chromosomes 1 to 6. Chromosome no 4 was chosen which has the best efficiency value. The values for ***x, y*** and ***efficiency*** for all the chromosomes are shown in the Table 4.

Table 4: Showing the value of x,y and efficiency

fitness function	x	y	q	cons	eff
chrom 1 third generation	0.7	0.73	0.5	100	71.5
chrom 2 third generation	0.86	0.48	0.5	100	66.8
chrom 3 second generation	0.71	0.59	0.5	100	65.4
chrom 4 second generation	0.83	0.62	0.5	100	72.8
chrom 5 first generation	0.63	0.49	0.5	100	55.8
chrom 6 first generation	0.68	0.55	0.5	100	63.5

The first offspring in the second generation **(chrom 4)** was chosen as the best with the 83% machine-part movement minimization and 62% machine utilization and 73% effective,

Block diagonal for the best chromosome

Table 5: Block diagonalization of the best chromosome

	P_1	P_2	P_9	P_3	P_4	P_5	P_6	P_{10}	P_{11}	P_{12}	P_7	P_8
M_1	1	1	1									
M_2	1	1	1									
M_5	0	1	0		l					L		
M_4				0	1	0	0	0	0	1		
M_6				1	0	1	1	0	0	1		
M_7				1	1	1	0	0	1	1		
M_8		l	l	1	1	1	0	0	1	1		
M_9				1	1	1	0	0	1	1		
M_{11}				1	1	1	0	0	1	1		
M_{12}	l	l	l	1	1	1	1	1	1	1		
M_{14}				1	1	1	0	0	1	1		
M_{15}				0	1	1	0	0	1	0		
M_{16}		l		1	0	1	0	0	1	0		
M_3						l	l		l		0	0
M_{10}		l		l					l		0	0
M_{13}	l		l					l	l		1	1

The block diagonalization results in the formation of three cells. This block diagonal shows that they are fewer movements as shown by 1(s) outside the block diagonal therefore fewer movements in the plant thereby fulfilling the objective of the project. The zeros represent voids in the cell. The 1(s) outside the diagonal block represents the exceptional elements (machines that cannot be assigned into cells.

Interpretation of the block diagonal

The block diagram shows a plant layout with three main cells. The first cell has three machines and is responsible for processing three main parts.

Cell 1

Machines: M_1 lathe, M_2 milling, M_5 manual press
Parts: P_1 shaft, P_2 disk, P_9 bosses
Exceptional parts: P_4 cyclone holder bars, P_{12} guard plates

Cell 2

Machines: M_4 hydraulic press, M_6 cropper, M_7 electrical bending, M_8 arch welding, M_9electrical pressing, M_{11} spraying, M_{12} drilling, M_{14} manual bending, M_{15} rolling, M_{16} oxy-acetylene

Parts: $\mathbf{P_3}$ frame parts, $\mathbf{P_4}$ cyclone holder parts, $\mathbf{P_5}$ mill plates, $\mathbf{P_6}$ beaters, $\mathbf{P_{10}}$ pins, $\mathbf{P_{11}}$cyclone plates, $\mathbf{P_{12}}$guard plates
Exceptional parts: $\mathbf{P_1}$ shaft, $\mathbf{P_2}$ disk, $\mathbf{P_9}$ bosses
Cell 3
Machines: $\mathbf{M_{10}}$ bosses, $\mathbf{M_{11}}$ cyclone plates
Parts: $\mathbf{P_7}$ spacers, $\mathbf{P_8}$ stud
Exceptional parts: $\mathbf{P_1}$ shaft, $\mathbf{P_3}$ frame parts, $\mathbf{P_{10}}$ pins, $\mathbf{P_{11}}$ cyclone plates

Testing the mathematical model

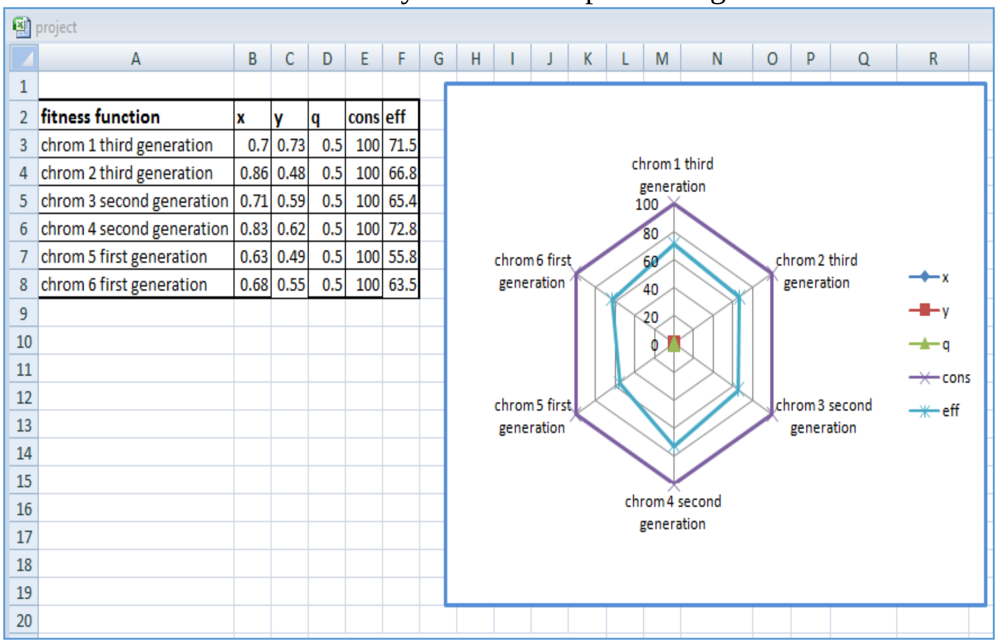
Using calculations: If ***(x)***= 0.6 and *(y)* = 0.8 we get 70% efficiency on the fitness function.

$$eff = [q(0.6) + (1 - 0.5)0.8]100 = 70\ \%\ \text{efficiency}$$

Using calculations: If ***(x)***= 0.8 and ***(y)*** = 0.9 we get 85% efficiency on the fitness function.

$$eff = [q(0.8) + (1 - 0.5)0.9]100 = 85\ \%\ \text{efficiency}$$

The above calculations show that the closer the values of ***(x)*** and ***(y)*** to 1, the more the increase in efficiency therefore the arrival at the best fitness chromosome. A change in the radar plot will also occur if we change the values of x and y in excel. The chromosome with the best fitness function will be shown with better clarity on the radar plot on Figure 4.



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chrom 5 first generation	0.63	0.49	0.5	100	55.8
chrom 6 first generation	0.68	0.55	0.5	100	63.5

Figure 4: Plots showing increase in efficiency with the increase (x) and (y) values

Conclusion

In this study, clusters of cells have been formed which enables minimization of distances between machines. From the block diagonalization it is shown that few ***(1s)*** are outside the diagonal box, the lesser the number of ones outside the diagonal the less the part movements therefore less material handling cost. From the objective function of the selected chromosome there is 83% machine part movement minimization which results in fewer movements therefore less material handling cost. From the selected chromosome fewer parts are going to visit machines. Since machines and parts are now arranged in cells from the block diagonal structure, waiting times due to delays in parts movements at each department are also reduced .

Recommendations

Plant layout plays an integral part in materials handling. Materials and workers should move shortest possible distance in the plant. The author recommends the company to implement the designed layout for shortest distances between crucial departments highlighted in this document. It is recommended that other organization do adopt the application of GGA on excel on platform to solve layout problems as it enables quantitative evaluation through modeling and simulation. This will decrease the number of accidents and throughput time thus enhancing productivity.There is need for further research into the impact of current machine layout arrangements in Zimbabwean companies, particularly focusing on small to medium-sized enterprises and the impact of cellular manufacturing on current performances.

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