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Jurnal Sistem dan Manajemen Industri

ISSN (Print) 2580-2887 ISSN (Online) 2580-2895

Intelligent optimisation for multi-objectives flexible manufacturing cells formation

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ARTICLE INFORMATION

Article history:

Received: January 3, 2024
Revised: April 13, 2024
Accepted: May 14, 2024

Keywords:

Flexible manufacturing cell formation
Genetic algorithms
Multi-objectives intelligent optimisation
Particle swarm optimisation

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A B S T R A C T

The primary objective of conventional manufacturing cell formation typically uses grouping efficiency and efficacy measurement to reduce voids and exceptional parts. This objective frequently leads to extreme solutions, such as the persistently significant workload disparity among the manufacturing cells. It will have a detrimental psychological impact on operators who work in each formed manufacturing cell. The complexity of the problem increases when there is a requirement to finish all parts before the midday break, at which point the formed manufacturing cells can proceed with the following production batch after the break. This research examines the formation of manufacturing cells using two widely recognised intelligent optimisation techniques: genetic algorithm (G.A.) and particle swarm optimisation (PSO). The discussed manufacturing system has flexible machines, allowing each part to have multiple production routing options. The optimisation process involved addressing four simultaneous objectives: enhancing the efficiency and efficacy of the manufacturing cells, minimising the deviation of manufacturing cells working time with the allocated working hours, which is prior to the midday break, and ensuring a balanced workload for the formed manufacturing cells. The optimisation results demonstrate that the G.A. outperforms the PSO method and is capable of providing manufacturing cell formation solutions with an efficiency level of 0.86, efficacy level as high as 0.64, achieving a minimum lateness of only 24 minutes from the completion target before midday break and a maximum difference in workload as low as 49 minutes.

1. INTRODUCTION

Flexibility, encompassing volume and product type, is a significant competitive factor in make-to-order supply chain systems. Nevertheless, an inverse relationship typically exists between flexibility and productivity. Therefore, it is crucial to identify the optimum balance between these two factors by considering production shop floor management that can increase production efficiency, safety, and quality [1]–[3]. From a technical standpoint, a production system that prioritises flexibility will adopt a job shop layout that involves grouping machines based on their function and forming several workstations. The utilised material handling system is highly adaptable, enabling the seamless transfer of semi-finished goods between workstations. In a job shop configuration, the manufacturing system can handle many product types without limits on the direction of the material flow. However, this results in a complex and lengthy material flow process, which increases the production cycle time. Increasing the duration of the production cycle time will lead to a decline in productivity and, consequently, an increase in production costs. Researchers have conducted numerous previous studies to minimise the production cycle time by minimising the scheduling makespan [4], [5] or total completion time [6].

The flowshop layout is also commonly used in manufacturing systems, where production machines are arranged based on product production routing [7], [8]. A production system with a fellowship configuration exhibits limited flexibility, necessitating serial or multiple flow shop systems [9] or creating a new production line tailored to the new products. A conveyor with a linear flow is the typical material handling equipment employed in production systems with a flow shop layout. The flow shop layout aims to streamline the material flow, resulting in a linear and simplified material-handling process. This condition reduces material transfer times and ultimately shortens production cycle times, and the short production cycles will enhance productivity and potentially lower production costs.

A hybrid layout combining the advantages of job shops and flowshop can enhance the flexibility and productivity of a manufacturing system [10]. The hybrid layout is commonly referred to as group technology, where the manufacturing system is divided into multiple manufacturing cells, each with a flow shop layout. The term commonly used to describe this manufacturing system is cellular manufacturing system (C.M.S.). A CMS exhibits greater flexibility than a flowshop, but is not as high as a job shop. Additionally, a C.M.S. demonstrates higher productivity than a job shop, although not as high as a flowshop. Implementing a C.M.S. can assist a manufacturing organisation in decreasing the rate of parts deficiency, reducing setup times and costs, shortening completion times, optimising factory space needs, and streamlining material routes [11].

In the analysis, the formation of manufacturing cells typically utilises input data, such as the incident matrix, which outlines the connection between parts and the machines required for their manufacturing processes. Subsequently, the incident matrix was organised into clusters to establish manufacturing cells. Various methods have been employed for this objective, including bicluster graph editing [12], simulation-based evolutionary system [13] and spectral clustering algorithm [14]. Typically, manufacturing systems in a make-to-order (M.T.O.) supply chain environment possess flexible machinery, enabling them to perform multiple manufacturing processes. It is conceivable for a part to have multiple production routes within its manufacturing system. As a result, the incident matrix will present all potential production routes for each part. In order to establish a cellular manufacturing system, it is important to concurrently determine the production route for each part while clustering the incident matrix based on the determined parts' production routing. To the best of our knowledge, no established algorithm has yet been implemented for this purpose.

Typically, in conventional approaches, the manufacturing cell formation is determined by an efficiency metric that evaluates the quality of machine-part clustering [15]. The pioneering work of Chandrasekharan & Rajagopalan introduced this metric [16]. Another metric that can be employed is efficacy, which was initially proposed by Kumar & Chandrasekharan [17]. These two measurements can be obtained by reducing the number of 0s in the diagonal cluster and the number of 1s outside the diagonal cluster in an incident matrix. These two measurements are highly efficient for forming manufacturing cells and have been utilised by numerous earlier researchers [18]–[22]. Nevertheless, these two measurements fail to consider the processing time of the parts on the machines, resulting in potentially extreme outcomes, such as considerable gaps in the manufacturing cell workload.

This study was conducted in an Indonesian industry operating in the M.T.O. supply chain environment, specifically focused on the production of office equipment. The industry manufactures 40 components, with 15 flexible machines on the production floor. Two production routing alternatives existed for each part, resulting in an incident matrix size of 80 × 15. It can be categorised as a large-scale case of forming C.M.S. The case can be viewed as a combinatorial optimisation problem with the solution to find the sequence of parts and machines in the incident matrix forming manufacturing cells. The complexity of the problem increases when there is a requirement to finish all parts before the midday break, at which point the formed manufacturing cells can proceed with the following production batch after the break. Therefore, ensuring that the workload in all the

http://dx.doi.org/10.30656/jsmi.v8i1.7974

formed manufacturing cells is effectively controlled is essential to avoid surpassing the allocated working time. Alternatively, if achieving this is not feasible, effective reduction of work overload is imperative.

Many researchers have commonly employed artificial intelligence (AI) systems or intelligent models to address the issue of forming large-scale C.M.S.. [23]–[25]. Nevertheless, most studies on C.M.S. formation continue to rely on the assessment of efficiency and efficacy. A study conducted by Farboodi *et al*. [26] considered workload balancing of the manufacturing cells; however, that study did not consider efficiency, efficacy, and designated working hours. To the best of our knowledge, no prior research on the C.M.S. formation considers the processing time of the parts at all of the machines to ensure that the C.M.S. operates within the designated working hours. In addition, the C.M.S. formation should consider the balanced workload distribution among all the manufacturing cells to mitigate any adverse psychological impacts on operators within the cells.

This study examines the formation of a C.M.S. by simultaneously addressing four objectives: maximising efficiency, maximising efficacy, minimising deviation of the formed C.M.S. working time from the allocated working hours, and minimising workload gaps among the formed manufacturing cells. With these objectives, this research will contribute substantially to research on C.M.S. formation. Currently, no formal algorithm can be used to form C.M.S. with those objectives concurrently. The existing established methods are just to form C.M.S. to maximise grouping efficiency and or efficacy [27].

This problem can be resolved by employing a conventional mathematical model that establishes the interaction between two parts or machines to ascertain the sequence of such parts or machines in the incidence matrix. Nevertheless, this method necessitates the use of $\frac{15!}{2!\times(15-2)!} = 105$ variables to represent the 15 machines sequence and $\frac{40!}{2!\times(40-2)!} = 780$ variables to indicate the sequence of parts with 2 alternate production routings. Additional variables are required to represent the values of 1 or 0 in the incident matrix, specifically, $15 \times 40 = 600$ variables. Furthermore, the variables need to reflect the processing time of each part of each machine, for a total of 600 variables. Hence, a minimum of 2085 variables was necessary. Given the many variables, an intelligent optimisation algorithm is considered significant as an alternative algorithm to address this problem.

This study employs two intelligent optimisation techniques, the genetic algorithm (G.A.) and particle swarm optimisation (PSO), to address extensive combinatorial optimisation problems [28]–[31]. G.A. exhibits proficient powers in exploration and exploitation, although its intricate algorithmic complexity burdens it. PSO exhibits proficient exploitation capabilities, although its exploration capability remains inferior to those of G.A. However, the PSO algorithm structure is less complex than that of G.A. The effectiveness of the suggested method will be measured after optimisation, and valuable insights for future study will be provided.

2. RESEARCH METHODS

2.1. Data collection

The data to be collected consists of operations process charts (O.P.C.) for 40 parts and their processing time in the 15 machines. In addition, a discussion was held with the manufacturing process planner to determine the specific manufacturing process required for forming the parts. The information obtained from the O.P.C. and subsequent conversations with the process planner are summarised in Table 1, and simultaneously represent the incident matrix of the parts and machines

2.2. G.A. modelling

2.2.1. *Chromosome design*

Three decision variables must be determined: the optimum production routing for the parts, the sequencing of parts, and the arrangement of machines in the incident matrix to establish the manufacturing cells. Consequently, the three genes within a chromosome reflect the decision variables, as shown in Fig. 1.

2.2.2. *Fitness function formulation*

The chromosome in the G.A. was evaluated based on its fitness value. In the context of G.A., the fitness value of the chromosomes is defined by a fitness function generated from the objective functions. The subsequent sections elaborate on converting the objective functions into the fitness function of the chromosome. The efficiency and efficacy formula used in this study is proposed by Chandrasekharan & Rajagopalan [16] and Kumar

http://dx.doi.org/10.30656/jsmi.v8i1.7974

Table 1. Processing time of the parts (in minutes)

Part	Routing Alternatives	Machines 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1						41			11						42
	2				28		10	8								
2	1	43		34					16							
	2		40	20					28	39						
3	1			11		40									18	
	2				24	28										10
4	1		25	29					12	19						
	2			20	41		41									
5	1							40	13	43			37	26		
	2						39			30			21			19
6	1				28				12		10					
	2			18	25			29								
7	1							26			17	29			29	
	2					35		19			19		22			
8	1	36		34					18							
	2			17				8				35				
9	1			8			42		17	31		8				
	2				17	23		19	27					42		
10	1											11	34	37	30	31
	2									36	32	31		39	21	
11	1		24	20					39							
	2				7	33			42							
12	1					27		22	37	33						
	2				30			17	30							
13	1										23	37			38	32
	2				23	27	29	19								
14	1					22	12									29
	2							11	37						40	
15	1	30	25					27	10							
	2		28	36										12	22	
16	1				25	13		23			11					
	2					39		8			33					23
17	1	27				36			40					7		
	2	29					20			12						
18	1				16		17					28			12	
	2				29		32			41						10
19	1	38		19		15							18			
	2	34	40	21							40					
20	1										11	38		13	22	
	2								12		13	8				35
21	1										18	14	22	13	35	
	2									9	30	16	13		10	
22	1	33			12				43					41		
	2					23		25				14				
23	1										36			12		
	2									16						15
24	1											30		22	36	11
	2										21	23	29	13		
25	1						13								27	24
	2						24						39	20		
26	1				21	15		8								
	2				13	10			17							
27	1			38	13	16			29							
	2	35	17	27					13							
28	1										17		29		30	36
	2	30		36		43									26	
29	1						12			38		23				36
	2			35					12		17		36		17	
30	1		23	25					25							
	2						25			13		19				
31	1		21		33		11	20		32						
	2				23		7					13		41	28	
32	1						22		43	32						
	2			41		20					28					
33	1		31					39	28					11		
	2										20	17		38	19	
34	1	35	35	14			22									
	2		22	38						25		7				
35	1											38	21		28	
	2						7			8	27					
36	1					18		16		31						
	2			41					21				28			
37	1	43			16				19							
	2		23			17		8								
38	1			34			32	15								39
	2										41	30	23	15		
39	1						39				37		28	36	24	
	2				35	21			37			32				
40	1						43				17					
	2				14			27								

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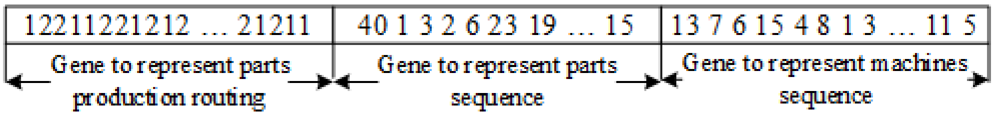

Fig. 1. Design of the chromosome for the C.M.S. formation

& Chandrasekharan [17] and represented by Eq. 1 and Eq. 2, respectively.

$$ge = (0.5 \times b_1) + (0.5 \times b_2)$$
$$b_1 = \frac{o - e}{o - e + v} \qquad (1)$$
$$b_2 = \frac{P \times M - o - v}{P \times M - o - v + e}$$

$$gc = \frac{o - e}{o + v} \qquad (2)$$

Where b_1: ratio of the number of 1s in the formed cells compared to the formed cells matrix size; b_2: ratio of the number of 0s in the off-formed cells compared to the total size of off-formed matrix size; o: number of 1s in the incident matrix; e: number of exceptional parts in the solution; v: number of voids (0s) in the solution; P, M: number of parts, machines; ge: grouping efficiency and gc: grouping efficacy.

Eq. 1 and Eq. 2 imply that ge and gc will reach their maximum values when v and e values are minimised. From a technical computing perspective, the v and e values can be minimised by minimising the total difference value between columns for all rows and the total difference values between rows for all columns. Fig. 2 illustrates the concept explained above.

(a) no cells formed

Parts \ Machines	1	2	3	4	5	dc
1	1		1	1		3
2		1			1	3
3		1			1	3
4	1		1	1		3
5		1			1	3
6	1		1	1		3
dr	4	4	4	4	4	38

(b) the cells formed perfectly

Parts \ Machines	1	3	4	2	5	dc
1	1	1	1			1
4	1	1	1			1
6	1	1	1			1
2				1	1	1
3				1	1	1
5				1	1	1
dr	1	1	1	1	1	11

Fig. 2. Illustration of no cells formed and cells formed

In Fig. 2, dc and dr represent the difference value between columns and the difference value between rows, respectively. An example calculation of dc for part 1 is $dc_1 = abs(1-0) + abs(0-1) + abs(1-1) + abs(1-0) = 3$, while the example calculation for machine 1 is $dr_1 = abs(1-0) + abs(0-0) + abs(0-1) + abs(1-0) + abs(0-1) = 4$. The perfect manufacturing cell formation will result in minimum total DC and dr. The minimum dc and dr values are equal to the number of parts and machines, respectively. Therefore, to maximise ge and gc simultaneously, Eq. 3 will be employed.

$$Min\ TCR = \sum_{p=1}^{P}\sum_{m=1}^{M-1}\left|el_{pm} - el_{pm+1}\right| + \sum_{m=1}^{M}\sum_{p=1}^{P-1}\left|el_{mp} - el_{mp+1}\right| \qquad (3)$$

Where TCR: total difference value between columns and rows; and el: element value in the incident matrix;

$$el_{pm} = \begin{cases} 1, if\ part(p)\ requires\ machine(m) \\ 0, otherwise \end{cases}$$

Each part of the industrial system under consideration has two production route alternatives, and the selection of a production route affects both the workload of the machines and the outcomes of manufacturing cell formation. The allocated working hours for one production batch of the analysed industrial system is 4 hours or 240 minutes, specifically from 8 am until the midday break at 12 noon. With the selected production routing of each part, in order to prevent the C.M.S. from becoming overloaded when its working time exceeds the allocated working hours and from becoming idle when its working time is less than the allocated working hours, Eq. 4 will be utilised.

$$Min\ dwt = Abs\left(Max\left(\sum_{p=1}^{P} t_{pm}; m = 1, 2, \dots, M\right) - 240\right) \qquad (4)$$

Where dwt: deviation of C.M.S. working time with the allocated working hours; and t_{pm}: processing time of part(p) on machine (m).

The workload of the formed manufacturing cells will be identified from their total working time, and minimising the workload gap among the formed manufacturing cells will be carried out by

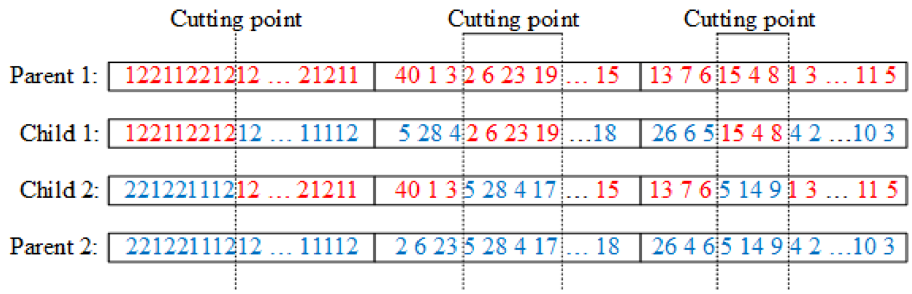

Fig. 3. Mechanism of the one-cut point and order crossover

minimising the smoothness index value proposed by Elsayed & Boucher [32] as expressed by Eq. 5.

$$Min\ si = \sqrt{\sum_{c=1}^{C}(MaxCt - Ct_c)^2}$$
$$Ct_c = Max\left(\sum_{p=1}^{P} t_{pmc};\ c = 1,..,C\right) \quad (5)$$

Where: *Si:* smoothness index; *MaxCt*: Maximum working time of formed manufacturing cells; *Ct*: working time of a manufacturing cells; c: formed manufacturing cell index; and C: number of formed manufacturing cells.

All of the functions above are minimisation functions, which is opposite to the concept of searching in G.A. and PSO, which considers the strongest chromosome or particle as the solution. Therefore, the fitness function for the chromosome must be converted from the minimisation function to the maximisation function, as shown in Eq. 6.

$$Eval_k = B - (TCR + dwt + si) \quad (6)$$

Where *Eval* : fitness of a chromosome in G.A. or particle in PSO; k : chromosome or particle index; and *B*: a significant number that always makes the Eval have positive results. In this case, B is set to 10000.

2.2.3. *Crossover mechanism*

In this study, two types of crossover mechanisms were applied: one-cut point crossover for the first gene and order crossover, as proposed by Smith in 1980 [33], for the second and third genes. The mechanism of the proposed crossover is illustrated in Fig. 3. The proposed crossover mechanism will be able to produce feasible child in every generation.

2.2.4. *Mutation mechanism*

In this study, two mutation mechanisms were proposed: flip mutation for the first gene, and swap mutation for the second and third genes. Fig. 4 shows the proposed mutation mechanism. The proposed mutation mechanism will be able to produce a feasible child in every generation

2.3. PSO modelling

When it comes to PSO, the particle design is the sole aspect that requires meticulous conside-ration. The particle is assessed using the fitness function employed by the G.A., as shown in Eq. 6. In this study, a particle consists of two sub-particles. The first sub-particle represents the optimum production route for each part, while the second sub-particle represents the sequence of machines and parts. Random numbers between 1 and 2 are assigned for the first sub-particle, while the second sub-particle is assigned random

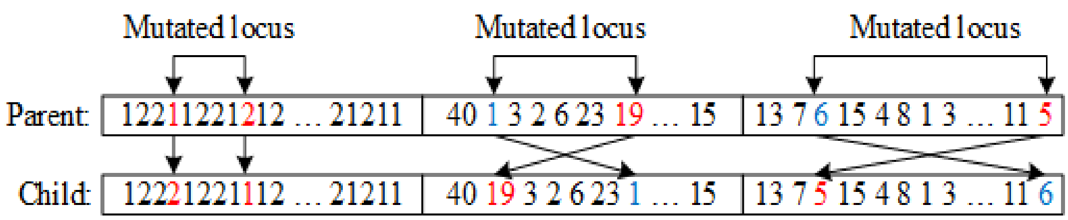

Fig. 4. Mechanism of the proposed mutation

http://dx.doi.org/10.30656/jsmi.v8i1.7974

Particle	12221221112 … 21211	0.32 0.12 0.97 ... 0.99	0.42 0.97 0.12 … 0.86
Represented solution	12221221112 … 21211	2 1 3 ... 40	2 4 1 … 3

Fig. 5. The proposed particle design in the PSO

numbers between 0 and 1.

These numbers indicate the order of the machine or part once they are sorted in ascending order. This representation technique is used because PSO was initially designed to address optimisation problems with real numbers. Every particle element must move concerning the optimum particle in the group (global best) and the most favourable position ever discovered by the particle (particle best position). Hence, the pure permutation representation in the PSO is not feasible. Fig. 5 depicts the proposed particle design and the represented solution.

In the proposed PSO, the position of each particle is updated using a standard formula, where the new position of the particle is the result of the particle's direction and the position of the best particle, as depicted in the following Eq. 7.

$$np_r = op_r + v_r$$
$$vc_r = vc_r + ac_1 \times r_1 \times (pbest_r - op_r) + ac_2 \times r_2 \times (gbest - op_r) \quad (7)$$

Where *r*: particle index; *np*: new position of a particle; *op*: old position of a particle; *vc*: velocity of a particle; *pbest*: the best position ever of a particle; *gbest*: the global best position; *ac*: accelerating coefficient; and *r*: random number, introducing the stochastic.

3. RESULTS AND DISCUSSION

While there is no formal procedure for determining the number of chromosomes in the G.A. or the number of particles in the PSO, it is important to consider the balance between the number of searching agents and the computational burden. The proposed G.A. has been run with the population size = 30, while the number of particles in the PSO is also 30. The crossover rate in the G.A. is set to 0.5 to introduce variability in the combination process within the population, and the mutation rate is set to 0.2 to allow the G.A. to escape from a monotone searching process while maintaining a controlled level of randomness. Both GA and PSO ran for 500 generations or iterations, and Fig. 6 shows the search results of the G.A. and PSO.

Fig. 6 demonstrates that the proposed G.A. and PSO effectively maintain the diversity of their respective searching agents, chromosomes in G.A. and particles in PSO. Therefore, it can be concluded that the proposed G.A. and PSO are not susceptible to monotone searching and are not confined to local optimum solutions. However, both methods can converge towards an optimum or nearly optimum solution. The solution generated by the G.A. is superior to the PSO's. Consequently, the optimised incident matrix obtained by the G.A. was utilised for the subsequent analysis,

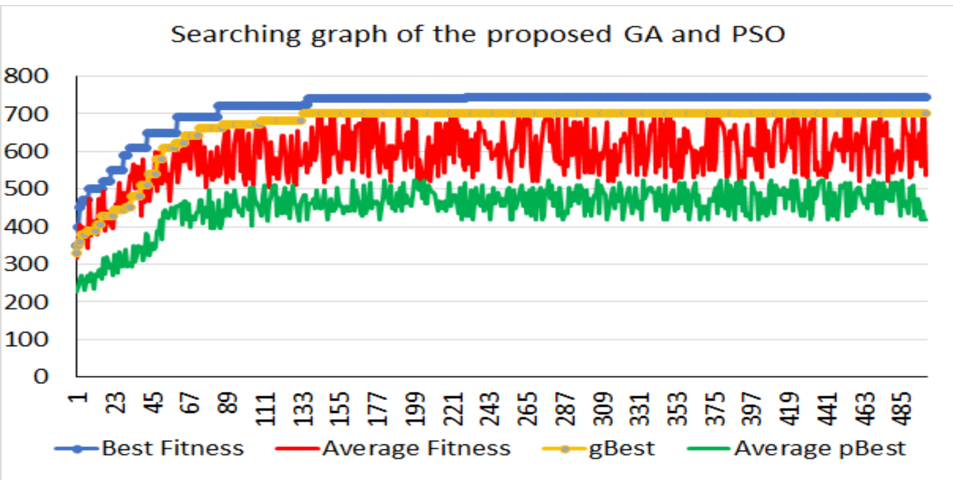

Fig. 6. Searching result of the proposed G.A. and PSO

as depicted in Fig. 7.

Part	Selected Routing	Machines														
		1	2	3	8	4	7	5	9	15	6	14	11	13	10	12
15	1	1	1	0	1		1									
2	1	1	0	1	1											
19	2	1	1	1	0										1	
34	1	1	1	1	0						1					
11	1	0	1	1	1						1					
27	2	1	1	1	1											
30	1	0	1	1	1											
4	1	0	1	1	1				1							
8	2			1		0	1	0					1			
22	2					0	1	1					1			
40	2					1	1	0								
6	2			1		1	1	0								
12	2				1	1	1	0								
37	2		1			0	1	1								
36	1					0	1	1	1							
7	2					1	0	1	1				1			
13	2					1	1	1			1					
26	1					1	1	1								
9	2				1	1	1	1						1		
16	1					1	1	1							1	
3	2					1	0	1		1						
14	1							1	0	1	1					
1	2								1	1	1					
5	2								1	1	1					1
17	2	1							1	0	1					
18	2					1			1	1	1					
23	2								1	1	0					
25	1								0	1	1	1				
29	1								1	1	1		1			
35	2						1		1	1	0					
32	1				1				1	0	1					
28	1									1		1	0	0	1	1
39	1										1	1	0	1	1	1
31	2					1					1	1	1	1	0	0
20	1											1	1	1	1	0
33	2											1	1	1	1	0
10	1											1	1	1	1	1
21	1											1	1	1	1	1
24	2											0	1	1	1	1
38	2											0	1	1	1	1

Fig. 7. The optimised incident matrix by proposed G.A.

In addition to preserving the diversity of chromosomes and particles, the proposed G.A. and PSO can also achieve convergence towards the solutions they discover. It Starts with the generation of 172. The search graph shows that G.A. is converging, and for over half of the generations, there has been no further improvement in the fitness value. Similarly, PSO achieved convergence starting at the 134th iteration. Additionally, it is evident that the proposed optimisation model for manufacturing cells formation is a convex model, hence possessing an optimum solution value.

Grouping efficiency (*ge*) and grouping efficacy (*gc*) based on Fig. 7 above are 0.86 and 0.64, respectively. According to this result, it can be concluded that the efficiency of the grouping is reasonably high, and the suggested G.A. is successful in forming the C.M.S., as indicated by a *gc* value of more than 0.5. The proposed solution's smoothness index (*si*) is 38.1, with working time of the formed manufacturing cell 1 to 4 being 215, 259, 264 and 262 minutes, respectively. The maximum lateness of the working time of the formed manufacturing cells from the allocated working hours is 264 – 240 = 24 minutes, while the maximum working time gap of the formed manufacturing cells is 264 – 215 = 49 minutes. The deviation in the working time of the formed manufacturing cells with the allocated working hours is shown in Fig. 8.

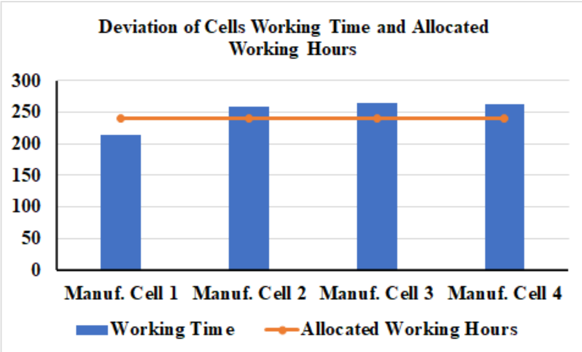

Fig. 8. Deviation of the cells' working time with the allocated working hours

Unlike the study conducted by Farboodi *et al*. [26], this study has considered production schedule factors relevant in practical situations, which is the midday break schedule for the operators. Thus, one of the main optimisation objectives in creating manufacturing cells is to minimise the discrepancy between the actual working time of each cell and the assigned working time. All the operators must synchronise their work and rest schedules to mitigate the adverse psychological effects on operators. It will minimise the resistance factor of the operators when the proposed solution is implemented.

The industry system being examined possesses flexible machines, enabling multiple production routes for a part. Nevertheless, this condition further complicates the optimisation model. It can be seen from Fig. 1, which requires a long solution representation, as it encompasses the arrangement of parts and machines and the selection of the production route. However, the proposed intelligent optimisation algorithm successfully optimised this problem.

http://dx.doi.org/10.30656/jsmi.v8i1.7974

In addition to making major contributions to the study of manufacturing cell formation, this study also offers valuable managerial insights. It reveals that the formation of the manufacturing cells does not necessarily require a physical re-layout of the plant. The suggested manufacturing cells can be logically established by controlling the movement of the parts to the formed manufacturing cells. The study findings also offer insights for managers to decrease the production time in manufacturing cells no. 2, 3, and 4 by roughly 24 minutes. It can be done by analysing unnecessary setup activities not yet considered in this study. It ensures that the production batch is completed before the midday break. If this can be achieved, decreasing the smoothness index value to 25 and the working time gap value to 25 minutes will be feasible. It will enhance the equilibrium of the workload in the production cells, resulting in a favourable psychological effect on the workers in each formed manufacturing cell.

4. CONCLUSION

Based on this study, it can be concluded that when establishing flexible manufacturing cells, the selection of parts production routing should be carried out concurrently with the formation of manufacturing cells. It is crucial as it directly affects the workload distribution among the manufacturing cells and the ability to meet designated working times. Maximising the grouping efficiency and efficacy can be achieved by minimising the number of voids and exceptional parts. It can be achieved by minimising the total difference in element values between the columns and rows in the incidence matrix. This study also discovered that the proposed G.A. and PSO possess strong abilities to preserve the diversity of chromosomes and particles in every generation and iteration. Nevertheless, the results of this study indicate that the G.A. outperforms the PSO.

This research still does not pay attention to batch scheduling for the parts, which can potentially reduce production time. In the future study, it is advisable to consider the potential for batch splitting to ensure compliance with the designated working times. In addition, the setup time reduction can be achieved by segregating internal setup tasks from external setup tasks. In the subsequent analysis, reliability analysis can be used to proactively anticipate the occurrence of machine breakdown

ACKNOWLEDGMENT

The authors thank the Department of Industrial Engineering, Universitas Islam Indonesia, for their kind financial support in publishing this paper.

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