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# A new meta-heuristics for optimum design of loop layout in flexible manufacturing system with integrated scheduling

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Abstract Flexible manufacturing system is the inception of an innovative manufacturing revolution that will credibly lead the manufacturing trade to levels of automation which is to be taken granted currently in the process-related industries. This paper speaks about multi-objective optimization related to flexible manufacturing systems (FMS) scheduling which act as a constraint in configuring the loop layout in optimum manner by various algorithms, i.e., meta-heuristics like genetic algorithm (GA), simulated annealing (SA), etc. The various loop layout problems are tested for enactment of objective function with respect to computational time and number of iterations involved in GA and SA. A simulation code is generated using programming language and executed using integrated development environment (IDE) tool. A comparative analysis of simulation results of different meta-heuristics with literature results has been done. The performance of this GA is proved to be the best among all the algorithms considered for this work.

Keyword Flexible manufacturing systems  $\cdot$  Loop layout  $\cdot$ Genetic algorithm . Simulated annealing . IDE tool

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## 1 Introduction

In the current scenario, automated manufacturing industries are under great pressure caused by the rising cost of energy, materials, labors, capital, and intensifying worldwide competition. While these trends will remain for a long time, the problem fronting manufacturing today run much yawning. In many cases, they stem from the very nature of the manufacturing process itself. In order to overcome that, flexible manufacturing systems (FMSs) are regarded as one of the most efficient methods to use in reducing or eliminating manufacturing problems. FMS is more than a technical solution; it is a businessdriven solution leading to improve profitability through reducing lead times and inventory levels and improved manufacturing effectiveness through increased operational flexibility, predictability, and control. Flexible manufacturing system [\[1\]](#page-19-0) combines collection of machine tools which are termed as numerical control machines that can arbitrarily process a cluster of jobs, taking automated material management and workstation control to balance resource exploitation over which the system can accept automatically to variation in jobs manufacture, amalgams, and stages of yield. The objective of FMS is flexibility in production without compromising the quality of products. Flexibility can mean future cost avoidance. This type of flexibility would be common among automotive and manufacturers, where high part volumes are common but future change in market demand are expected and anticipated.

Material handling is important, yet sometimes it is an overlooked aspect of automation. The main function of an MHS is to supply the true materials at the exact locations and at the right time; the cost of material handling has high priority in total cost of production. It means handling

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cost is equal to two-thirds of the total manufacturing cost [\[2](#page-19-0)]. This fraction varies depending on type and quantity of production and the degree of automation in the material handling function. Finally, material handling plays an important role in FMS.

The FMS layout involves allocating diverse reserve for attaining full competence. The arrangement has an influence on the make span and cost [[3\]](#page-19-0) which should be determined in the inception of the FMS [[4](#page-19-0)]. In practice, the most commonly used type of FMS layouts [[5\]](#page-19-0) are as follows:

- 1. Line or single row layout
- 2. Loop layout
- 3. Stepladder layout
- 4. U-shaped layout

Among the above layouts, this paper focus on loop layout design with integrated scheduling using genetic algorithm (GA) and simulated annealing (SA).

## 2 Literature survey

During former epoch, FMS layout design with integrate scheduling has got extra emphasis since of its prominence from both hypothetical and real-world points of sight. Early investigation was intense, mainly on the origination and explanation of the problem as the mathematical model, such as branch and bound method and dynamic programing [[6\]](#page-19-0), but these approaches can only be useful for small problems. Heuristic methods can solve the small problem and also combinatorial optimization problems. The heuristic methods are usually computationally efficient, but easily trap into local optimal solution and no assurance that they will catch optimal solutions. Recently, meta-heuristic has been applied, such as tabu search, simulated annealing, genetic algorithm, and ant colony optimization. Wei-jun Xia and Zhi-ming Wu [[7\]](#page-19-0) developed a new approximation algorithm for the problem of finding the minimum makespan in the job-shop scheduling environment. They combine the two existing algorithm and developed new algorithm which is known as hybrid optimization algorithm. Kumar et al. [[4](#page-19-0)] introduced an ant colony optimization (ACO) algorithm for the layout design with integrated scheduling by applying priority dispatching rules using Giffler and Thompson algorithm. Tiwari and Chang [\[8](#page-19-0)] proposed the pareto-optimal blockbased EDA using bivariate model for multi-objective flow shop scheduling problem. They apply a bivariate probabilistic model to generate block which have the better diversity along with the non-dominated sorting technique to filter the solutions.

Muthuswamy and Vélez-Gallego [[9\]](#page-19-0) propose a mathematical formulation and present a particle swarm optimization (PSO) algorithm. Their objective is to batch the jobs and sequence the batches such that the makespan is minimized. Ayough and Zandieh [[10](#page-19-0)] present a new model dealing with the job rotation scheduling problem. They used new software called Lingo software for simulating two search algorithms, GA and imperialist competitive algorithm (ICA), designed to conquer the algorithmic complexity of model, and their parameters adjusted using Taguchi's method were used. Filho and Barco [[11\]](#page-19-0) proposed that a classification system encompasses six main dimensions: FMS type, types of resource constraints, job description, scheduling problem, measure of performance, and solution approach. They analyzed literature using the proposed classification system, which provides the following results regarding the application of GAs to FMS scheduling:

- 1. Combinations of GAs and other methods were relatively important in the reviewed papers.
- 2. Although most studies deal with complex environments concerning both the routing flexibility and the job complexity, only a minority of papers simultaneously consider the variety of possible capacity constraints on an FMS environment, including pallets and automated guided vehicles.

Udhayakumar and Kumanan [[12](#page-19-0)] generated an active schedules and optimal sequence of job and tool that can meet minimum makespan schedule for the flexible manufacturing system. They proposed ACO algorithm to derive near optimal solutions which adopt the Extended Giffler and Thompson algorithm for active feasible schedule generation. They used this proposed algorithm to solve the number of problems taken from the literature. Costa and Cappadonna [\[13](#page-19-0)] focused on skilled workforce assignment (SWA) to machines of a given shop floor may represent a key issue for enhancing the performance of a manufacturing system. Their literature addressed about the group scheduling problems and identified the effect of human factor on the performance of serial manufacturing systems which was ignored by researchers.

Javadian and Fattahi [[14\]](#page-19-0) addressed the hybrid flow shop scheduling problems considering time lags and sequence-dependent setup times. They presented a mathematical model which is capable of solving the small size of the considered problem in a reasonable time. Ranjbar and Razavi [[15](#page-19-0)] proposed a new method to synchronously make the arrangement and planning decisions in a job shop situation. Wangta and Pongcharoen [[16](#page-19-0)] presented the application of SA and TS for minimizing the material handling distance associated with the layout required for manufacturing process of multiple products. They developed a computer-based machine layout designed tool and tested using five datasets from literature. Khamseh and Jolai [[17](#page-19-0)] integrates flexible flow shop group scheduling problem with sequence-dependent setups and preventive maintenance activities in order to minimize the total completion time (makespan). They exploited the Taguchi robust parameter design method. Karthikeyan and Asokan [\[18\]](#page-19-0) presented a hybrid discrete firefly algorithm to solve the multi-objective flexible job shop scheduling problem with limited resource constraints. They considered the minimization of makespan, maximal workload, and total workload of machines as three different objectives and instead of applying the standard firefly algorithm. Pooranian and Shojafar [[19\]](#page-19-0) developed a new hybrid scheduling algorithm GGA that combines GA and the gravitational emulation local search (GELS) algorithm.

#### 3 Problem description

- The problem formulation procedure adopted by Liu and Abraham [\[20\]](#page-19-0) has been used in this research work. We focus on design of loop layout in flexible manufacturing system with flexible batch scheduling problem (FBSP) as constraint with the following parameters.
- $JobsJ = {j_1, j_2, \ldots, j_n}$
- Batches  $B = {B_1, B_2, \ldots, B_n}$  is a set of *n* jobs /*n* batches to be scheduled respectively. Each job  $J_i$  consists of a predetermined sequence of operations.  $O_{i,j}$  is the operation  $\mathbf{j}$  of  $\mathbf{J}_i$ .
- Machines  $M = \{M_1, M_2, \dots, M_m\}$  is a set of m machines.
- Slots  $S = \{S1, S2, S3, \ldots, S_m\}$  is a set of N fixed slots
- Flexible FSP usually is classified into two types as follows:
- Total FBSP {T-FBSP}; every operation can be managed on any machine of M.
- Fractional FBSP {P-FBSP}; every operation can be handled on one machine of set of M.
- Authors adopted P-FBSP integrated with facility layout problems for our research work.

## 3.1 Multi objective mathematical models

In this section, we introduce the multi-objective function and use it to solve the flexible batch scheduling problems which are integrated with loop layout pattern design leads to minimize the make span and to obtain an optimal layout plan for

the machines by minimizing the total transportation cost increased in the system.

## 3.1.1 Notations

The notations [\[21\]](#page-19-0) which are used to develop a mathematical model of the design of line layout are defined and interpreted as follows.



#### 3.2 Objective functions

(I) Minimize make span  $F(S_{\text{max}})$ Minimize,  $F(S_{\text{max}})=S_{n,m}$ 

Sub to

1. conjunctive constraints



Fig. 1 Loop layout arrangements of FMS for six machines

$$
S_{i,j,k} \leq S_{i,j+1,k} - T_{i,j+1},
$$
 for  $j = 1, 2, 3...p$   
for  $j = 1, 2, 3...p$   
for  $j = 1, 2, 3...p$ 

#### 2. Resource constraints

 $O_{I,j,k}=1$  if job i scheduled before job i' on machine  $k=0$ , otherwise for  $O \in S$  (i,j,k) for  $j=1, 2, 3...p$ 

#### 3. Disjunctive constraints

 $B_{i, k}=1$  if job *i* processed only once on machine  $k=0$ , otherwise for  $B \in S$  (i,j,k)

for  $i, i'=1, 2, 3, \ldots, n$  $k, k'=1, 2, 3...m$ 



Fig. 2 Loop Layout Arrangements of FMS for 7 machines



Fig. 3 Loop layout arrangements of FMS for nine machines

(II) Minimize total transportation cost  $(Z)$  =

$$
\left[\sum_{m_{i}=1 m_{j}=1}^{M} \left(M F_{m 1 m_{i}} * M H_{m 1 m_{i}} * R D_{n 1 n_{i}}\right) + LOC_{mi} + ULOC_{mj}\right]
$$

Sub to

∑ M  $m_i=1$  $X_{m_im_j} = 1$ ; if machine  $m_i$  is at assigned to slot  $N=0$ , otherwise

∑ M  $m_j=1$  $X_{m_im_j} = 1$ ; if machine  $m_j$  is at assigned to slot  $N=0$ , otherwise

X mi mj È <sup>o</sup>f g <sup>0</sup>; <sup>1</sup> ; mi; mj <sup>¼</sup> <sup>1</sup>; <sup>2</sup>;…………::<sup>N</sup>

#### 3.2.1 Configuration of loop layout

Figures 1, 2, and 3 shows the loop layout configurations of FMS of six, seven and nine machines respectively.

#### 3.2.2 Procedure for neighborhood creation

The vicinity may be created by any one of the following methods.

- Couple wise interchange of neighboring jobs
- Random exchange of operation sequence with repair function

Out of two methods, we used random exchange of operations sequence with repair function which is considered for neighborhood creation.

## 3.2.3 Procedure for batch scheduling methodology with repair function

Example: A scheduling comprises 3 machines and 3 batches (each batch contains 100 jobs) and 3 operations are considered. The total there are 9 operations, and the chromosome consists of 9 genes



<span id="page-4-0"></span>

Batch scheduling methodology Batches are scheduled based on the batch permutation sequence derived by the priority dispatch rule based on precedence constraint. Initially, jobs are carried from the load/unload station to the respective workstations where the operations of all jobs are scheduled as per priority dispatch rule within the precedence relations. Finally, optimum makespan is determined. This type of scheduling methodology helps in reducing the waiting times and thus helps in improving the resource utilization and the throughput. As mentioned in above table, there are two types of chromosomes, one is unfeasible and the other is feasible. There is a procedure to convert unfeasible to feasible chromosomes by repair function.

Repair function A repair function [\[22](#page-19-0)] is used to repair the unfeasible chromosome which violate the precedence constraints and convert into feasible one

- Step 1: Find the position of the batch operations, which violate the precedence relations.
- Step 2: Compute the inter slot distance between the machines of violating operations.
- Step 3: If the inter slot distance between them is less than half the chromosome length then swap the operations.
- Step 4: Otherwise, randomly pick any one operation and insert it before or after the other depending on the precedence.

#### 4 Proposed methodology

The general explanation of the suggested procedures is shared out as follows.

Table 2 Outline of production system

Layout pattern			machines batches operations stations	No. of No. of No of Load/unload No of	AGV
Loop	$\frac{1}{\sqrt{2}}$	$\gamma$			

Table 3 Outline of production system



#### 4.1 Genetic algorithm

Genetic algorithms are population-based optimization algorithms centered on the procedure of regular inheritances and expected choice. It is also called as a stochastic search procedure for combinational optimization problems. These search technique is commonly used to generate fruitful solutions to optimization and search problems by using the principle of Charles Darwin of "survival of the fittest," where weak individuals die before reproducing, while healthier ones breath longer and bear many offspring and breed children, who often inherit the qualities that enabled their parents to survive the reproduced children are in most cases stronger than their parents. The element and mechanism of genetic algorithm are representation, population, evaluation, selection operator, and parameter.

## 4.1.1 GA parameters



#### 4.2 Simulated annealing algorithm

Simulated annealing (SA) is a meta-heuristic for the overall optimization problem of applied mathematics, namely locating a good estimation to the global minimum of a given function in large search space. Simulated annealing was first introduced by Kirkpatrick. Gelett, and Beechi in

Table 4 Batch varieties with batch sizes of the loop layout with six machines with six jobs

Batch number	B1.	B <sub>2</sub>	B <sub>3</sub>	<b>B4</b>	<b>B5</b>	B6.	
Batch varieties CBS 100			100	100	100	100	100
	VBS.	50	40	60	30	10	25

<span id="page-5-0"></span>Table 5 Batch varieties with batch sizes of the loop layout with seven machines with seven jobs

Batch number		B1.			B <sub>2</sub> B <sub>3</sub> B <sub>4</sub> B <sub>5</sub> B <sub>6</sub> B <sub>7</sub>	
Batch varieties CBS 100 100 100 100 100 100 100		VBS 50 40 60 30 10 25				90

1983 and Cerny in 1985 to solve optimization problem. It is based on the comparison between finding an optimal solution in solving optimization problems and finding a low-energy state in the annealing process of solids. Annealing is a physical process for obtaining a low-energy state of a solid in two steps:

- 1. The metal is heated up to the recrystallization point.
- 2. The temperature of the metal is reduced slowly by cooling, allowing it to attain thermal balance at each temperature.

The integral part of an annealing algorithm is its neighborhood generation scheme, on the basis of which different annealing algorithms are developed.

## 4.2.1 SA parameters



REOSWRF random exchange of operation sequence with repair function

Table 6 Batch varieties with batch sizes of the loop layout with nine machines with nine jobs

Batch number			B1 B2 B3 B4 B5 B6 B7 B8 B9			
Batch varieties CBS 100 100 100 100 100 100 100 100 100						
	VBS 50 40 60 30 10 25 90 15 70					



Table 7 Processing time and process routing matrices for configurations of loop layout with seven machines and seven jobs or

#### 4.2.2 SA algorithm

The procedure as follows:

- Step 1: Choose an initial point  $a^{(0)}$ , a stop criterion  $(S.C)$ . Set  $T$  a sufficiently high valve, number of iterations to be performed at a particular temperature.
- Step 2: Calculate a neighboring point  $a^{(t+1)} = N(a^{(t)})$  usually, a random point in the neighborhood is created.
- Step 3: If  $\triangle HE = HE[a^{(t+1)}]$ ]-HE( $a^{(t)}$ ) <0,
- Step 4: Set  $t=t+1$ , else create a random number (¥) in the range (0,1). If  $r \leq \exp(\Delta H E/T)$ , set  $t=t+1$ ; else go to step 2.
- Step 5: If  $\int_{a}^{(t+1)} -a^{(t)}$  <(S.C) and T is small terminate, else if  $(t \text{ mode } n)=0$ , then lower T according to a cooling schedule, else go to step 2.

Table 8 Processing time and process routing matrices for configurations of loop layout with six machines and six jobs

Batch $O_1$			O <sub>2</sub>		$O_3$		$O_4$		O <sub>5</sub>		O <sub>6</sub>	
								M T M T M T M T M T M T				
$B_1$	$1 \quad$	8	2					7 3 14 4 9 5 3			6 4	
B <sub>2</sub>	2	10	$\overline{3}$					$17 \t6 \t6 \t4 \t13 \t1$			$4 \quad 5 \quad 3$	
$B_3$	$5^{\circ}$	18	$\overline{1}$					16 4 11 2 12 6			$3 \quad 3$	$\overline{3}$
$B_4$			16 6	7				3 11 5 4	$\overline{4}$	$\overline{4}$	2 13	
$B_5$	4	12						2 15 5 9 6 11	$\overline{\mathbf{3}}$	$\overline{3}$	$\mathbf{1}$	$\overline{4}$
B <sub>6</sub>	3	8	2	7		6 9 1			6 5		$11 \quad 4$	-12

<span id="page-6-0"></span>Table 9 Processing time and process routing matrices for configurations of loop layout with nine machines and nine jobs

Batch	O <sub>1</sub>		O <sub>2</sub>		$O_3$		$O_4$		O <sub>5</sub>		O <sub>6</sub>		O <sub>7</sub>		$O_8$		O <sub>9</sub>	
	M	T	М	T	M	T	M	T	M	T	М	T	M	T	М	T	M	T
$B_1$	2	11	$\overline{4}$	10	6	7	5	19	7	8		$7\phantom{.0}$	9	9	3	10	8	13
B <sub>2</sub>	5	$\overline{4}$	4	12	9	14	3	6		$\overline{2}$	6	$\overline{4}$	8	$\mathfrak{Z}$	$\overline{2}$	8	7	9
$B_3$	3	13	5	16	$\mathbf{1}$	4	6	9	$7^{\circ}$	10	$\overline{2}$	$\overline{4}$	8	3	$\overline{4}$	$\tau$	9	2
$B_4$	2	9	$\overline{4}$	12	$7\phantom{.0}$	8	6		5	9	$\mathfrak{Z}$	$\overline{4}$	9	$\mathfrak{Z}$	8	9		$7\phantom{.0}$
$B_5$	8	14	6	$7^{\circ}$	5	16	4	$7^{\circ}$	2	6	9	10	$7^{\circ}$	$\overline{4}$	1	5	3	6
$B_6$	9	9	8	13	6	4	$\tau$	$\overline{2}$	5	6	$\overline{4}$	6	$\mathfrak{Z}$	$\overline{4}$		$7^{\circ}$	2	3
$B_7$	$\overline{4}$	5	2	14	7	3	9	12	5	17	8	$7\overline{ }$	$\overline{3}$	16	6	5		6
$B_8$	1	6	2	$\overline{4}$	6	3	7	$\overline{2}$	8	$7^{\circ}$	5	5	3	6	$\overline{4}$	5	9	9
$B_9$	4	15	1	14	8	6	9	12	5	$7\overline{ }$	$\tau$	2	3	16	6	2	2	6

#### 4.3 Arithmetical illustrations

An attempt is made to apply the GA and SA algorithms on FMS scheduling to determine best solution in terms of minimum completion time and obtaining the batch sequence on each machine which facilitates in arranging machines in optimum manner in loop layout to determine non intersecting arrangement of machine owing to that total transportation cost of making necessary mobility of parts are reduced.

# 4.3.1 The arithmetical illustration of suggested genetic algorithm for case problem (2) is styled below

- 1. Choose a feasible chromosomes based on number of operations in case FMS scheduling and based on the number of machines in single row layout of as shown below
	- GA applied to loop layout
	- Chromosomes 1 and 2 are randomly selected

Feasible chromosome 1 2 4 1 5 6 3

Table 10 Inter-slot distance matrix for loop layout with six machines Slots  $S_1$   $S_2$   $S_3$   $S_4$   $S_5$   $S_6$  $S_1$  0 4 8 10 14 10  $S_2$  4 0 4 8 10 14 S3 8 4 0 4 8 10  $S_4$  10 8 4 0 4 8  $S_5$  14 10 8 4 0 4  $S_6$  10 14 10 8 4 0

total transportation cost= $f(x)$ =84 Rs

chromosome 2 4 6 3 1 5 2

total transportation cost= $f(x)$ =154 Rs

2. Roulette wheel selection procedure

- Calculate raw fitness for above chromosomes
- Develop the mating pool

Feasible chromosome 1 2 4 1 5 6 3

raw fitness= $F(x) = 1 / (1 + f(x))$  $=1/(1+84)=0.0117$ 

chromosome 2 4 6 3 1 5 2

raw fitness= $F(x) = 1 / (1 + f(x))$  $=1/(1+154)=0.00645$ 

Finally in mating pool, we got different chromosomes than previous due to reproduction, suppose we got

Table 11 Inter-slot distance matrix for loop layout with seven machines

Slots	$S_1$	$S_2$	$S_3$	$S_4$	$S_5$	$S_6$	$S_7$
$S_1$	$\boldsymbol{0}$	2	4	8	12	12	10
$S_2$	2	$\mathbf{0}$	$\overline{c}$	4	8	12	12
$S_3$	4	2	$\mathbf{0}$	2	4	8	12
$S_4$	8	4	2	$\mathbf{0}$	2	4	8
$S_5$	12	8	$\overline{4}$	2	$\mathbf{0}$	2	4
$S_6$	12	12	8	4	2	$\mathbf{0}$	2
$S_7$	10	12	12	8	4	$\mathcal{D}_{\mathcal{L}}$	$\boldsymbol{0}$

<span id="page-7-0"></span>Table 12 Inter-slot distance matrix for loop layout with nine machines

Slots	$S_1$	$S_2$	$S_3$	$S_4$	$S_5$	$S_6$	$S_7$	$S_8$	$S_9$
$S_1$	$\mathbf{0}$	2	4	6	8	10	12	10	8
$S_2$	2	$\mathbf{0}$	2	4	6	8	10	12	10
$S_3$	4	2	$\boldsymbol{0}$	2	4	6	8	10	12
$S_4$	6	4	2	$\boldsymbol{0}$	2	4	6	8	10
$S_5$	8	6	4	2	$\mathbf{0}$	2	4	6	8
$S_6$	10	8	6	4	2	$\boldsymbol{0}$	2	4	6
$S_7$	12	10	8	6	4	2	$\mathbf{0}$	2	4
$S_8$	10	12	10	8	6	$\overline{4}$	2	$\mathbf{0}$	2
$S_9$	8	10	12	10	8	6	$\overline{4}$	2	0



Likewise, the new chromosome is replaced with older one; go for next generation for evaluating objective function.

4.3.2 The arithmetical illustration of suggested simulated annealing for case problem (10) is styled below

Let TTC=84 Rs

- set HE(1)=84 at T=100<sup>o</sup>c
- best solution so for is  $E(1)=84$

At next iteration,

Table 13 Load and unload matrices for loop layout with six machines

<b>Slots</b>	יפ	$\mathcal{S}^{\mathcal{D}}$	Эı	$S_4$	S <sub>5</sub>	$S_6$
Load station			12	14	10	O
Unload station	6	10	14	12		

Table 14 Load and unload matrices for loop layout with seven machines

<b>Slots</b>	S <sub>1</sub>	$S_{2}$	S <sub>3</sub>	$S_4$	S <sub>5</sub>	S <sub>6</sub>	$S_7$
Load station		6	8	12	10	x	O
Unload station	6	8	10	12	8		

If neighboring valve  $(TTC)=85$  Rs

- set HE(2)=85 at T=100<sup>0</sup>c

– calculate the difference b/n two energy levels, i.e.,

- $H$  HE(2)-HE(1)
- Now H f H Then Calculate the probability of acceptance  $(R) = exp(-\Delta HE/T)$
- If  $R \leq \exp(-\Delta H E/T)$ , Then reject the current solution and do not change the best solution

# 5 Data set details for loop layout with FBSP

The combination of the scheduling of parts into a flexible manufacturing system layout, succeeded by the automated material handling and by means of computer control, can effect in manufacturing systems described by flexibility, great productivity, and little cost per unit formed. The response to the FMS schedule is a best routing of parts acquired from the production schedule that let off the transfer activities of the FMS. Here, the transfer activity is included. The transportation cost depends on the inter slot distance between machines, incidence of trips of parts from machine to machine and loading/unloading station, and material handling cost. The AGV moves in forward and reverse direction, i.e., loading station-machines-unloading station vice versa.

A production system with the summary and batch sizes and the layout of FMS are shown in Tables [1,](#page-4-0) [2,](#page-4-0) and [3](#page-4-0). The data set details of batch varieties and sizes are given in Tables [4](#page-4-0), [5,](#page-5-0) and [6.](#page-5-0) Let there be parts to be processed on machine for various operations which requires the processing time and part routing with the operation sequence of parts which steers the parts on various machines are depicted in Tables [7](#page-5-0), [8,](#page-5-0) and [9.](#page-6-0)

Table 15 Load and unload matrices for loop layout with nine machines

<b>Slots</b>			$S_2$ $S_3$ $S_4$ $S_5$ $S_6$ $S_7$ $S_8$ $S_9$		
Load station 4 6 8 10 12 12 10 8 Unload station 6 8 10 12 12 10 8				6	6

Transportation cost per unit distance=1 Rs

Load and unload cost per unit distance=1 Rs

<span id="page-8-0"></span>

# 6 Data set details of batch varieties and sizes

 $(CBS = constant batch size, VBS = variable batch size)$ 

The way of part/batch moves over the machines is given in the same Tables [7,](#page-5-0) [8,](#page-5-0) and [9](#page-6-0) as an input for FMS scheduling, where the objective is to arrive at a layout, which determines non-intersecting best arrangement of machines such that total transportation cost of making necessary mobility of parts are reduced.



Fig. 4 Comparison of proposed algorithm for makespan with constant batch size for loop layout



Fig. 5 Comparison of proposed algorithm for makespan with constant batch size for loop layout

Instance $(M \times J/B \times O)$	GA			$\operatorname{SA}$			
	BWT (min)	<b>MASEQ</b>	MWT (min)	BWT (min)	<b>MASEQ</b>	MWT (min)	
KMN1 $(6 \times 5 \times 5)$	$B_1: 3000$ $B_2: 2100$ $B_3: 1100$ $B_4$ : 2900 $B_5: 2100$	6, 2, 5, 4, 3, 1	$M_1: 3300$ $M_2$ : 2800 $M_3$ : 800 $M_4$ : 1500 M <sub>5</sub> : 5500 $M_6$ : 4400	B1: 3300 B2: 2400 B3: 1400 B4: 3200 B5:2400	6, 2, 5, 4, 3, 1	M1:3600 M2: 3100 M3: 1100 M4: 1800 M5: 5800 M6: 4700	
KMN <sub>2</sub> $(6\times6\times6)$	B1:2900 B <sub>2</sub> : 2100 B3:1200 B4: 1900 B5: 2000 B6:2100	5, 6, 4, 3, 1, 2	M1: 2000 M2: 1000 M3: 1900 M4: 1300 M5: 2600 M6: 3400	B1: 3600 B2: 2800 B3:1900 B4: 2600 B5: 2700 B6: 2800	1, 2, 3, 4, 5, 6	M1:2700 M2: 1700 M3: 2600 M4: 2000 M5: 3300 M6: 4100	
KMN 3 $(7\times7\times7)$	B1:800 B2: 3900 B3:2600 B4: 3200 B5:2300 B6: 3200 B7:3500	7,5,2,1,4,6,3	M1: 2900 M2: 2400 M3: 2900 M4: 3200 M5: 2200 M6: 3000 M7: 2900	B1: 1200 B2: 4300 B3: 3000 B4: 3600 B5:2700 B6: 3600 B7: 3900	1, 4, 6, 7, 5, 2, 3	M1: 3300 M2: 2800 M3: 3300 M4: 3600 M5: 2600 M6: 3400 M7: 3300	
KMN4 $(7\times6\times6)$	B1:1800 B2: 800 B3:2700 B4:2800 B5: 1200 B6:2700	7,4,6,2,3,1,5	M1: 1500 M2: 3900 M3: 3500 M4: 3400 M5: 1700 M6: 1800 M7: 2500	B1:2200 B2: 1200 B3: 3100 B4: 3200 B5: 1600 B6: 3100	7, 4, 5, 1, 3, 6, 2	M1:1900 M2: 4300 M3: 3900 M4: 3800 M5: 2100 M6: 2200 M7: 2900	
KMN 5 $(7\times7\times4)$	B1:200 B2:2700 B3:1800 B4: 1600 B5:2600 B <sub>6</sub> : 2400 B7:2300	4,6,5,2,3,1,7	M1: 3600 M2: 1500 M3: 1700 M4: 400 M5: 1700 M6: 2900 M7: 1800	B1:200 B2: 2700 B3: 1800 B4: 1600 <b>B5:2600</b> B6: 2400 B7: 2300	4, 6, 5, 2, 3, 1, 7	M1: 3600 M2: 1500 M3: 1700 M4: 400 M5: 1700 M6: 2900 M7: 1800	
KMN 6 $(7\times7\times5)$	B1:3600 B2: 3300 B3: 3900 B4: 2600 B5:4500 B <sub>6</sub> : 3300 B7: 4600	3,6,2,5,4,1,7	M1: 5800 M2: 3200 M3: 5500 M4: 6000 M5: 200 M6: 1800 M7: 3300	B1: 3600 B2: 3300 B3: 3900 B4: 2600 B <sub>5</sub> : 4500 B6: 3300 B7: 4600	7, 1, 2, 6, 3, 4, 5	M1:5800 M2: 3200 M3: 5500 M4: 6000 M5:200 M6: 1800 M7: 3300	
KMN7 $(7\times7\times6)$	B1:1700 B2:2800 B3: 3100 B4: 4500 B5:600 B6: 4900 B7: 1500	3,4,2,6,1,5,7	M1: 3600 M2: 4100 M3: 1400 M4: 2400 M5: 3400 M6: 2900 M7: 1300	B1: 2600 B2: 3700 B3: 4000 B4: 5400 B5: 1500 B <sub>6</sub> : 5800 B7: 2400	7, 5, 3, 4, 2, 6, 1	M1: 4500 M2: 5000 M3: 2300 M4: 3300 M5: 4300 M6: 3800 M7: 2200	
KMN 8 $(9 \times 5 \times 5)$	B1:1500 B2:2500 B3:0 B4:100 B5:600	1, 6, 7, 3, 5, 4, 2, 8, 9	M1: 3100 M2: 3400 M3: 3400 M4: 2300 M5: 3500 M6: 1700 M7: 2300 M8: 4100 M9: 3300	B1:1700 B2: 2700 B3:200 B4: 300 B5:800	9, 1, 5, 4, 2, 3, 8, 7, 6	M1:3300 M2: 3600 M3: 3600 M4: 2500 M5: 3700 M6: 1900 M7: 2500 M8: 4300 M9: 3500	
KMN 9	B1:2600	1, 4, 2, 6, 8, 9, 5, 3, 7	M1: 3000	B1:2500	2, 7, 5, 1, 9, 8, 3, 6, 4	M1: 3700	

<span id="page-9-0"></span>Table 17 Comparison of arithmetical results of the proposed evolutionary algorithms for CBS=100 numbers in a batch and same quantity in all batches



Table 17 (continued)



# 7 Data set details of processing time of parts and processing sequence of machines

The inter slot between machines, i.e., the gap between machine measures in units are given in Tables [10,](#page-6-0) [11](#page-6-0), and [12.](#page-7-0) The loading/unloading distance matrix specifies distance from machines to load/unload station are shown in Tables [13](#page-7-0), [14,](#page-7-0) and [15,](#page-7-0) unit material handling cost per unit, i.e., the carrying cost of parts between machines is unit cost. With the collected information from various literature, it is applied that Tables [1,](#page-4-0) [2,](#page-4-0) and [3](#page-4-0) dataset details are considered as integrated data for both layout design and FMS scheduling where scheduling is constraint for layout design. Tables [4](#page-4-0), [5](#page-5-0), [6,](#page-5-0) [7,](#page-5-0) [8,](#page-5-0) and [9](#page-6-0) dataset details are concern to FMS scheduling which act as important parameters for optimum allocation of jobs with predefined processing time and routing for generating minimum makespan. Tables [10](#page-6-0), [11,](#page-6-0) [12](#page-7-0), [13](#page-7-0), [14,](#page-7-0) and [15](#page-7-0) dataset details are used for loop layout design such as interslot distance tables shows that the predefined clearance between slots over which machines are assigned by means of permutation rule. Further load and unload matrix are calculated based on the clearance between machines and direction of parts. Also, the reason for integrating the loop layout design with FMS scheduling is the data set details of Tables [7](#page-5-0), [8,](#page-5-0) and [9](#page-6-0) are used for calculating the frequency of trips between machines as one of the key input parameter for loop layout design which is not mentioned in dataset details because it is developed in simulation code. Though the input data from Tables [1,](#page-4-0) [2,](#page-4-0) and [3](#page-4-0) as well as Tables [10 11](#page-6-0), [12,](#page-7-0) [13,](#page-7-0) [14](#page-7-0), and [15](#page-7-0) is entered manually in IDE tool in which simulation code is executed but data of frequency of trip between machines is calculated by code itself and taken as additional input for loop layout design. The necessary pseudo code for calculation of frequency of trips is shown below.

Pseudo code for frequency of trips permutation for loop layout design

```
BEGIN void
Genetic::FromTochatObjfunction(int
RR[MAX_MC][MAX_BAT])
  {
  for (i=1; i \leq no machines; i++) {
  for (j=1; j \leq no machines; j++){ FromTochat[i][\dot{\eta}=0;
  }
  }
  for (i=1; i \leq no batchs; i++) {
  for (j=1; j< no operations; j++)
  {
  if (RR[i][j] := RR[i][j+1])FromTochat[RR[i][j]][RR[i][j+1]] +=
(Bsizes[i]);
  }
  } for (i=1; i \leq no machines; i++) {
```

```
for (j=1; j \leq no machines; j++) {
if (FromTochat[i][j] < FromTochat[j][i])
FromTochat[i][j]=FromTochat[j][i];
else
FromTochat[j][i]=FromTochat[i][j];
} END
```
# 8 Data set details of inter-slot distance between machines

Tables [10,](#page-6-0) [11,](#page-6-0) and [12](#page-7-0) shows details of inter-slot distance between machines of FSM for six, seven and nine machines.

# 9 Data set details of load, unload matrices for loop layout

Tables [13](#page-7-0), [14](#page-7-0), and [15](#page-7-0) shows details of load and unload matrices for loop layout with six, seven and nine machines respectively.

# 10 Results and discussions

In the present work, the optimal solution for loop layout with integrated scheduling uses non-traditional optimization techniques such GA and SA. So far, only non-traditional methods are used for solving such kind of problems. In traditional methods to calculate minimum total transportation cost, it is necessary to check  $(n!)$ , for example : $(6!)(1.393140695$  \*  $10^{17}$ ) sequences in order to find the optimal sequences. The major advantage of using non-traditional algorithms is that even though the number of possible sequences is very high, an optimal solution can be obtained within a fraction of seconds while compiling on a standard PC. These algorithms are verified through computer simulation for various physical life problems area found to be very operative.

One anxiety provoked by the investigators in any research is to compare their approaches with those of other researchers. If the standard usual test problems are open, the performances of different algorithms can be compared on closely the same set of test problems. For this reason, we chose 21 benchmark problems from Kumanan et al. [\[18\]](#page-19-0) (KMN) as the test problems for this study. These benchmark problems are categorized into two groups, i.e., constant batch size (CBS) problems and variable batch size (VBS) problems. Kumanan has produced a set of problems with seven and nine machines with two and four jobs. There are 2 instances for  $(nxm=6\times6)$  problem combination and 5 instances for  $(nxm=7\times7))$  and 14 instances for ( $n \times m = 9 \times 9$ ). Totally, there are 42 problem instances.

<span id="page-13-0"></span>

Fig. 6 Comparison of proposed algorithm for transportation cost with variable batch size for loop layout

Table [16](#page-8-0) shows the results of test problems for CBS from KMN1 to KMN21 and is understood that the test problems are solved through the proposed algorithm, and the results are compared and found that performance of GA and SA for calculating total transportation cost (TTC) and make span (MAKSP) is varying as per the problem size. By relative analysis, we observed that solutions are optimized for GA and found that GA can afford the best solution when compared with SA to all test problems. Furthermore, the computational time of GA fluctuates as the problem size varies but the computational time of SA is zero for all problems. Comparison of make span and total transportation cost for CBS by the proposed evolutionary algorithms for different problem sizes is depicted in Figs. [4](#page-8-0) and [5](#page-8-0). The plot shown in Figs. [4](#page-8-0) and [5](#page-8-0) is styled for instance KMN 1–KMN 21. It is observed that there are moderate variations in results of TTC and MAKSP against problem instances shown in the plot for GA and SA. It is found that TTC and MAKSP are low at small size problems



Fig. 7 Comparison of proposed algorithm for makespan with variable batch size for loop layout



Fig. 8 Comparison of proposed algorithm for computational time with constant batch size of loop layout

and reaches to high value as problem size increases. Furthermore, GA curve fluctuates at lower values than SA curve.

Table [17](#page-9-0) shows the results of test problems for CBS from KMN 1 to KMN 21 and is figured out that the test problems are solved through the proposed algorithm, and the results are compared and found that performance of GA and SA for calculating batch waiting time (BWT) and machine waiting time (MWT) obtained for corresponding problem instances is varying as per the problem size and based on MAKSP value. By relative analysis, we observed that GA shows minimum waiting times when compared with SA to all test problems (Figs. 6, 7, 8, and 9). Comparison of BWT and MWT for CBS by the proposed evolutionary algorithms is depicted in Figs. [10](#page-14-0) and [11.](#page-14-0) The plot shown in Figs. [10](#page-14-0) and [11](#page-14-0) is styled for instance which has seven batches/jobs. It is observed that BWT and MWT for constant batch size are less for GA when compared with SA.

Table [18](#page-15-0) shows the results of test problems for VBS from KMN1 to KMN21 and is understood that the test problems are solved through the proposed algorithm, and the results are compared and found that performance of GA and SA for calculating TTC and MAKSP is varying as per the problem size. By relative analysis, we observed that solutions are optimized for GA and found that



Fig. 9 Comparison of proposed algorithm for computational time with variable batch size of loop layout

<span id="page-14-0"></span>

Fig. 10 Comparison of proposed algorithm for batch waiting time with constant batch size for the problems with seven batches

GA affords best solution when compared with SA to all test problems. Furthermore, the computational time of genetic algorithm fluctuates as the problem size varies, but the CPU time of simulated annealing is zero for all problems. Comparison of make span and total transportation cost for VBS by the proposed evolutionary algorithms for different problem sizes is depicted in Figs. [6](#page-13-0) and [7](#page-13-0). The plot shown in Figs. [6](#page-13-0) and [7](#page-13-0) is styled for instance KMN 1– KMN 21. It is observed that there are moderate variations in results of TTC and MAKSP against problem instances shown in the plot for GA and SA. It is found that TTC and MAKSP are low at small size problems and reaches to high value as problem size increases and also in Fig. [7.](#page-13-0) MAKSP variations are almost closer for both GA and SA. Furthermore, GA curve fluctuates at lower values than SA.

Table [19](#page-16-0) shows the results of test problems for VBS from KMN 1–KMN 21 and is understood the test problems are solved through the proposed algorithm, and the results are compared and found that performance of GA



Fig. 11 Comparison of proposed algorithm for machine waiting time with constant batch size for the problems with seven batches

<span id="page-15-0"></span>Table 18 Comparison of arithmetical results of the proposed evolutionary algorithms (for VBS with number of iterations=100)



and SA for calculating BWT and MWT obtained for corresponding problem instances is varying as per the problem size and based on MAKSP value (i.e., if make span is the same for both algorithm, then waiting times will also be the same, vice-versa). By relative analysis, we observed that GA shows minimum waiting times when compared with SA to all test problems. Furthermore, the required machine sequences (MASEQ) are depicted in the same table.

Comparison of computational time (seconds) by the proposed evolutionary algorithm for CBS and for VBS are shown in Figs. [8](#page-13-0) and [9.](#page-13-0) It is observed that GA requires a fraction of a second for computing given input to optimum solution, but SA gives the results with zero time because it is a single solution method which is well known as trajectory-based heuristic, whereas GA is population-based heuristic which has many solutions (chromosomes) in a mating pool which can be reproduced as new offspring's (new solutions). Actually, GA is an effective algorithm in searching local optima when compared with SA. Furthermore, a necessary simulation code is generated and the code is run by the IDE tool in which C++ compiler used as plug in. This tool has eclipse-based features which afford the competency to figure, correct, steer, and sort out the tasks that use  $C++$  as a programming language using Intel core i3-380 M processor. Furthermore, it is more convenient to user to print and display the results and errors if any in execution.

## 11 Conclusion

This paper conveys the modeling of loop layout design with integrated scheduling in which the frequency of trips between machines, the clearance between the machines with loading and unloading distance from loading/unloading station to all machines, and unit material handling cost (MHD) are estimated differently. The problem is framed as the quadratic assignment problems (QAP) formulation of facility layout problem. This is owing to the point that in the QAP models, the distance between the positions of slots is identified well in advance but it is order-dependent for the instances considered in this paper.

From the results, we conclude that loop layout is optimized using GA and is better than SA with constant MHD cost and frequency of trips between machines. The parameter like

<span id="page-16-0"></span>

# Table 19 (continued)



Table 19 (continued)



Para parameters, BWT batch waiting time, GA genetic algorithm, TTC total transportation cost, MWT machine waiting time, SA simulated annealing, MAKSP total make span, CPU computational time, MASEQ machine sequence

transportation cost with machine sequences considering scheduling parameters as constraints such as MAKSP is determined for loop layout by running the C++ code on eclipse (IDE) tool for ten test runs. The performance of the proposed algorithm is tested over a number of problems selected from the literature and comparison is made between GA and SA. The experimental results reveal that the proposed genetic algorithm is effective and efficient for loop layout design. From

<span id="page-19-0"></span>the graph, it is clear that for loop layout, the total transportation cost is less for lower level problems and reaches to high value as the problem size enhanced. Furthermore, it is concluded that GA provides optimum solutions than SA, but computational time is more than SA.

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