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ORIGINAL ARTICLE

Reentrant FMS scheduling in loop layout with consideration of multi loading-unloading stations and shortcuts

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Abstract The scheduling problem in flexible manufacturing systems (FMS) environment with loop layout configuration has been shown to be a NP-hard problem. Moreover, the improvement and modification of the loop layout add to the difficulties in the production planning stage. The introduction of multi loading-unloading points and turntable shortcut resulted on more possible routes, thus increasing the complexity. This research addressed the reentrant FMS scheduling problem where jobs are allowed to reenter the system and revisit particular machines. The problem is to determine the optimal sequence of the jobs as well as the routing options. A modified genetic algorithm (GA) was proposed to generate the feasible solutions. The crowding distance-based substitution was incorporated to maintain the diversity of the population. A set of test was applied to compare the performance of the proposed approach with other methods. Further computational experiments were conducted to assess the significance of multi loading-unloading and shortcuts in reducing the makespan, mean flow time, and tardiness. The results highlighted that the proposed model was robust and effective in the scheduling problem for both small and large size problems.

Keyword Reentrant FMS scheduling · Multi loading-unloading and shortcuts · Genetic algorithm · Crowding distance-based substitution

1 Introduction

FMS are important systems to satisfy the flexibility and productivity needs of manufacturing enterprises. A FMS typically consists of CNC machines with automated tool magazines, material handling systems, and computer workstations, connected together mechanically and controlled by a computer control system. Operation management in FMS is an intractable task for engineers as well as technical manager due to the complexity of the systems. Therefore, to manage the FMS effectively, more performance-related decision-making is implemented when compared to conventional manufacturing systems, which use a transfer line or job shop production system [1].

FMS covers a wide variety of automated manufacturing systems. A loop layout, consisting of several machines connected by a material handling system in circular form, is one of the most commonly used configurations in FMS. Material flows and part routes in FMS using loop layouts are more complex than the in-line layout. Due to its cyclical nature, the machine visiting sequence of a part is different from its operation sequence, depending on the machine arrangement. Previous studies have concerned about the improvement in loop layout configurations. Recently, the addition of multi loading-unloading (L/U) stations and shortcuts greatly improves the performance of loop layout configurations with significant decreases in the traveling distance [2, 3]. However, the improvements increase the complexity of the loop layout system. As a result, improvements in production planning and control are also required. Scheduling, considered as the heart

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of production planning and control, is also affected and needs to be updated.

The scheduling problem of FMS is known to be a NP-hard problem where the increase of problem size causes the times to solve the optimization problem to escalate exponentially. Moreover, production planning and control in FMS are more difficult than those of mass production systems [4]. FMS can process different parts while using the same configuration of machines where each machine in FMS can perform various operations. The combinatorial characteristic of the assignments and tasks sequencing decisions encountered is the source of complexity of scheduling in FMS. In addition, FMS scheduling also takes into account the technological, capacity, and availability constraints as the limiting resources, such as machines, buffers, tools, and material handling devices [5].

Studies on the scheduling aspect are required to catch up with the improvement in the design sector. Since most previous research addressed the scheduling problem for simple loop layout based FMS, improved scheduling models are needed to accommodate the addition and modification in loop layout based FMS. The improvements in layout design increase the complexity of the scheduling problems. Hence, improvement in the optimization method is essential to solve the scheduling problem effectively and efficiently. This research deals with the reentrant FMS scheduling problem with consideration of the improvements in the loop layout design. In particular, the scheduling model for accommodating the issues in addition of multi L/U stations and turntable shortcut in loop layout configurations is considered as the main contribution. A modified GA is proposed to determine near optimal solutions within acceptable solution times. The approach employs a substitution based on crowding distance to replace the individuals with close proximity. The use of meta-heuristic techniques is necessary since the FMS scheduling problem is more complicated than scheduling in a conventional system. Furthermore, discrete event simulation based modeling is developed to verify the outcome of the model. The simulation is used to validate and evaluate the part schedule and routing options generated by the modified GA approach.

The rest of the article is organized as follows. Section 2 provides a brief literature review of FMS scheduling. Section 3 presents the definition and formulation of the scheduling problem in loop layout based FMS. Section 4 explains the proposed approach. In Sect. 5, numerical results and simulation experiments are reported and discussed. Finally, conclusions are outlined in Sect. 6.

2 Literature review

FMS scheduling has been an active research area because of its importance in the today's manufacturing industry. Due to a high degree of product variability in FMS, the part routing and part flows are of considerable concern. There are two operational policy in the FMS scheduling. The first is the tool movement policy where parts are assigned to machines and necessary tools are brought to the machines to finish the operations. The second option is part movement policy where parts are transferred from one machine to the others based on the operation process. Part movement policy is implemented in most manufacturing systems because it has the advantage of ensuring that all parts can be processed using the capabilities of the machines. Besides that, there has been research of other scheduling problems such as that by Hall et al. [4] which considered the material handling scheduling. Some studies have also attempted to integrate part scheduling with tool selection and/or material handling scheduling like the study by Gamila and Motavalli [5] and Zeballos et al. [6]. Nevertheless, the majority of the research considered the part movement policy as the main concern.

Based on the types of FMS, a classification system was proposed by MacCarthy and Liu [7], consisting of single flexible machine (SFM), flexible manufacturing cell (FMC), multi-machine flexible manufacturing system (MMFMS), multi-cell flexible manufacturing system (MCFMS), and unspecified system. The simple loop layout can be classified as FMC. However, the modified loop layout configuration can fall into MMFMS and/or MCFMS dependent on the complexity. The studies by Haq et al. [8] and Keung et al. [9] are examples of research which have addressed FMC scheduling. Due to the growth of complexity, MCFMS has been extensively highlighted in recent years. The studies by Das and Canel [10], Sankar et al. [11], and Jerald et al. [12] are examples of research that took into account MCFMS configuration.

The cyclic scheduling problems have been reviewed, mostly in the form of reentrant flow shop scheduling problem (RFSP). Huang et al. [13] addressed the reentrant two-stage multiprocessor flow shop scheduling with due windows. The same problem was also concerned by Jeong and Kim [14] while considering the sequence-dependent setup times. However, the reentrant scheduling has not been widely addressed in FMS problems. In contrast to RFSP, different operation sequences of jobs are given in the reentrant FMS scheduling problem. Das and Canel [10] considered the scheduling problem in MCFMS with standard loop and sequential configuration which used the fixed type automated handling such as belt conveyors, tow lines, and roller conveyors. The study focused on the higher-level batch scheduling which was the sequence of batches to be processed in the machine cell. The FMS configuration addressed by Burnwal and Deb [15] consists of several FMC serviced by AGV to transport the parts between FMCs. The configuration used a single loading/unloading points and an automated storage/retrieval system to store work in progress. Souier et al. [16] also employed single loading/

unloading points with one AGV to transport the parts between machines.

The previous studies did not necessarily highlight the same problems as they differed in the type of FMS, scheduling problems, scheduling type and the objective functions used. Joseph and Sridharan [17] evaluated the effect of dynamic due-date assignment models, routing flexibility levels, sequencing flexibility levels and part sequencing rules on the performance of FMS in standard loop configurations. The study proposed the development of a model called dynamically estimated flow allowance (DEFA). Cardin et al. [18] presented the group scheduling method using an emulation of a complex FMS with loop configuration. The study focused on determining the ability of the group scheduling in absorbing uncertainties in complex FMS. Udhayakumar and Kumanan [19] addressed the integration between production schedule and material handling schedule for a U Loop layout in the FMS. In the first phase, the FMS production schedule, with minimizing makespan as the objective function, was generated using the Giffler and Thompson algorithm. Then, the output of production scheduling was used to develop material handling schedules.

Hsu et al. [20] attempted to minimize the work in process to satisfy economic constraints. A two-step resolution approach was presented to solve the problem. Petri net modelling of the production process was applied for constructing the model of the problem. Afterward, a genetic algorithm was used to obtain the sequence of tasks for a flexible manufacturing cell. In addition to the static environment, dynamic scheduling has been developed as an alternative approach to mimic real-life dynamic environments. Qin et al. [21] examined dynamic scheduling for an interbay automated material handling system configuration. The configuration was a single loop, spine type interbay material handling route. The AGVs moved around the path in unidirectional movement. Alternative shortcut paths were placed to connect the upper and lower rows of the main loop. A genetic programming based CDR generator was proposed to generate the composing dispatching rule that can be used in real-life dynamic production. The dispatching of AGV in the FMS was also concerned by Caridá et al. [22] in which the factory layout was modeled in Petri nets.

Objective functions hold the central role for optimization in FMS scheduling problems. Several measurements have been used as the indicators of system performance. Minimizing makespan is the most common objective function, as indicated by researchers in the FMS scheduling problems [23–27]. Other research has tried to use other approaches, i.e. reducing work in process [20, 28]. However, in practical applications, there are many objectives that have been considered in scheduling problems. This has indicated that evaluating a single objective is not satisfactory for improving the performance of the complete manufacturing systems [29]. In addition, satisfying a single objective cannot resolve the trade-off between criteria. Therefore, it is important to consider multiple objective functions simultaneously since a greater variety of performance indicators can be accommodated. Joseph and Sridharan [17] employed mean flow time, mean tardiness, percentage of tardy parts and mean flow allowance. Prakash et al. [30] utilized bi-objective functions which are mean flow time and throughput to quantify performance. Jerald et al. [12] aimed to minimize idle time and the penalty cost for not meeting delivery dates by proposing simultaneous scheduling of parts and AGV. Ebrahimi et al. [31] used the combination of minimizing makespan and tardiness. These criteria represent the two important issues in the industries, the maximizing productivity of line production and fulfilling the customer expectation.

Related to the methods used, there are two categories of approach: optimization methods for exact solutions using mathematical programming and meta-heuristic algorithms for near optimal solutions. An example of the use of mathematical programming methods is the branch and bound solution method proposed by Das and Canel [10] to exploit the special structure of the problem in developing strong lower bounds. The problem was modeled for a MCFMS with flowshop characteristics. A MCFMS consists of a number of flexible manufacturing cells, and possibly a number of single flexible machines, connected by an automated material handling system. Minimizing makespan was set as the objective function.

In recent research, meta-heuristic became the trend of related studies since they possess the learning ability, which the traditional scheduling techniques do not have [32]. Some meta-heuristics have been shown to provide good performance solutions in previous studies. Low et al. [33] proposed the combination of Simulated Annealing (SA) and Tabu Search (TS). The hybrid heuristic was used to solve the addressed FMS scheduling problem with three performance indicators, mean flow time, mean machine idle time, and mean job tardiness, simultaneously. Two heuristic procedures from their previous work [34] called sequence-improving procedure (SIP) and routing-exchange procedure (REP) were implemented using SA and TS. As a result four different hybrid searching structures were generated, depending on which searching procedure was adopted in REP and SIP, respectively. Baruwa and Piera presented timed colored Petri nets, combining evaluation methods (simulation) and search methods (optimization) [35]. The proposed approach was aimed to find the near optimal solutions in short computation time. Other methods commonly used in the scheduling problems belong to Swarm intelligence family, including ant colony optimization [36], pheromone approach [37] and chemotaxis-enhanced bacterial foraging algorithm [38].

Genetic algorithms are the most popular meta-heuristic techniques used in FMS scheduling problems. Kim et al.

[39] developed a network-based hybrid GA. The proposed method was combined with the neighborhood search technique in a mutation operation to improve the solution of the FMS problem and to enhance the performance of the genetic search process. Prakash et al. [30] developed a novel approach called a knowledge based genetic algorithm (KBGA) by combining GA with knowledge management. Godinho Filho et al. [40] reviewed the use of genetic algorithms to solve scheduling problems in FMS. There were four conclusions from this literature study: (i) there was a switch of direction where metaheuristics, especially GA and its hybrid have become popular (ii) although most studies dealt with complex environments concerning both the routing flexibility and the job complexity, only a minority of papers simultaneously considered the variety of possible capacity constraints on an FMS environment (iii) local optimization methods were rarely used; (iv) makespan was the most widely used measurement of performance. In summary, the GA has proven successful when implemented in various FMS scheduling problems. Thus, it is worth developing a modified GA for further study.

From the point of view of layout system complexity, previous studies considered relatively simple configuration. Meanwhile, the loop layout configuration has recently been extensively modified to increase its performance and flexibility. Some examples of improvement in the loop layout design are the addition of turntable shortcuts [2] and multi loading-unloading points [3]. Since these additions have not previously been included, more studies are required to cover the gap in the complex loop layout system. Thus, based on the literature review and our best knowledge, this study emphasizes the development of a part scheduling model for complex loop layout in FMS. The model accommodates the addition of multi loading-unloading points and turntable shortcut in the configuration. A modified GA with crowding distance based substitution is proposed to solve the reentrant FMS scheduling problem.

3 Problem formulation

3.1 Reentrant FMS scheduling

Loop layout consists of several machines connected by material handling in a circular form. The reentrant characteristic allows the part to reenter the system and revisit particular parts, thus forming cyclic traveling routes. In this study, the term of job and part are interchangeable, in which both indicate the same meaning. Scheduling in FMS can be considered as the combination of flowshop and jobshop scheduling with additional constraints. Figure 1 illustrates the example configuration of the modified loop layout.

An example taken from previous literature [19] with additional properties is presented to illustrate the scheduling

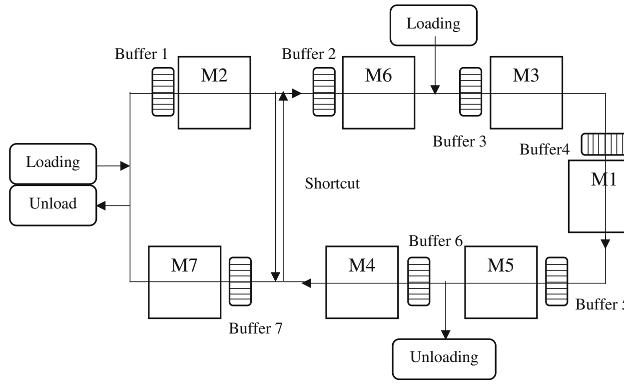


Fig. 1 Example of modified loop layout configuration

problem in loop layout FMS. There are four parts to be processed in seven different machines with distinct due dates. In particular operations, there are alternative machines which can be used to substitute the main machine. Thus, there are many possible routing options for the parts. The number of possible processing sequence depends on the alternative machines, which can be calculated as 2^n, where n is the number of alternative machines corresponding to each part. Table 1 shows an example of operation sequence.

In the example, the number of alternative machines $n=3$ that can be used to process part 1, thus there are $2^3=8$ possible processing sequence. The parts are allowed to enter and exit from the system which results in minimum travel distance. The parts enter using the nearest loading point prior to the machine used to process the first operation, and exit from the nearest unloading point subsequent to the machine used to process the last operation. The model is also built based on the assumption that whenever circumstances are possible, a shortcut is always used to minimize the travel distance.

This study addresses the determination of two criteria in production planning, the part dispatching schedule and routing choice. The dispatching schedule is a permutation variable that indicates the dispatching sequence of the parts. Since this study covers the multi loading and unloading point addition, the permutation characteristic is exclusively applied

Table 1 Example of operation sequence matrix

Part types	Operation sequence				Due date
	1	2	3	4	
Part 1	M_1	M_4	M_2	M_7	200
	M_3	–	M_6	M_5	
Part 2	M_1	M_6	M_3	M_4	180
	M_2	M_5	–	M_7	
Part 3	M_2	M_6	M_3	M_5	140
	M_1	M_4	–	–	
Part 4	M_3	M_4	M_2	M_7	190
	M_6	M_5	–	M_1	

for the parts at the same loading point. Unlike in conventional manufacturing systems, FMS allows the parts to be processed by alternative machines for particular operations. This condition results in the various routing options for the parts. The routing choice not only determines the machine visiting sequence, but also the processing time and setup time for each operation that will affect the completion time of the parts. Thus, the proposed model considers the routing choice of each part to get the most optimized schedule.

3.2 Mathematical model

The FMS considered consists of a set of machines *J*, which are arranged in a cyclic layout connected with a conveyor. There are several shortcuts inside in particular positions. The main conveyor of the loop is unidirectional, while the shortcuts' conveyor is bidirectional. Beside the main loading-unloading point, there are extra loading-unloading points placed inside the loop. These points can either contain only loading or unloading points or can also contain both loading-unloading points. The parts can enter the system using any loading point *l* and leave the system as a product from any unloading point *u*.

There is a set of parts *K* that must be processed. A set of operations *I* corresponding to part *k* is processed by specific machine *j*. Every process follows the job sequence of each part denoted by S_k. This means that an operation i_{kt} of part *k* cannot be processed before the predecessor operation i_{kt-1} has been completed. The transport time is denoted by τ, which depends on distance to be traveled by the part to perform operation *i* after completion of operation *i*−1, denoted by *d*. In the case of transport time in shortcuts and from/to loading-unloading points, the same symbol is applied. Table 2 lists the notations use in the mathematical model.

The machines can only process one part at the same time. The parts will be placed in the buffer which is positioned just before the machine if there is another part being processed by that machine. The duration between the parts entering the buffer until the part enters the machine is described as delay *d*. The manufacturing process of part *k* in machine *j* will take some time expressed by the processing time φ_{ijk}. In FMS, each machine can perform various operations for different parts. However, a particular time is needed to setup the machine before processing a different type of parts. This is denoted by the setup time ε_{ijk} which corresponds to part *k* and machine $j_{\cdot 1}$.

Multi-objective functions, consisting of minimizing makespan *Cmax*, mean flow time *Tf* and tardiness *Tt*, were used as the approach to measuring production efficiency and resource utilization. The objective functions also represent the interest in the real problem faced by the manufacturing industries [20].

Objective functions:Minimize

$$C\max = \max_{i,j,k}\left(C_{ijk}\right) \tag{1}$$

$$Tf = \frac{1}{P}\sum_{k=1}^{P}\max_{i,j}\left(C_{ijk}\right) \tag{2}$$

$$Tt = \sum_{k=1}^{P}\max\left\{\max_{i,j}\left(C_{ijk}\right)-td_k, 0\right\} \tag{3}$$

Equations 1, 2, and 3 describe the objective functions, which are makespan, mean flow time, and total tardiness, respectively. C_{ijk} is the integer value of the completion time of operation *i* on machine *j* for each part *k*. td_k is the due date of part *k*. The total fitness is the sum of each objective function

Table 2 Lists of notations

Index Subscripts	Description	Index Parameters	Description
k	Part to be processed	τ_j	Transport time
i	Operations of the parts to be machined	φ_{ijk}	Processing time of operation *i* of part *k* in machine *j*
j	Machines that carry out the operations	ε_{ijk}	Setup time of operation *i* of part *k* in machine *j*
u	Loading point	C_{ijk}	Completion time of operation *i* on machine *j* for part *k*
l	Unloading point	St_{ijk}	Starting time of operation *i* on machine *j* for part *k*
h	Turntable shortcut	td_k	Due date of part *k*
Sets		t	Time
K	Set of parts	α_{ijk}	Decision variable which has the value 1 if the operation *i* of part *k* is assigned to machine *j*, 0 otherwise
I	Set of operations	μ_{ku}	Decision variable which has the value 1 if part *k* is loaded using loading point *u*, 0 otherwise
J	Set of machines	λ_{kl}	Decision variable which has the value 1 if part *k* is unloaded using unloading point *l*, 0 otherwise
S_k	Set of operations sequence of part *k*		

with equal weighting factor. Thus, each objective function has equal significance. The objective functions are subject to the following constraint.

$$\sum_{J}^{M} \alpha_{ijk} = 1, \quad \forall i, k \tag{4}$$

$$C_{ijk} \geq C_{[i-1]jk} + \phi_{ijk} + \tau_{ii'} + \varepsilon_{ijk}, \qquad i = 2, 3, \ldots I_k \quad \forall j, k \tag{5}$$

$$\tau_{ii'} = \sum_{j=1}^{M} \sum_{j'=1}^{M} \sum_{i'=1}^{I} d_{jj'} \cdot \alpha_{ijk} \cdot \alpha_{i'j'k'} \qquad \forall i, k \tag{6}$$

$$C_{ijk} \geq 0, \qquad \forall i, j, k \tag{7}$$

$$St_{ijk} \geq 0, \qquad \forall i, j, k \tag{8}$$

$$\sum_{u}^{U} \mu_{ku} = 1, \qquad \forall k \tag{9}$$

$$\sum_{l}^{L} \lambda_{kl} = 1, \qquad \forall k \tag{10}$$

$$St_{ijk} \geq C_{(i-1)jk} + \tau_{j'} \qquad \forall j, k \tag{11}$$

Equation 4 states that one machine must be selected for each operation. α_{ijk} is a decision variable which will have the value 1 if the *i*th operation of part *k* is assigned to machine *j*, and 0 otherwise. Equation 5 ensures that the completion time of operation *i* on machine *j* for part *k*, must be greater than the predecessor operation *i*−1, by at least the processing time required for an operation *i* plus transport time and setup time for operation *i* of part *k* on machine *j*. Equation 6 defines the transport time which is calculated by the distance between machine *j* used to process operation *i* and machine *j'* used to process operation *i'*.

Equation 7 defines that each operation begins after time zero. Equation 8 describes the nonzero property of completion time operation *i* of part *k*. Equations 9 and 10 ensure that the parts can only be loaded and unloaded by one loading and one unloading station. Note that μ_{ku}=1 if part *k* is loaded by loading *u*. Similarly, λ_{kl}=1 if part *k* is unloaded using unloading *l*, 0 otherwise. Equation 11 ensures that the starting time of operation *i* of part *k* must not be earlier than the sum of completion time of the predecessor operation *i*−1 of the same job and the transport time.

4 Proposed approach

In solving the scheduling and assignment problems of FMS, past studies have adopted mathematical programming techniques. However, in real-world problem instances, it has been seen that the traditional techniques cannot reach optimal solutions [17]. Thus, the use of meta-heuristic optimization, also known as artificial intelligence techniques, has been considered. This study addresses the use of a modified genetic algorithm to solve the scheduling problem. The GA aims to seek the optimum value of objective function *f* which is influenced by a vector of decision variables *x*. Each individual represents a potential solution to the problem at hand. Then, the individual is evaluated to give some measures of its fitness. Some individuals experience stochastic transformation by means of genetic operations to form new individuals. There are two types of transformation: crossover, which creates new individuals by combining parts from two parent individuals, and mutation, creating new individuals by making changes in a single chromosome.

One of the keys to good performance in GAs is maintaining the diversity where it should be prominent in any application [41]. In the GA, the nature of crossover leads to premature convergence since it tends to produce uniform offspring. Moreover, the implementation of roulette wheel selection allows the good individuals to be selected repeatedly. This condition results in difficulty in maintaining the population diversity. As a solution, the modified GA incorporates the crowding distance to evaluate the similarity between individuals. Individuals' substitution engaging the elitist based re-combination and re-mutation method is used to produce the substitute. The scheme of the proposed approach is illustrated in Fig. 2.

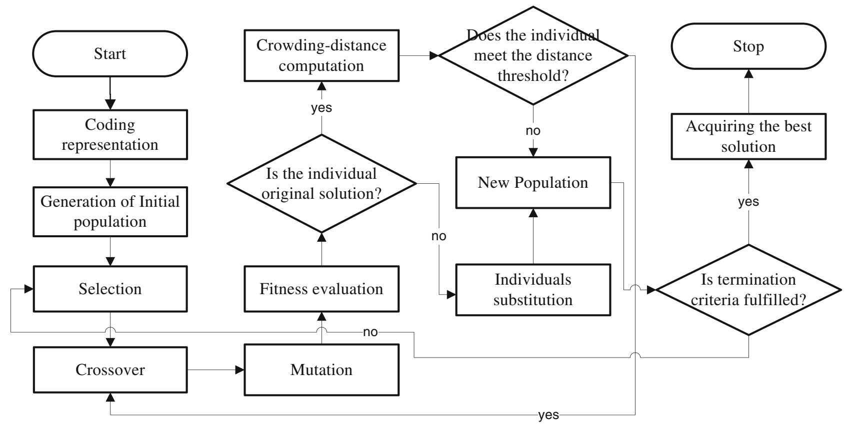
After several generations, the algorithm converges to the best individual, which represents an optimal solution. The GA parameters in the proposed approach are set as follows: the population size *Ps*=20, crossover rate *Pc*=0.8, and mutation rate *Pm*=0.025 [12, 42]. The loop process continues until the termination criterion is fulfilled, when the numbers of generations *N*=100.

4.1 Coding representation

The GA process starts with coding representation. In optimization problems of FMS scheduling, the main decision variable is the sequence of each part that will enter the system. Each part number may be considered to be a gene on chromosome represented using integer permutation chromosomes. Since each gene represents a part number, the greater number of parts means longer chromosomes. Table 3 depicts the integer permutation chromosomes; the numbers represent the part codes.

The chromosomes represent the two variables to be optimized. The first layer depicts the input part sequence. It is an integer permutation, corresponding to the loading groups. The second layer describes the selected route of each part. Each part may have a different number of routing options

Fig. 2 Scheme of modified GA



depending on the operations, layout structure, and the alternative machines that can be used to process the part.

4.2 Parent selection

The initial population of solutions is produced by utilizing a stochastic technique. A set of decision variables is portrayed by coded strings of finite length. A roulette wheel is employed as the parent selection method, in which the probability of an individual i being selected is dependent on its fitness value f_i as defined in Eq. 12.

$$pi = fi \Big/ \sum_{i=1}^{n=1} fi \tag{12}$$

When the inequality $p0+p1+\ldots+pi-1<\gamma\leq p0+p1+\ldots+pi-1+pi$ is met, the individual i is selected for the next generation. To ensure that good chromosomes have a higher possibility of being picked, ranking schemes are always adopted. This scheme is performed by sorting the population on the basis of fitness values and then the selection operation is undergone based upon the rank. Therefore, individuals with high fitness values have a greater chance of being chosen as parents.

4.3 Crossover

The crossover operator used in this research is a partially matched crossover (PMX). The crossover operator divides each selected individual into two or more sections and swaps the divided sections of the individual. Figure 3 illustrates the crossover operation involving PMX techniques.

Table 3 Integer permutation chromosome illustration

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Sequence	9	1	3	8	6	2	4	5	7	10
Selected route	2	3	1	4	2	4	1	3	4	5

4.4 Mutation

Since an integer permutation representation is used in this study, the exchange mutation, also called swap mutation, is applied. In this technique, two genes are picked randomly and their alleles get exchanged. Figure 4 shows the mutation process using swap mutation.

Unlike the crossover which operates on the individual level (swapping certain parts between two individuals), mutation operators operates on the gen level. Therefore, the process may result to an infeasible string where route choices may not be available. To accommodate this issue, we perform an adjustment process for allele value which violates the constraints, i.e., the value of selected route exceeds the number of possible routes. The new values are randomly generated among all possible routes.

4.5 Crowding distance calculation

The level of population diversity can be estimated using crowding distance, which is an estimate of the perimeter of the cuboid formed by using the nearest neighbors as the vertices [43]. The proposed approach uses the genotype based crowding distance, calculated using the Euclidean distance. Since there are two variables to be optimized, the computation uses a two dimension average Euclidean distance calculation,

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Parent 1	9	1	3	8	6	2	4	5	7	10
	2	3	1	4	2	4	1	3	4	5
Parent 2	8	3	7	4	5	6	1	10	2	9
	3	1	4	5	3	1	4	2	5	2
Offspring 1	9	1	3	8	5	6	1	10	7	10
	2	3	1	4	3	1	4	2	4	5
Offspring 2	8	3	7	4	6	2	4	5	2	9
	3	1	4	5	2	4	1	3	5	2

After adjustment

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Offspring 1	9	2	3	8	5	6	1	10	7	4
	2	3	1	4	3	1	4	2	4	5
Offspring 2	8	3	7	1	6	2	4	5	10	9
	3	1	4	5	2	4	1	3	5	2

Fig. 3 PMX crossover

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Original chromosome	9	1	3	8	6	2	4	5	7	10
	2	3	1	4	2	4	1	4	4	5
Mutated chromosome	9	5	3	8	6	2	4	1	7	10
	2	2	1	4	2	4	1	3	4	5

Fig. 4 Mutation process using swap mutation

presented in Eq. 13.

$$d(p,q) = \frac{1}{N}\sum_{n=1}^{N}\sqrt{(p_{nx}-q_{nx})^2\left(p_{ny}-q_{ny}\right)^2} \qquad (13)$$

where p is the allele value of individual i and q is the allele value of individual $i-1$. Subscript x represents the part schedule. Subscript y represents the routing options. The order of allele is represented by n, where N indicates the length of chromosomes. The distance computation requires sorting the population according to objective function value in descending order of magnitude. In this scheme, the elitist individual will always be kept. Individuals which have close proximity with the predecessor solutions will be replaced.

4.6 Individuals substitution

The distance computation results in several solutions which do not meet the threshold. To maintain the fixed population size, new generated offspring are used as substitutes from the replaced individuals. The substitution of an individual involves two genetic processes, re-combination and re-mutation, to generate distinct solutions. Re-combination is based on the crossover approach involving the elitist individual and the individual to be replaced. Re-mutation is achieved by changing an allele with a new randomly generated value.

4.7 Population replacement

Having finished the genetic operator, elitism is applied to allow the best solution to be preserved in the next generation. In this scheme, the surviving best solution replaces the worst individual, which either comes from the previous iteration or as the result of the crossover and mutation operators. Thus, the good offspring will not be lost due to population replacement.

5 Results and discussion

5.1 Datasets and layout properties

The proposed approach was tested to measure performance. The test beds were taken from previous literatures [44–46, 19] with some modifications to conform the FMS environment. The jobs visit the machines in an operation sequence with the choice of selecting alternative machines for the operations. The operation sequence for each job is a random permutation of the machines, while the processing times and setup times are uniformly distributed. Each job has a deadline, which is uniformly distributed on an interval determined by the expected workload of the system and other parameters. Since the datasets lack some of the parameters, such as setup time and deadline, the missing data were generated artificially. The layout properties were affected by the datasets used, especially the number of machines, parts and operation sequence. The details of point to point distance between machines and layout properties are given in Appendixes 1 and 2, respectively. Table 4 shows the instances used to test the algorithms.

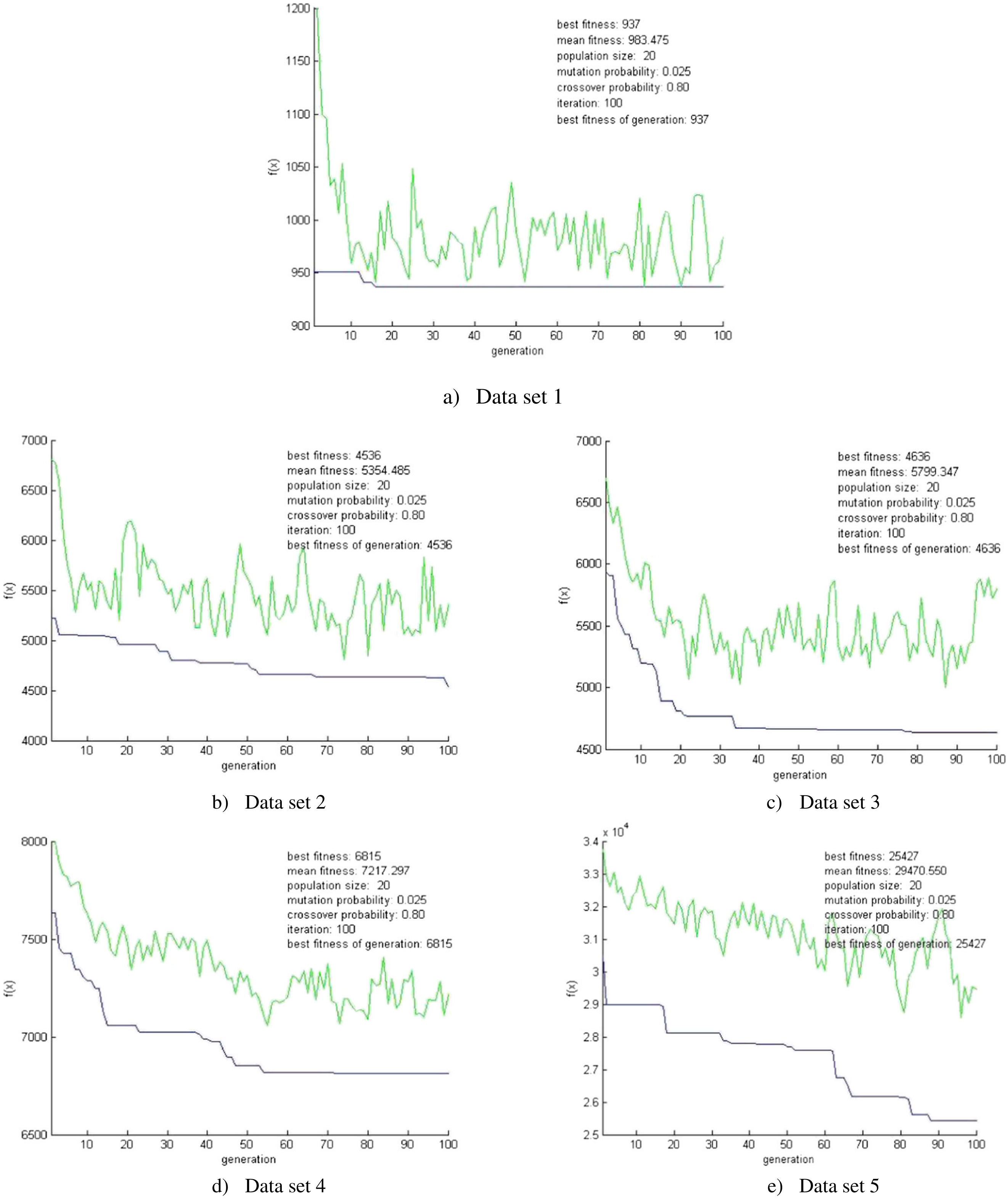
5.2 Improvement and robustness test

A comparative study was conducted to measure the performance of the proposed genetic algorithm optimization model. The approach was contrasted with dispatching rule techniques such as shortest processing time (SPT), longest processing time (LPT), earlier due date (EDD), and other meta-heuristics, such as conventional GA and SA. The comparison was based on the objective functions which are minimizing makespan, mean flow time, and total tardiness. The experiments were done by ten repetitions for each method. Figure 5 presents the iteration charts of the modified GA in each dataset. The upper line represents the average fitness of the generation. The lower line represents the best fitness obtained.

The iteration process indicated that in small datasets, e.g., dataset 1, the GA quickly reached a stable state because there was only a small solution space to be explored. Meanwhile, in large datasets, there were huge solution spaces with many

Table 4 Data sets and configurations for the case studies

Dataset	No. of part types	No. of machines	Load station	Unload station	Machine arrangement
1	4	7	2	2	2-6-3-1-5-4-7
2	10	10	2	2	1-2-3-4-5-6-7-8-9-10
3	15	12	2	2	1-2-3-4-5-6-7-8-9-10-11-12
4	20	15	2	2	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15
5	20	20	2	2	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20



a) Data set 1

b) Data set 2

c) Data set 3

d) Data set 4

e) Data set 5

Fig. 5 Iteration charts of the proposed method

combinations of sequences and possible routing options. Thus, the searching process in large datasets took more iterations to converge than in small datasets. Besides comparison of each objective function, the total fitness was also contrasted. The improvement rate *IR* of the proposed approach over method *A* is defined in Eq. 14.

Table 5 Value of objective functions obtained and improvements

Indicator	Method	Datasets				
		1	2	3	4	5
Makespan	SPT	330	1852	1358	945	4669
	LPT	382	1880	1220	962	4465
	EDD	382	1773	1357	1040	4624
	SA	322	1769	1248	955	4294
	GA	322	1768	1308	889	4525
	Modified GA	322	1727	1219	900	4147
Mean flow time	SPT	265	1616	1121	722	3873
	LPT	302	1648	1058	731	3810
	EDD	302	1591	1122	721	3883
	SA	265	1557	1056	713	3719
	GA	265	1547	1030	688	3635
	Modified GA	265	1493	1023	684	3622
Total tardiness	SPT	349	1923	3749	5662	22,750
	LPT	499	2240	2803	5848	21,381
	EDD	498	1703	3756	5655	22,843
	SA	350	1440	2804	5489	19,972
	GA	350	1328	2519	4980	18,363
	Modified GA	350	997	2366	4910	17,658
Total fitness	SPT	944	5391	6228	7329	31,292
	LPT	1183	5768	5081	7541	29,656
	EDD	1182	5067	6235	7416	31,350
	SA	937	4766	5108	7157	27,985
	GA	937	4643	4857	6557	26,523
	Modified GA	937	4217	4608	6494	25,427
Improvement rate *IR* of modified GA over	SPT	0.74 %	21.78 %	26.01 %	11.39 %	18.74 %
	LPT	20.79 %	26.89 %	9.31 %	13.88 %	14.26 %
	EDD	20.73 %	16.78 %	26.09 %	12.43 %	18.89 %
	SA	0.00 %	11.52 %	9.79 %	9.26 %	9.14 %
	GA	0.00 %	9.18 %	5.13 %	0.96 %	4.13 %

Table 6 Robustness improvement ratio of modified GA, in contrast to SA and GA

Datasets	SA		GA		Modified GA		Robustness improvement ratio	
	Best (worst)	Average (std.)	Best (worst)	Average (std.)	Best (worst)	Average (Std.)	mGA vs. SA	mGA vs. GA
1	937	945	937	942	937	939	96.64 %	90.54 %
	964	8.02	954	4.78	940	1.47		
2	4766	4992	4643	4977	4217	4402	16.42 %	60.53 %
	5286	131.91	5188	191.97	4590	120.60		
3	5108	5456	4857	5126	4608	4806	21.83 %	32.76 %
	5637	154.99	5450	167.11	5057	137.03		
4	7157	7328	6557	6822	6494	6573	43.44 %	75.18 %
	7440	83.82	7008	126.53	6685	63.04		
5	27,985	28,944	26,523	27,541	25,427	26,193	17.15 %	30.51 %
	29,746	566.03	28,558	618.04	26,977	515.22		

$$IR = \frac{fi(A) - fi(mGA)}{fi(A)} \times 100\% \tag{14}$$

where $fi(mGA)$ denotes the total fitness obtained by the proposed approach and $fi(A)$ denotes the total fitness obtained by heuristics method A. Table 5 shows the best results of each method and the improvements, in term of total fitness, obtained by the proposed approach compared to other methods.

Based on the numerical results, the modified GA outperformed the other methods in all case studies in terms of overall fitness value. The results of case studies also depicted the consistency of modified GA, either applied in small or large datasets. To further examine the performance of modified GA, this study calculates the robustness improvement ratio in contrast to the simple GA and SA as defined in Eqs. 15 and 16. The results of robustness test are described in Table 6.

Robustness improvement ratio in contrast to simple GA

$$= 1 - \frac{\sigma^2(mGA)}{\sigma^2(GA)} \times 100\% \tag{15}$$

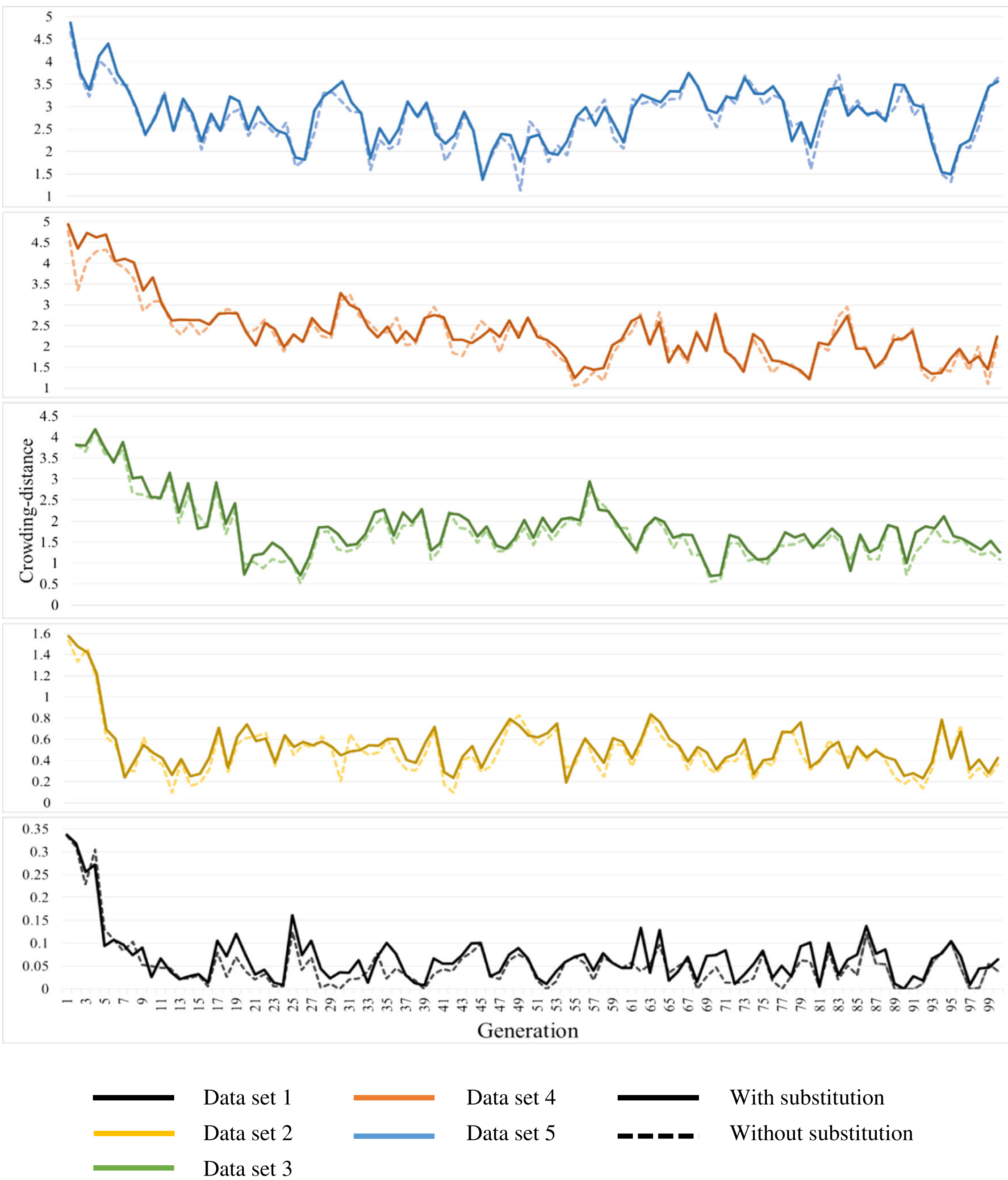


Fig. 6 The crowding distance of each generation

Table 7 Average Euclidian distance

Data set	Euclidian distance		Improvement on diversity
	Without substitution	With substitution	
1	0.053	0.068	28.30 %
2	0.485	0.533	9.90 %
3	1.731	1.867	7.86 %
4	2.289	2.369	3.49 %
5	2.736	2.827	3.33 %

$$\text{Robustness improvement ratio in contrast to SA} = 1-\frac{\sigma^2(mGA)}{\sigma^2(SA)} \times 100\% \qquad (16)$$

The results demonstrated a significant robustness improvement of modified GA relative to simple GA and SA both in small and large data. The improvement was more prominent against the simple GA. GA tends to narrow its search space to small neighborhoods when it finds a local optima and failed to explore better solutions in other neighborhoods. When the experiments were replicated, the search space of simple GA was focused to different neighborhoods, thus it has the lowest standard deviation. In contrast to simple GA, SA has better ability to explore wider neighborhoods. However, the fitness obtained by SA was lower than GA and modified GA. Although SA had better robustness than GA, it was less effective. In modified GA, the crowding distance based substitution gives more opportunity to broaden the search space without discarding the current neighborhoods. Therefore, the modified GA was more stable, robust and effective than other methods.

5.3 Similarity level analysis

A similarity level analysis was carried out to measure the robustness of the proposed approach. The comparison used the crowding distance as an approach to determine the similarity level. Figure 6 presents the comparison of the crowding distance before and after the individual substitution in each generation. The graphs indicate that the earlier generations had a low similarity level. Since the initial population was stochastically generated, the individuals have a high degree of diversity. As the iteration process continues, the diversity level decreases. The crossover and roulette wheel selection causes individuals to move toward convergence because roulette wheel selection allows the individuals with good fitness to be selected with high probability. As a result, the good individuals dominate the next iteration and increase the similarity level in that generation.

The increasing of similarity results in premature convergence since the algorithm will fail to explore new solution space. Due to this effect, the simple GA is prone to be caught in suboptimum solutions. The results of experiments indicated that the simple GA failed to obtain better solutions as observed in the Table 6. It was proved that the GA was trapped in premature convergence. As a solution, the proposed modified GA approach was intended to solve the similarity level. The approach involves pairwise comparison between individuals. When a pair of individuals has a low crowding distance, the worse solution will be substituted with a newly generated solution.

As indicated by Table 7, the individual substitutions increased the average distance and reduced the similarity level. It effectively improved the population diversity in all instances, thus reducing the possibility of being trapped in premature convergence. The trend of the improvement rate shows that small problems have higher sensitivity to the substitution and the large data sets are more resistant toward the change. In the instance with fewer parts to be processed, the modification of a gene will significantly alter the overall fitness of the chromosomes. Thus, it can be stated that the number of parts affects the improvement rate on diversity.

5.4 Significance of multi L/U and shortcuts

The performance of FMS is affected by the jobs' operation routes as well as the traveling routes of the parts. In case of the configuration discussed, the addition of extra loading-unloading and shortcuts offer the alternative of part traveling

Table 8 Improvement obtained by adding extra L/U stations and shortcut

Dataset	Total fitness				Improvement		
	Without L/U and shortcuts	With extra L/U	With shortcut	With extra L/U and shortcuts	Addition of L/U stations	Addition of shortcut	Addition of both L/U and shortcut
1	1040	983	995	*937*	5.55 %	4.40 %	*9.93 %*
2	5126	4894	4593	*4217*	4.52 %	10.39 %	*17.73 %*
3	4955	4826	4726	*4608*	2.60 %	4.62 %	*7.01 %*
4	8833	8173	7343	*6494*	7.47 %	16.87 %	*26.48 %*
5	29,812	29,584	27,323	*25,537*	0.76 %	8.35 %	*14.34 %*

The highlighted values (lowest total fitness and highest improvement) have been pointed out in italics

Table 9 Parameters of simulation model

Parameter	Value
Loop conveyor length	91 m
Shortcut conveyor length	8 m
Conveyor speed	1 m/s
Distance machine to machine (start from machine 1)	3-4-4-3-3-5-5-4-6-5-4-5-6-4-5-3-4-4-4-3
Distance of load point 1 to next machine	5 m
Distance of load point 2 to next machine	2 m
Distance of unload point 1 from previous machine	3 m
Distance of unload point 2 from previous machine	2 m
Buffer capacity	Unlimited
Machine capacity	1
Part schedule (obtained from numerical study)	Load point 1: 7-11-14-16-17-18 Load point 2: 1-2-3-4-5-6-8-9-10-12-13-15-19-20

routes. This section presents the analysis of the significance of extra loading-unloading stations and shortcut addition into the loop layout in reducing the objective functions, makespan *C*-max, mean flow time *Tf*, and tardiness *Tt*.

A set of computational experiments was carried out by examining the four types of configurations, which are the simple loop layout, the addition of extra loading-unloading station only, the addition of shortcut only and the addition of both extra loading-unloading stations and shortcut. The position of loading-unloading stations and shortcut were randomly generated among the feasible position with assumption the number of L/U stations $l=1$, $u=1$, and shortcut $h=1$. The experiments were based on the same parameters to ensure the performance stability of the proposed approach.

Table 8 tabulates the result of experiments. We found that multi L/U stations and shortcuts result on significant improvement in reducing the total objective function. The addition of shortcut showed a more substantial effect since it exceptionally important in cutting traveling distance of reentrant parts. The shortcut increases the number of possible routes to be optimized, thus providing opportunities to generate the shortest feasible routes. The addition of L/U stations had moderate improvement in that the effect is limited to particular parts which belong to the extra L/U stations. However, it should be underlined that the position of each material handling held important effect to the effectiveness. Therefore, the positioning of extra L/U and shortcuts in design study is very critical.

5.5 Simulation test

Discrete event simulation models using FlexSim software were constructed to evaluate the part dispatching sequence generated by the proposed approach. As in the numerical study, three performance indicators were employed to validate the results of the proposed method, namely flow time, tardiness, and makespan. The result of flow time and makespan can be acquired directly from the FlexSim simulation report. However, since tardiness is a derivation of flow time, it was calculated as the deviation between due date and acquired flow time. The results of both methods were compared to see the difference between them.

The main input for the simulation study was the schedule obtained by the proposed GA model, consisting of the arrival

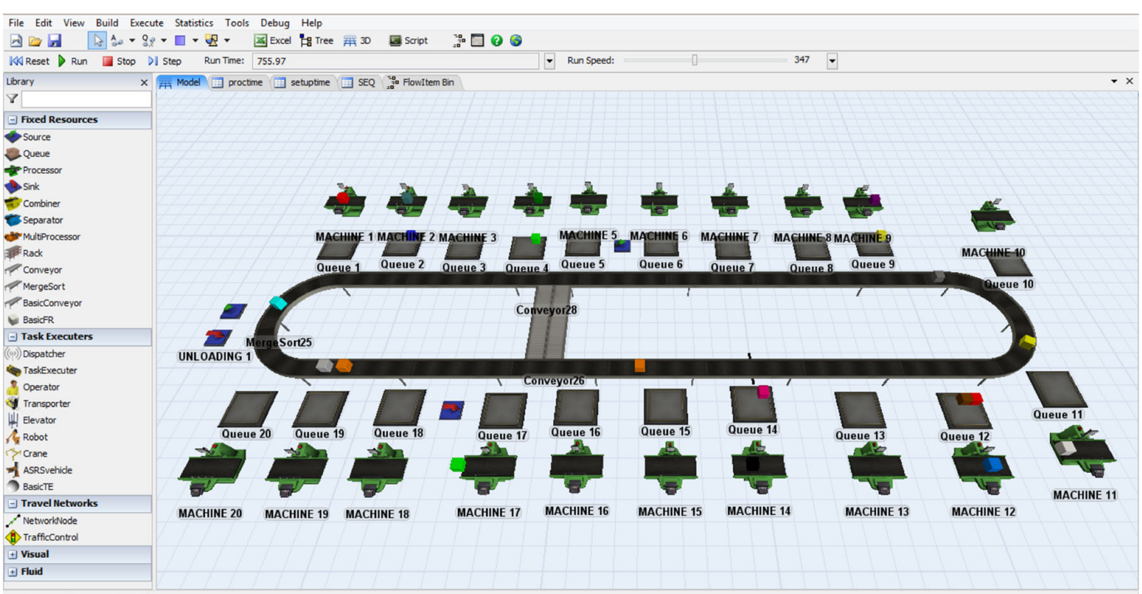


Fig. 7 Simulation model in FlexSim

Table 10 Comparison of the result of simulation and numerical study

Part	Simulation result		Numerical result		Part	Simulation result		Numerical result	
	Flow time	Tardiness	Flow time	Tardiness		Flow time	Tardiness	Flow time	Tardiness
1	2944	120	2967	143	11	3706	1336	3618	1248
2	3704	1457	3717	1470	12	4161	1578	4249	1666
3	3778	642	3834	698	13	4125	1976	4219	2070
4	3781	910	3372	501	14	3342	1033	3479	1170
5	4056	1855	4086	1885	15	3770	1026	3694	950
6	4174	788	4252	866	16	3634	1467	3890	1723
7	3898	1123	3911	1136	17	3062	–	3095	–
8	3145	3	3146	4	18	3930	1314	3770	1154
9	3654	313	3593	252	19	3489	647	3491	649
10	4108	1401	4109	1402	20	3266	50	3266	50

sequence and routing options of the parts. To compare the results of both methods, the simulation model study used the same parameter as used in the numerical study. The overall system was set to the same conditions as the numerical study, both on data sets (sequence, processing, and setup time) and layout properties (machine arrangement and travel distance). Table 9 summarizes the parameters of the simulation model.

An experimental example of the simulation study involved data set 5 since it is the most complex system in this study. The main element of this model was the loop conveyor, constructed using MergeSort in FlexSim. The shortcut was represented by two conveyors with opposite movement directions. The pick and drop points were placed along the MergeSort and connected to queues and machines, as well as loading and unloading points. The capacity of queue was assumed to be unlimited. Meanwhile, the machines have single capacity meaning they can only process one part at a time. Figure 7 illustrates the example of simulation models on FlexSim. The results of the simulation experiment in FlexSim are presented in Table 10.

Compared to the results of numerical study, there is a slight difference between both results. Generally, the value of the simulation result was somewhat lower than the numerical study result due to the different policy regarding the positioning of pick and drop points. In the numerical study, it was assumed that both pick and drop point of each machine were positioned at the same point. Meanwhile, in the simulation study, there was a space between pick and drop points along the conveyor. Nevertheless, the comparison indicated that both results are similar as depicted in Table 11.

Table 11 Comparison of obtained objective functions value

Objective function	Numerical	Simulation	Difference
Makespan	4252	4174	1.83 %
Mean flow time	3688	3686	0.05 %
Total tardiness	19,037	19,040	0.02 %

6 Conclusion

Effective and reliable model is critical for solving the reentrant scheduling problems in FMS with consideration of the addition of multi loading-unloading points and turntable shortcut into the loop layout configuration. As a solution, a modified genetic algorithm was developed to generate the near optimal solution. The crowding factor calculated using the Euclidian distance was employed to measure the population diversity of the generations. Substitution based on the re-combination and re-mutation was performed to modify the individuals with close similarity. A comparison study between the proposed approach and other conventional methods showed that the proposed approach exhibited better performance and robustness than conventional methods for both small and large datasets. The similarity analysis demonstrated that the proposed algorithm can tackle the population diversity issue by improving the crowding distance. Thus, the probability of obtaining near optimal solutions increases by avoiding early convergence.

Although increasing the complexity, the addition also offers alternative routes which can be shorter in distance than the current. The results of experiments with different designs indicated that the addition L/U stations and shortcut has significant effect in reducing the makespan, mean flow time, and total tardiness by cutting the traveling time of jobs. The outcomes of simulation confirmed that both studies were running alike and there were no errors in the numerical study computation. In future studies, it is worth considering the other variables to develop integrated FMS scheduling by combining the parts scheduling and vehicle routing as well as tool selection-allocation problems to constitute a complete scheduling system. It would also be interesting to investigate the relationship between the improvement in productivity and investment cost of extra L/U stations and shortcut.

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Appendices

Appendix 1 Point to point distance

Table 12 Point to point distance in case study 1

Stations	L/U point	M_2	M_6	M_3	M_1	M_5	M_4	M_7
L/U point	–	3	7	11	16	20	24	27
Shortcut 1	27	30	2	6	11	15	19	22
Shortcut 2	6	9	13	17	22	26	30	1
M_2	29	–	4	8	13	17	21	24
M_6	25	28	–	4	9	13	17	20
M_3	21	24	28	–	5	9	13	16
M_1	16	19	23	27	–	4	8	11
M_5	12	15	19	23	28	–	4	7
M_4	8	11	15	19	24	28	–	3
M_7	5	8	12	16	21	25	29	–

Table 13 Point to point distance in case study 2

Stations	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
Central L/U	5	8	12	16	19	22	27	32	36	42
Extra load	40	43	2	6	9	12	17	22	26	32
Extra unload	16	19	23	27	30	33	38	43	2	8
Shortcut 1	36	39	43	2	5	8	13	18	22	28
Shortcut 2	21	24	28	32	35	38	43	3	7	13
M_1	–	3	7	11	14	17	22	27	31	37
M_2	42	–	4	8	11	14	19	24	28	34
M_3	38	41	–	4	7	10	15	20	24	30
M_4	34	37	41	–	3	6	11	16	20	26
M_5	31	34	38	42	–	3	8	13	17	23
M_6	28	31	35	39	42	–	5	10	14	20
M_7	23	26	30	34	37	40	–	5	9	15
M_8	18	21	25	29	32	35	40	–	4	10
M_9	14	17	21	25	28	31	36	41	–	6
M_{10}	8	11	15	19	22	25	30	35	39	–

Table 14 Point to point distance in case study 3

Stations	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
Central L/U	5	8	12	16	19	22	27	32	36	42	47	51
Extra load	49	52	2	6	9	12	17	22	26	32	37	41
Extra unload	14	17	21	25	28	31	36	41	45	51	2	6
Shortcut 1	36	39	43	2	5	8	13	18	22	28	33	37
Shortcut 2	20	23	27	31	34	37	42	47	51	3	8	12
M_1	–	3	7	11	14	17	22	27	31	37	42	46
M_2	51	–	4	8	11	14	19	24	28	34	39	43
M_3	47	50	–	4	7	10	15	20	24	30	35	39
M_4	43	46	50	–	3	6	11	16	20	26	31	35
M_5	40	43	47	51	–	3	8	13	17	23	28	32
M_6	37	40	44	48	51	–	5	10	14	20	25	29
M_7	32	35	39	43	46	49	–	5	9	15	20	24
M_8	27	30	34	38	41	44	49	–	4	10	15	19
M_9	23	26	30	34	37	40	45	50	–	6	11	15
M_{10}	17	20	24	28	31	34	39	44	48	–	5	9
M_{11}	12	15	19	23	26	29	34	39	43	49	–	4
M_{12}	8	11	15	19	22	25	30	35	39	45	50	–

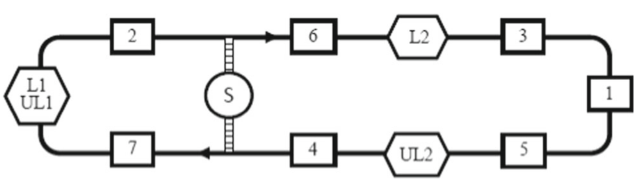
Table 15 Point to point distance in case study 4

Stations	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}	M_{13}	M_{14}	M_{15}
Central L/U	5	13	20	27	36	43	50	57	64	66	72	78	86	92	98
Extra load	74	82	89	96	3	10	17	24	31	33	39	45	53	59	65
Extra unload	25	33	40	47	56	63	70	77	84	86	92	98	4	10	16
Shortcut 1	84	92	99	4	13	20	27	34	41	43	49	55	63	69	75
Shortcut 2	25	33	40	47	56	63	70	77	84	86	92	98	4	10	16
M_1	–	8	15	22	31	38	45	52	59	61	67	73	81	87	93
M_2	94	–	7	14	23	30	37	44	51	53	59	65	73	79	85
M_3	87	95	–	7	16	23	30	37	44	46	52	58	66	72	78
M_4	80	88	95	–	9	16	23	30	37	39	45	51	59	65	71
M_5	71	79	86	93	–	7	14	21	28	30	36	42	50	56	62
M_6	64	72	79	86	95	–	7	14	21	23	29	35	43	49	55
M_7	57	65	72	79	88	95	–	7	14	16	22	28	36	42	48
M_8	50	58	65	72	81	88	95	–	7	9	15	21	29	35	41
M_9	43	51	58	65	74	81	88	95	–	2	8	14	22	28	34
M_{10}	41	49	56	63	72	79	86	93	100	–	6	12	20	26	32
M_{11}	35	43	50	57	66	73	80	87	94	96	–	6	14	20	26
M_{12}	29	37	44	51	60	67	74	81	88	90	96	–	8	14	20
M_{13}	21	29	36	43	52	59	66	73	80	82	88	94	–	6	12
M_{14}	15	23	30	37	46	53	60	67	74	76	82	88	96	–	6
M_{15}	9	17	24	31	40	47	54	61	68	70	76	82	90	96	–

Table 16 Point to point distance in case study 5

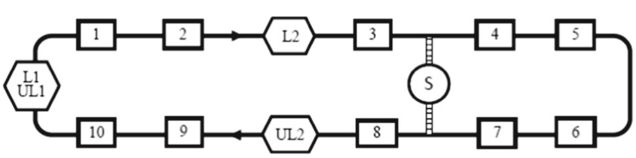
Stations	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}	M_{13}	M_{14}	M_{15}	M_{16}	M_{17}	M_{18}	M_{19}	M_{20}
Central L/U	5	8	12	16	19	22	27	32	36	42	47	51	56	62	66	71	74	78	82	86
Extra load	74	77	81	85	88	2	7	12	16	22	27	31	36	42	46	51	54	58	62	66
Extra unload	18	21	25	29	32	35	40	45	49	55	60	64	69	75	79	84	87	2	6	10
Shortcut 1	77	80	84	88	2	5	10	15	19	25	30	34	39	45	49	54	57	61	65	69
Shortcut 2	22	25	29	33	36	39	44	49	53	59	64	68	73	79	83	88	2	6	10	14
M_1	–	3	7	11	14	17	22	27	31	37	42	46	51	57	61	66	69	73	77	81
M_2	86	–	4	8	11	14	19	24	28	34	39	43	48	54	58	63	66	70	74	78
M_3	82	85	–	4	7	10	15	20	24	30	35	39	44	50	54	59	62	66	70	74
M_4	78	81	85	–	3	6	11	16	20	26	31	35	40	46	50	55	58	62	66	70
M_5	75	78	82	86	–	3	8	13	17	23	28	32	37	43	47	52	55	59	63	67
M_6	72	75	79	83	86	–	5	10	14	20	25	29	34	40	44	49	52	56	60	64
M_7	67	70	74	78	81	84	–	5	9	15	20	24	29	35	39	44	47	51	55	59
M_8	62	65	69	73	76	79	84	–	4	10	15	19	24	30	34	39	42	46	50	54
M_9	58	61	65	69	72	75	80	85	–	6	11	15	20	26	30	35	38	42	46	50
M_{10}	52	55	59	63	66	69	74	79	83	–	5	9	14	20	24	29	32	36	40	44
M_{11}	47	50	54	58	61	64	69	74	78	84	–	4	9	15	19	24	27	31	35	39
M_{12}	43	46	50	54	57	60	65	70	74	80	85	–	5	11	15	20	23	27	31	35
M_{13}	38	41	45	49	52	55	60	65	69	75	80	84	–	6	10	15	18	22	26	30
M_{14}	32	35	39	43	46	49	54	59	63	69	74	78	83	–	4	9	12	16	20	24
M_{15}	28	31	35	39	42	45	50	55	59	65	70	74	79	85	–	5	8	12	16	20
M_{16}	23	26	30	34	37	40	45	50	54	60	65	69	74	80	84	–	3	7	11	15
M_{17}	20	23	27	31	34	37	42	47	51	57	62	66	71	77	81	86	–	4	8	12
M_{18}	16	19	23	27	30	33	38	43	47	53	58	62	67	73	77	82	85	–	4	8
M_{19}	12	15	19	23	26	29	34	39	43	49	54	58	63	69	73	78	81	85	–	4
M_{20}	8	11	15	19	22	25	30	35	39	45	50	54	59	65	69	74	77	81	85	–

Appendix 2 Layout of the systems



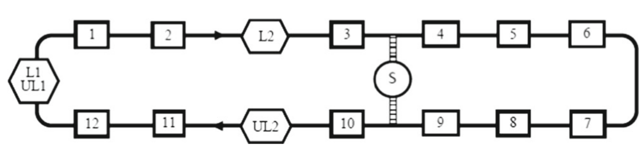
(i) Layout in case study 1

Fig. 8



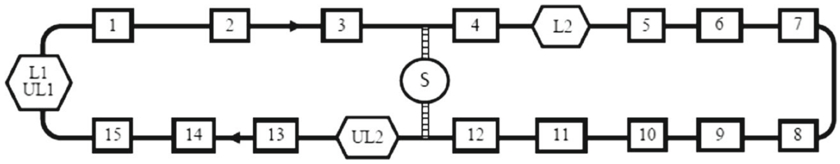
(ii) Layout in case study 2

Fig. 9



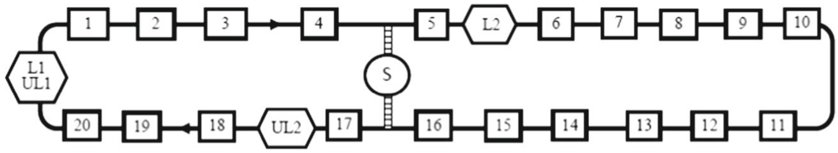
(iii) Layout in case study 3

Fig. 10



(iv) Layout in case study 4

Fig. 11



(v) Layout in case study 5

Fig. 12

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