International Journal of Process Management and Benchmarking

ISSN online: 1741-816X - ISSN print: 1460-6739
https://www.inderscience.com/ijpmb

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DOI: 10.1504/IJPMB.2023.10061276

Article History:

Received:	26 December 2022
Last revised:	27 December 2022
Accepted:	28 December 2022
Published online:	02 January 2025

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Abstract: This paper focuses the allocation of facilities into flexible manufacturing system deals in single and multi-row layout with equal and/or unequal area of facilities. The proposed mathematical model offers the effective utilisation of facilities with minimum throughput time and material handling subjected to production-derived constraints. The facility layout design is a combinatorial problem generates alternative feasible solution with the help of available computer software. However, selection of the best alternative solution from the available set of feasible alternatives is crucial in consideration of the distance between the facilities and the adjacency requirement of facility types for a given production layout. A genetic algorithm based solution approach is used to elicit the optimal rectilinear distance among different workstations in a realistic way minimises the total material handling costs. The modest genetic operators are embedded with the emendation operation enables the mapping of optimal results with the benchmark instances reported in the literature. The results obtained using the genetic algorithm are found better than the previous best known results.

Keywords: facility layout; quadratic assignment problem; QAP; flexible manufacturing system; combinatorial optimisation; material flow; genetic algorithm.

Reference to this paper should be made as follows: Deep, K. (2025) ‘Facility layout for flexible manufacturing system using genetic algorithm’, *Int. J. Process Management and Benchmarking*, Vol. 19, No. 1, pp.89–107.

Biographical notes: Kamal Deep received his undergraduate degree in Mechanical Engineering from the Basaveshwar Engineering College, Bagalkot, in 1999, post-graduate degree in Production Technology from the Janardan Rai Nagar Rajasthan Vidyapeeth University, Udaipur, in 2005, and PhD in Mechanical Engineering from the Sant Longowal Institute of Engineering and Technology, Longowal, in 2018. He has more than ten years of teaching and research experience, including two years of industrial experience. He has been with Guru Jambheshwar University of Science and Technology, Hisar, since 2006 and currently he is an Assistant Professor at the Department of Mechanical Engineering. His areas of interest include GT/CMS, manufacturing system modelling, productivity, non-traditional optimisation and material management.

1 Introduction

The facility layout problem (FLP) considers the optimum selection of alternative locations for the facility types along with available workforce and market. In the last two decades, several mathematical models have been developed for the facility layout problem to minimise the frequency of distance traversed between facility types and the material handling cost for a production system. Tompkins and White (1996) discussed on the total operating expenses that can be reduced by 50% through the appropriate allocation of facilities in the layout.

Several models have been proposed to represent the FLP reported in the literatures; mixed integer programming, graph theoretic approach, and space partitioning method, etc. The FLP can also be formulated as quadratic assignment problem (QAP) considers the discrete allocation of facility types in equal size (Singh and Sharma, 2006 and Drira et al. 2007). The QAP of facility layout is NP-hard and incompetent to solve problems of large size (Heragu and Alfa, 1992 and Heng and Love, 2000).

Unequal area of facility layout problems (UA-FLP) deals with evaluation of optimum organisation of indivisible facilities. The FLPs of unequal area can be expressed as a fixed shape and a flexible bay; the fixed shape structure arranges fixed length and width of the facility types, and the flexible bay concludes the fixed area of facility with flexible length and width. The layout arrangement for unequal areas (UA) of facilities is most commonly accounted in the production and the service sectors originally formulated by Armour and Buffa in the early 1960s.

A flexible manufacturing system accounts equal and/or unequal area of facility types with several patterns of production layout; single and/or multi-row, U-shape and circular loop, etc. Anjos and Vieira (2017) presented coverages in the one-dimensional facility layout leads the single row in FLPs, the two-dimensional facility layout frames the departments of unequal area, and the three dimensional facility layout covers multi-floor layout problems. The UA-FLP is rigorous to attempt using exact optimisation method. Several heuristic methodologies have been evolved to attain near optimum solution in a finite time span.

Gen and Cheng (1995) derived the concept of fuzzy clearance for the multi row FLP using the genetic algorithm. The algorithm defines a new arithmetical crossover along with the mutation operator to improve the diversity in offsprings. Ficko et al. (2004) considered the genetic algorithm for the facility layout arrangement. The developed heuristic effectively evaluates the sequence of machine types for multiple rows in the layout. Anjos et al. (2005) considered one dimensional space allocation problem with varying dimensions of facilities in a straight line to alleviate the total cost associated with the material handling. The memory requirement and computational time are the major restriction to solve the large instances using semidefinite programming. Satheesh et al. (2008) proposed a scatter search methodology to solve the single row UA-FLP for the flexible manufacturing system. The comparative of results on the benchmark problems validate the solution technique. Samarghandi and Eshghi (2010) proved the theorem on linear placement of facility type in ascending order to optimise the solution for single row facility layout. The results obtained on the benchmark problems approve the computational efficacy using a Tabu search algorithm. Amaral (2012) formulated a mixed integer programming problem (MIP) to allocate the facility types in corridor minimises the transportation cost of material. The computational performance exhibits the excellent performance of the proposed formulation in comparison of previously reported results in the literature. Chase et al. (2013) formulated a linear programming mathematical model for the multi row layout problem addressing the non-symmetric material flow. A constructive heuristic is used to obtain the optimal locations for the machine types in row layout. The results obtained substantiate the efficacy of developed heuristic in the quality of solutions and the computational effort. Zuo et al. (2014) evolved a linear programming model for a double row layout. The established formulation allocates the facilities in rows minimising the asymmetric material flow and the total layout area. Ingole and Singh (2017) implemented the firefly algorithm for the fixed-shape facility layout of the unequal-area. The result comparative obtained on numerical instances substantiate the computational performance of the algorithm. Tubaileh and Siam (2017) addressed the multi-row facility layout to optimise the total cost of material handling between the facility types. The optimum facility layout is implemented in single-row and double-row using the ant colony and the simulated annealing algorithm. Wei et al. (2019) utilised a Tent mapping strategy to generate the initial solution set using a genetic algorithm for the dynamic facility layout. The proposed research work compares the implemented outcomes of traditional algorithms to approve the efficacy of the Tent chaotic genetic algorithm. Liu and Liu (2019) proposed an enhanced ant colony optimisation algorithm based on the local pheromone communication embedded with a niche methodology for the UA-FLP. The developed algorithm deals with material handling and the closeness ratio between the facilities simultaneously to optimise the production layout. The experimental results on the benchmark instances exhibit the validity of solution algorithm. Garcia-Hernandez et al. (2020) developed the coral reefs optimisation algorithm with substrate layers (CRO-SL) to address the UA-FLP. The solution mechanism ensembles several operators in the substrate layers of algorithm to avoid the local minima trap. The rigorous experimental study of developed algorithm is carried out on the benchmark instances to substantiate the efficacy of the algorithm. Hunagund et al. (2020) developed a robust approach for UA-dynamic facility layout problem using a mixed integer programming model. The robust formulation evolves a single layout of facility types for the multi period planning horizon. The efficacy of the proposed model is analysed by the simulated annealing algorithm using the numerical instances reported in the literature. Pourvaziri et al. (2020) presented a realistic robust approach to deal with the part demand volatility in the facility layout planning. The mathematical model effectively determines the alternative part route and optimal location of each facility in the multi- period production planning. The results obtained approve the effectiveness of genetic-Tabu search algorithm in solving large size problems reported in the literature. Liu et al. (2021) optimised the material handling and the closeness rating in facility layout for the multi-objective UA-FLP. The efficacy of the proposed model is evaluated using the niche technology embedded with Pareto optimisation. The developed heuristic is testified on the benchmark instances reported in the literature. Bhuiyan et al. (2021) developed a branch and bound algorithm to minimise the make span by maximising the closeness rating for UA-facility layout. The subjected constraints ensure the optimal arrangement of facility types in the bounded area of production layout. The proposed model enables the decision makers to adopt a compatible layout for the different realistic production scenarios. Ingole and Singh (2021) considered the fixed and flexible shapes of departments for FLPs to minimise the distance between facilities using biogeography-based optimisation (BBO) algorithm. Ahmadi-Javid and Ardestani-Jaafari (2021) studied UA-FLP with the flexible bay structure to minimise the single loop path associated with automated guided vehicle

(AGV) used for the material handling. A simulated annealing based heuristic is used to design the facility layout upto the problem size of 62 departments with 40% improvement over the traditional solution approach. Subulan et al. (2023) introduced capability based facility layout to consider the overall processing capacity of UA-FLP. The decomposition based iterative approach is used to solve the real size problems in a feasible time span. The computational results exhibit 33.25% better layout score in terms of total material flow in comparison of Gurobi's standard non-linear programming solver.

The literature cited above reveals the several optimisation algorithms for the successful implementation of FLP. It cannot be denied that the computational procedures for the FLP still need effective amelioration to enhance the quality of solution in a finite time span (Aarts and Lenstra, 1997, Alhamdy et al., 2012, Amaral, 2012, Chen et al., 2016 and Yossef et al., 2001).

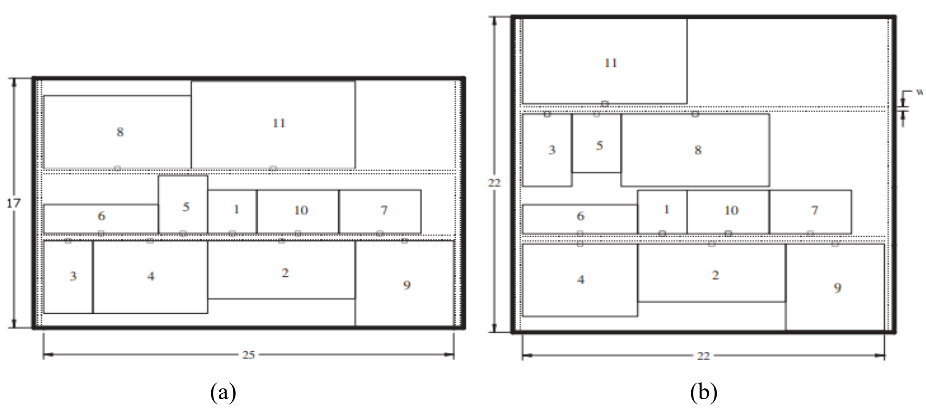
This paper addresses the genetic algorithm approach to optimise the total frequency of material flow for the Single row and/or multi row facility layout in the flexible manufacturing system. The efficacy of the proposed solution approach is evaluated on the benchmark instances reported in literature.

The rest of the paper is structured as follows. Section 2 describes the mathematical formulation of FLP. Section 3 illustrates the genetic algorithm based solution methodology. Section 4 presents computational illustration and result comparative with bench mark problems. Conclusion and future aspects are described in Section 5.

2 Mathematical formulation

Facility layout in the FMS interprets the determination of optimal locations for the non-overlapping departments. The arrangement of Facilities in single and/or multi row layout concludes the minimisation of material transportation among the facilities (Armour and Buffa, 1963). The rectilinear configuration of facility layout confines the horizontal and vertical dimensions with pickup and drop-off point allocated at the centroid of either facility sides (Figure 1).

Figure 1 Rectilinear configurations of layout with variation in length of rows



The solution procedure for the FLP in FMS is evolved in the two steps: The first step deals with the arrangement of facility types in rows, and the second step evaluates the required number of rows for the assignment of facilities within the production layout. The procedure iterates in two steps in an order to obtain the optimal configuration of the facility layout.

The following mathematical notations are used to develop the objective function:

n Number of facility types

x_i The x-coordinate of the centre of department i

y_i The y-coordinate of the centre of the department i

l_i The length of facility i in the X direction

w_i The width of facility i in the y direction

l_T The length of row in X direction

w_T The width of column in y direction

C_{ij} The transportation cost for the material flow between facilitites i and j

D_{ij} Rectilinear distance between locations of facility types i and j

2.1 Mathematical model

$$Min = f(x,y) = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} C_{ij} * Dij \tag{1}$$

where

$$Dij = |x_i - x_j| + |y_i - y_j|$$

Subjected to:

$$|x_i - x_j| - \frac{1}{2}(l_i + l_j) \geq 0 \quad \text{if} \, |y_i - y_j| - (w_i + w_j) < 0 \tag{2}$$

$$|y_i - y_j| - \frac{1}{2}(w_i + w_j) \geq 0 \, \text{if} \, |x_i - x_j| - (l_i + l_j) < 0 \tag{3}$$

$$\left(x_i - \frac{1}{2}l_i\right) + \frac{1}{2}l_T \geq 0 \qquad \forall i \tag{4}$$

$$\frac{1}{2}l_T - \left(x_i + \frac{1}{2}l_i\right) \geq 0 \qquad \forall i \tag{5}$$

$$\left(y_i - \frac{1}{2}w_i\right) + \frac{1}{2}w_T \geq 0 \qquad \forall i \tag{6}$$

$$\frac{1}{2}w_T - \left(y_i + \frac{1}{2}w_i\right) \geq 0 \qquad \forall i \tag{7}$$

$$l_T{}^{\max} \leq \min(l_i, w_i) \qquad \forall i \tag{8}$$

The equation set (1) describes the objective function minimising the total cost of material handling, multiple of total distance traversed between the facility types. The subjected equations (2–3) state the non-overlap allocation of facility types in rows and column maintains the sum of centre distance of facilities in x or y direction less than the length of row or width of the column. The constraint equations (4)–(7) confine the adjacency of facility types, facility's upper surface is retained beneath the next facility's lower surface and the lower surface of a facility is maintained above the upper surface of facility type in a column. Similarly, the right wall of a facility type is to the left wall of the next facility type and the left wall of a facility type is to the right wall of the next facility type in a row. The constraint equation (8) defines the maximum length of a row.

3 Solution methodology

The GAs are the robust adaptive search and optimisation method explores the entire search space of population set and avoids convergence to local optima yielding a near global solution in moderate time span (Sinriech and Meir, 1998, Caux et al., 2000, DeLit and Falkenauer, 2000). It has some unique features, such as independence of the gradient information, and flexibility to hybridise with domain-dependent heuristics. The GA can be quite suitable for the machine component grouping problem having a complex solution search space that can not be easily attempted using traditional optimisation techniques. The genetic algorithm is highly compatible for large size instances rigorous to solve with available heuristic algorithms.

The solution schema of an individual solution generates the initial random solution set describes the centroid locations and the rectilinear dimensions of the facility types is encoded in a two-level chromosome as shown in Figure 2.

Figure 2 Encoding of chromosomes

Centroid Location	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	-	-	X_{n-1}	X_n
	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8	-	-	Y_{n-1}	Y_n
Dimenssion	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8	-	-	l_{n-1}	l_n
	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	-	-	w_{n-1}	w_n
Facility Types	3	1	10	12	4	9	7	2	-	-	6	11

The objective function (equation set 1) computes the summation of material flow for each permutation chromosome of a solution set. The fitness of a solution schema in the GA is evaluated as a maximisation of the objective function. Therefore the fitness value of the objective function is transformed into minimisation of the FLP in the following manner.

The equation set (9) appraises the fitness F_i of a random solution in the populace size n by having the division of least objective function value $f(x_i, y_i)_{min}$ with the objective function $f(x_i, y_i)$ of the string i in the current generation.

$$F_i = \frac{f(x_i, y_i)_{\min}}{f(x_i, y_i)}, \qquad i = 1, 2, \ldots n. \qquad f(x_i, y_i) > 0 \tag{9}$$

The comparative fitness value of each chromosome solution is assessed by contesting the binary tournament for a populace set of the current generation. The elite parents are grouped in a pool to regenerate the descendants by applying the genetic operators with a certain probability value for crossover and mutation.

The crossover operator generates the descendants by randomly exchanging the segments of a parent solutions. Figure 3 is representing the crossover schema for offspring production preserving the partial properties of their parent solutions.

Figure 3 Genetic crossover (see online version for colours)

Parent 1	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	-	-	X_{n-1}	X_n
	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8	-	-	Y_{n-1}	Y_n
	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8	-	-	l_{n-1}	l_n
	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	-	-	w_{n-1}	w_n
Parent 2	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	-	-	X_{n-1}	X_n
	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8	-	-	Y_{n-1}	Y_n
	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8	-	-	l_{n-1}	l_n
	b_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	-	-	w_{n-1}	w_n
Child 1	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	-	-	X_{n-1}	X_n
	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8	-	-	Y_{n-1}	Y_n
	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8	-	-	l_{n-1}	l_n
	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	-	-	w_{n-1}	w_n
Child 2	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	-	-	X_{n-1}	X_n
	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8	-	-	Y_{n-1}	Y_n
	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8	-	-	l_{n-1}	l_n
	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	-	-	w_{n-1}	w_n

The swap mutation technique is employed to extend the search in the local space that simply selects the two random strings of a chromosome to swap their contents at the sub points as shown in Figure 4.

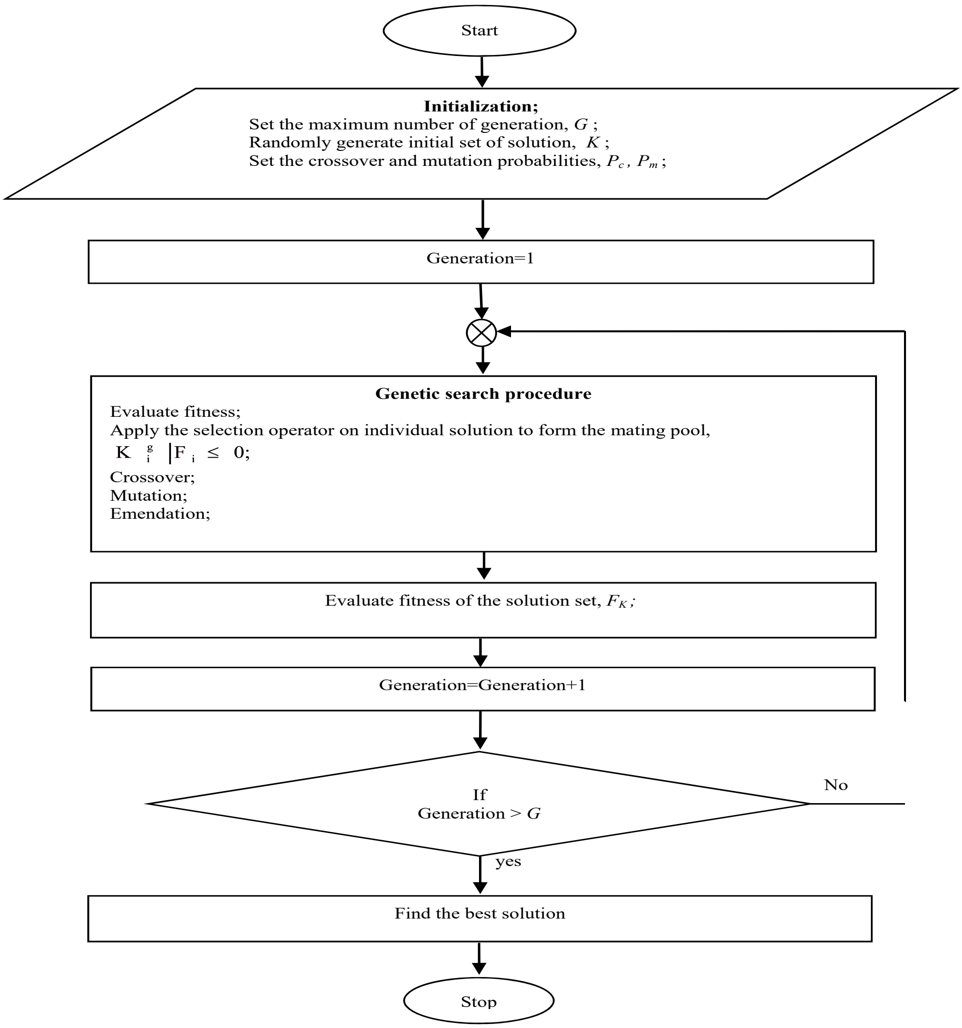
Figure 4 Genetic mutation (see online version for colours)

Parent 1	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	-	-	X_{n-1}	X_n
	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8	-	-	Y_{n-1}	Y_n
	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8	-	-	l_{n-1}	l_n
	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	-	-	w_{n-1}	w_n
Child 1	X_1	Y_2	X_3	X_4	X_5	Y_6	X_7	X_8	-	-	X_{n-1}	X_n
	Y_1	X_2	Y_3	Y_4	Y_5	X_6	Y_7	Y_8	-	-	Y_{n-1}	Y_n
	l_1	w_2	l_3	l_4	l_5	w_6	l_7	l_8	-	-	l_{n-1}	l_n
	w_1	l_2	w_3	w_4	w_5	l_6	w_7	w_8	-	-	w_{n-1}	w_n

The crossover and mutation genetic operators may distort the child solutions enclosing the rectilinear length parameters of facility types more than the maximum length of a row. The distorted offsprings deficits in confined rows length are emendated by exchange of facility types short in length or width from the other rows to gratify the constraint equation (8).

The GA stops functioning after the evolution of pre-specified number of generation. The flow chart shown in Figure 5 describes the detailed solution procedure.

Figure 5 Flow chart of the genetic algorithm based heuristic



3.1 Parameter setting of genetic algorithm

The GA is a discrete search strategy to elicit the alternative solutions for the problem instance with a variable parametric value of genetic operators. The mutation operator performs the local search by random exchange of key elements of a parent string with the probability value P_m. For each problem instance the probability of mutation is testified on the values ranging from 0.1 to 0.3 in the sub steps of 0.1. For all the values of P_m, ten trials are performed on each benchmark instance with the crossover probability range from 0.3 to 0.8 in the sub steps of 0.05 and a total of 30 iterations are executed for each problem. The mutation probability of 0.2 is recorded as the most appropriate for all the crossover probability values o.3 < p_c < 0.8.

The developed GA is run for each problem instance with the maximum population size of 100 per 50 generations. It has been observed in the experimental evolution for most of the problem instances that the difference in the obtained optimal solution from the best known global solution lies within 8%, except for an instance having variation up to 12%. The best parametric values of genetic operators for each problem instance and their corresponding optimum cost are presented in Table 1.

Table 1 GA parameters

SL no	*Type of FLP*	*Problem*	*Probability of crossover (p_c)*	*Probability of mutation (p_m)*	*Computational time in (sec)*	*OFV*
1	UA single row FLP	n = 5	0.75	0.2	3.2946	151.0
2		n = 8	0.75	0.2	5.9276	2,324.5
3		n = 10	0.70	0.1	10.235	2,789.5
4		n = 11	0.75	0.2	15.185	6,933.5
5		n = 11	0.80	0.2	18.326	6,933.5
6		n = 20	0.80	0.1	308.732	17,229
7		n = 30	0.75	0.1	479.234	47,588.0
8	Multi-row quadratic FLP	Nug-5	0.70	0.1	3.0277	25
9		Nug-6	0.80	0.1	3.1926	43
10		Nug-7	0.75	0.1	4.735	75
11		Nug-8	0.70	0.1	6.232	113
12		Nug-12	0.80	0.2	80.916	293
13		Scr12	0.80	0.2	97.358	15,705
14		Had12	0.70	0.2	123.270	830
15		Had14	0.75	0.2	152.679	1,367
16		Nug-15	0.75	0.2	185.389	594
17		Scr15	0.80	0.2	193.698	28,338
18		Had16	0.75	0.2	224.275	1,912
19		Had18	0.80	0.2	273.354	2,723
20		Chir18b	0.80	0.2	269.3680	778.5
21		Nug-20	0.80	0.2	329.4915	1,305
22		Scr20	0.80	0.2	358.476	61,011
23		Nug-30	0.80	0.2	716.200	3,374
24		Tho30	0.80	0.2	847.300	84,365
25	UA multi-row FLP	n = 15	0.80	0.2	66.552	5,371.8
26		n = 20	0.80	0.2	118.976	10,164
27		n = 30	0.80	0.2	273.7282	24,653
28		n = 40	0.80	0.2	554.043	415,510
29		n = 50	0.80	0.2	922.7752	1,713,800

Table 2 Comparative of computational results with proposed genetic algorithm for single-row facility layout problem

SL no	Problem size	Problem instance	Heragu and Kusiak (1991)		Heragu and Kusiak (1992)		Proposed genetic algorithm			
			OFV	*Time (sec)*	*OFV*	*Time (sec)*	*OFV*	*Time (sec)*	*Percentage deviation*	*Permutations of facilities*
1	n = 5	Love and Wong (1976b)	151.0	0.13	151.0	10.351	151.0	3.2946	0	2, 1, 5, 3, 4
2	n = 8	Simmons (1969)	2,341.5	0.59	2,324.5	11.803	2,324.5	5.9276	0	7, 8, 1, 5, 4, 6, 3, 2
3	n = 10	Simmons (1969)	2,781.5	0.84	2,781.5	19.815	2,789.5	10.235	0.287	9, 3, 1, 7, 10, 5, 4, 2, 6, 8
4	n = 11	Simmons (1969)	7,274.5	2.18	6,933.5	23.103	6,933.5	15.185	0	11, 8, 5, 6, 3, 4, 10, 1, 2, 7, 9
5	n = 11	Love and Wong (1976b)	6,933.5	0.95	6,933.5	29.176	6,933.5	18.326	0	6, 9, 3, 4, 1, 5, 2, 7, 8, 10, 11
6	n = 20	Heragu and Kusiak (1991)	16,109.0	7.82	16,109.0	603.376	17,229	308.732	6.95	19, 13, 9, 15, 2, 14, 16, 20, 12, 18, 4, 11, 8, 7, 6, 5, 10, 17, 1, 3
7	n = 30	Heragu and Kusiak (1991)	46,139.0	35.74	46,139.0	585.947	47,588.0	479.234	3.14	2, 26, 5, 14, 4, 29, 9, 27, 20, 10, 11, 30, 3, 23, 8, 16, 19, 21, 13, 7, 17, 22, 25, 18, 1, 24, 15, 6, 12, 28

4 Computational illustration

The three distinct experimental sets have been analysed on the benchmark numerical instances to evaluate the computational efficiency of the proposed solution approach. The first experiment set explores a comparative set of results for the UA – single row FLPs. The second set of experimental evaluation concludes the efficacy of the proposed solution strategy applied to seventeen benchmark numerical instance of multi-row quadartic assignment problems reported in the literature. The third experimental study investigates the applicability of the solution approach on the UA- multi-row FLPs of different sizes solved using the meta heuristic approaches informed in the literatures. The algorithm is programmed in MATLAB-2013 and run on MS Window 10 using 1.90 MHz Pentium workstation.

4.1 UA – single-row facility layout

In the single-row facility layout in FMS, facility allocations are along the linear passage of AGV used to handle the material within a row layout of unlimited path. The unequal area of facility types are assumed to be rectangular with pickup/drop-off points located at the centroid of either facility sides. In a single row facility layout the minimum cost of material handling is computed by the product of rectilinear distance between the facility types and the total number of material units traversed the distance from facility to facility. Comparative of computational results for the six benchmark numerical instances adopted from the different literature (Simmons; 1969, Love and Wong, 1976; Heragu and Kusiak, 1991), presented in the Table 2.

The efficacy of the proposed algorithm has been approved for the Objective Function Values for the all the test problems in comparison of computational time and previous best known solutions reported in the literature (Table 2). Picard and Queyranne (1981) applied the dynamic programming approach requires large space (2. 2n) for the memory locations and could not verify the optimal solution for the large size problem seven. However, the small size problems two and five could have solved optimally. The proposed algorithm requires maximum of 50 iterations to solve all the problems ranging from small to large size.

4.2 Multi-row facility layout in quadratic assignment

The multi row FLP in its simplest form can be addressed as a QAP under the restrictions of similar orientations for all the facility types allocated at equal size locations in the production layout. The rectilinear material flow between the facility types can be optimised by assigning each facility to a location in a order to minimise the throughput time of the production system.

The QAPs are classified as NP-hard problems and cannot be solved using the exact optimisation method for large size problems in a feasible time span (Heragu and Alfa, 1992). The heuristic solution approaches are significantly used to obtain the near optimal solution in a shortest computational duration. Several authors have conducted a comparative study on the different heuristic methodologies considering the number of iterations required to obtain quality of the solution (Aarts and Lenstra, 1997; Alhamdy et al., 2012). The heuristic solution approaches are efficient and robust to solve the combinatorial problems of specific types Yossef et al. (2001).

Table 3 The results comparative of the proposed GA with the distinct strategic heuristic on the problem instance taken from Burkard et al. (1997)

SL no.	*Problem – size*	*Global optimum solution*	*Drezner (1987)*	*Hergu and Kusiak (1991)*	*Kulkarni and Shankar (2007)*	*Singh and Sharma (2008)*	*Proposed GA*		
			Avg				*Objective function value*	*Percentage deviation*	*Permutations of facilities*
1	Nug-5	25	--	-	25	25	25	0	4, 1, 5, 2, 3
2	Nug-6	43	47.5	43	43	48	43	0	6, 5, 4, 3, 2, 1
3	Nug-7	73	--	-	74	74	75	2.73	7, 3, 2, 1, 6, 5, 4
4	Nug-8	107	118.8	131	107	116	113	5.60	8, 4, 7, 6, 3, 1, 2, 5
5	Nug-12	289	322.2	320	302	296	293	1.38	12, 8, 4, 5, 9, 7, 11, 6, 3, 1, 2, 10
6	Scr12	15,705	--		--	17,738	15,705	0	6, 4, 3, 9, 7, 2, 10, 1, 8, 5, 12, 11
7	Had12	826	--		--	833	830	0.48	8, 3, 10, 11, 2, 12, 5, 1, 6, 7, 4, 9
8	Had14	1362	--		--	1,364	1,367	0.36	3, 8, 13, 5, 10, 2, 6, 14, 12, 11, 7, 1, 9, 4
9	Nug-15	575	630.8	630	640	592	594	3.30	9, 11, 12, 5, 15, 8, 13, 7, 14, 6, 1, 2, 4, 3, 10
10	Scr15	25,570	--		--	28,041	28,338	10.04	1, 9, 2, 4, 12, 3, 7, 8, 10, 14, 13, 6, 11, 15, 5, 0
11	Had16	1,860	--		--	1,860	1,912	2.79	15, 9, 4, 16, 1, 8, 11, 10, 7, 6, 13, 12, 14, 5, 2, 3
12	Had18	2,679	--		--	2,692	2,723	1.64	13, 5, 2, 17, 3, 12, 14, 11, 7, 6, 10, 18, 16, 15, 9, 8, 1, 4
13	Chir18b	767	--		--	896	778.5	1.49	18, 8, 6, 4, 11, 9, 16, 10, 2, 17, 15, 7, 14, 12, 1, 3, 13, 5
14	Nug-20	1,285	1,416.4	1,398	1,474	1,314	1,305	1.55	17, 19, 8, 5, 13, 4, 15, 20, 7, 6, 11, 2, 12, 1, 10, 16, 18, 14, 3, 9
15	Scr20	55,015	--		--	56,690	61,011	10.89	13, 1, 16, 11, 15, 14, 17, 3, 9, 10, 12, 19, 20, 8, 7, 2, 5, 6, 18, 4
16	Nug-30	3,062	3,436.4	3,418	3,518	3,482	3,374	10.18	14, 15, 2, 5, 12, 4, 20, 29, 17, 26, 30, 27, 16, 13, 24, 22, 3, 9, 6, 10, 11, 8, 19, 7, 1, 23, 18, 21, 25, 28
17	Tho30	74,968	--		--	--	84,365	12.53	13, 20, 25, 22, 4, 24, 17, 5, 1, 30, 15, 12, 9, 23, 11, 26, 16, 28, 8, 19, 18, 6, 27, 21, 10, 3, 7, 2, 14, 29

The computational results for the proposed model of multi-row quadratic facility layout is presented as facility permutation in the Table 3. Computational performance of the developed algorithm has been evolved on the seventeen numerical instances adopted form Burkard et al. (1997) and compared with the benchmark results reported in Drezner (1987), Hergu and Kusiak (1991), Kulkarni and Shankar (2007), and Singh and Sharma (2008).

The performance of solution approach in the nine problems out of sixteen problems is better than the results attained by the constructive algorithm (Singh and Sharma 2008). The quality of near optimal solutions achieved using the proposed algorithm dominate for all the six problems reported in Drezner (1987), Hergu and Kusiak (1991), except for the results of the problems 3 and 4 obtained by Kulkarni and Shankar (2007).

4.3 Unequal area multi-row facility layout

The UA FLP deals with the optimal arrangement of non-overlapping indivisible facility types (Armour and Buffa, 1963). The UA multi-row FLP is an extension of the single row facility layout, assigns facilities in the multiple rows confined by total length (L) and width (W) of the production layout (Lee and Lee, 2002 and Scholz et al., 2009). The flow of materials between the facility types traverse on a track along the corridors of production layout with the objective to optimise the total flow of material. This concept has been widely applied in the fields of semiconductor manufacturing, construction industry, warehouse layout, campus planning, keyboard design, mother board framing (Hungerländer and Anjos, 2015).

A study is performed to analyse the computational efficacy of the proposed genetic algorithm in terms of speed and quality of the solution. The developed heuristic has provided significantly improved results in comparison of the meta-heuristics used by the previous researchers. The mathematical equation (10) concludes the percentage improvement in the results in compare of the best known previous results.

$$Percentage\,improvement = \frac{(Best\,known\,solution - obtained\,\,solution)}{Best\,known\,solution} \times 100 \qquad (10)$$

The comparative of results with the benchmark outcomes of Schnecke and Vornberger (1997), Lee and Lee (2002) and Scholz et al. (2009), Ingole and Singh (2017), and Ingole and Singh (2021), are presented in Table 4.

Computation time is an important and most commonly used factor for evaluating the efficacy of the heuristic approaches. For the first three problems of size 15, 20 and 30 facilities, the comparison on CPU time is presented in the Table 5 for the heuristic used by Schnecke and Vornberger (1997), Ingole and Singh (2017, 2021).

The hybrid Genetic Algorithm used by Schnecke and Vornberger (1997) requires a large number of generations to escape from the local optima, on the other hand the biogeography-based optimisation and the firefly algorithm practiced by Ingole and Singh (2017, 2021) relies on higher number of generations to maintain the diversity in the solution set. It is observed that the computational time required to obtain the optimal solution is less with the developed Genetic algorithm based heuristic embedded with a block mutation that escalates local search in the offsprings.

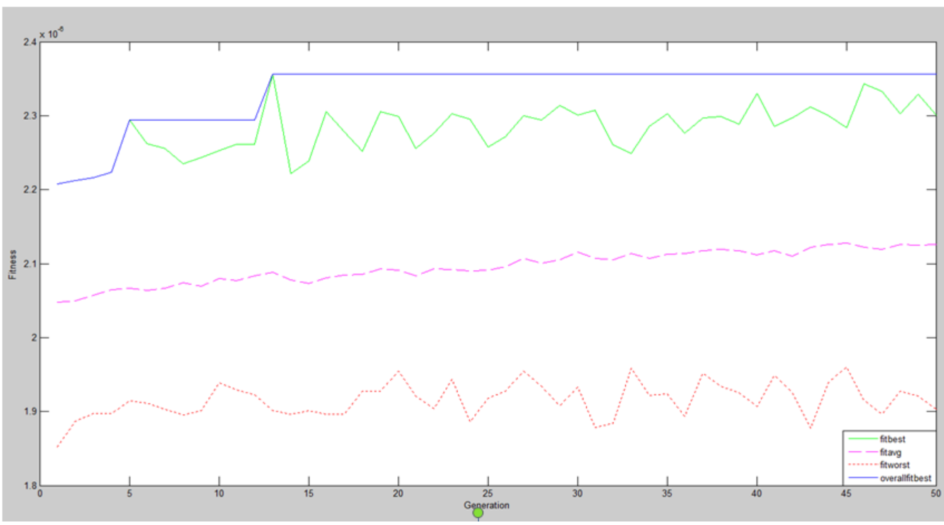
Table 4 Comprative of results on unequal area multi-row facility layout

<table>
<tr><th rowspan="2">Problem no</th><th rowspan="2">Number of facility</th><th rowspan="2">Schnecke and Vornberger (HGA) (1997)</th><th rowspan="2">Lee and Lee (GA) (2002)</th><th rowspan="2">Lee and Lee (HGA) (2002</th><th rowspan="2">Scholz et al. (TS) (2009)</th><th rowspan="2">Ingole and Singh (FA) (2017)</th><th rowspan="2">Ingole and Singh (BBO) (2021)</th><th colspan="3">Proposed GA</th></tr>
<tr><th>Objective function value</th><th>Percentage improvement</th><th>Facility permutation</th></tr>
<tr><td>1</td><td>n = 15</td><td>6,813</td><td>9,120</td><td>6,941.4</td><td>6,615.81</td><td>5,838.2</td><td>5,657.5</td><td>5371.8</td><td>5.32</td><td>|12, 4, 14, 11, 8| |5, 15, 3, 13, 2| |10, 6, 9, 7, 1|</td></tr>
<tr><td>2</td><td>n = 20</td><td>13,190</td><td>21,885</td><td>14696</td><td>13,198.40</td><td>11,505</td><td>10,952</td><td>10164</td><td>7.19</td><td>|10, 13, 4, 5, 11| |3, 7, 20, 2, 19, 8| |18, 6, 15, 1, 12| |14, 9, 17, 16|</td></tr>
<tr><td>3</td><td>n = 30</td><td>35,358</td><td>50,492</td><td>32,386</td><td>33,721.20</td><td>29,115</td><td>25,300</td><td>24653</td><td>2.55</td><td>|6, 15, 16, 25, 20, 1, 5| |22, 29, 19, 4, 26, 9, 2| |3, 27, 7, 12, 21, 28| |14, 10, 17, 30, 18, 24| |8, 11, 23, 13|</td></tr>
<tr><td>4</td><td>n = 40</td><td>-------------</td><td>-----------</td><td>----------</td><td>-----------</td><td>495940.1</td><td>417,554.6</td><td>415510</td><td>0.492</td><td>|4, 1, 6, 9, 24, 21, 8| |30, 2, 23, 13, 27, 12, 7| |33, 36, 25, 37, 17, 26, 39, 14, 3| |31, 9, 35, 40, 5, 10, 18| |34, 16, 32, 15, 38, 22, 11| |29, 28, 20|</td></tr>
<tr><td>5</td><td>n = 50</td><td>-------------</td><td>-----------</td><td>----------</td><td>-----------</td><td>2,046,281.0</td><td>1,922,378</td><td>1,713,800</td><td>10.84</td><td>|38, 22, 34, 44, 31, 46, 13, 12, 50, 39, 29| |27, 32, 11, 19, 23, 1, 36, 18, 14| |4, 25, 49, 5, 7, 15, 41, 6, 30| |45, 21, 48, 37, 47, 3, 28, 40, 26| |9, 20, 10, 8, 42, 16, 35, 17, 24, 33, 2|</td></tr>
</table>

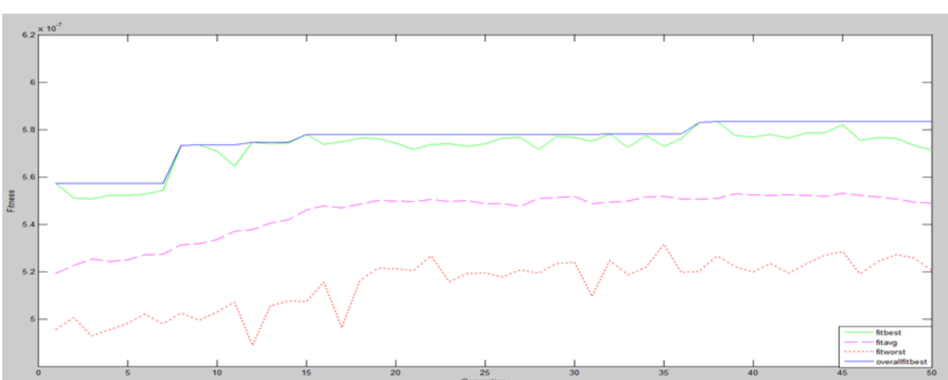
Table 5 CPU time compared with Schnecke and Vornberger (1997), Ingole and Singh (2017, 2021)

Problem no	*Number of facilities*	*CPU time (seconds)*			
		Schnecke and Vornberger (HGA) (1997)	*Ingole and Singh (FA) (2017)*	*Ingole and Singh (BBO) (2021)*	*Proposed GA*
1	n = 15	-	81.21	78.46	66.552
2	n = 20	2,400	167.59	160.88	118.976
3	n = 30	6,000	284.01	283.44	273.7282
4	n = 40	-----------	495,940.1	417,554.6	554.043
5	n = 50	-----------	2,046,281.0	1,922,378	922.7752

Figure 6 Convergence graph for the proposed genetic algorithm, (a) n = 40, (b) n = 50 (see online version for colours)



(a)



(b)

The computational efficiency of the proposed algorithm is evaluated on the two large size test problems of facility's size 40 and 50 adopted from Ingole and Singh (2021). The performance of the genetic algorithm is evaluated with the same genetic parametric values used for the first three problems set with small to medium size to have a fair comparison with the BBO and FA used by Ingole and Singh 2021. The considered GA evolves solution with better computational efficiency compared to BBO and FA (Table 4). In both problems of size 40 and 50 facilities, the proposed GA improves the solutions by 0.492% and 10.84% respectively. The improvement in solutions substantiates the computational efficacy for the proposed GA in discrete combinatorial optimisation problems. The convergence graph for the proposed genetic algorithm is shown in Figure 6, n = 40, n = 50.

5 Conclusions and future aspects

The facility layout significantly impacts the material handling costs, the work-in-process inventory levels, and the overall productivity of the FMS. The FLPs in the FMS are additionally constrained with orientation, shape and size, and pickup /drop-off point of facility types in comparison of the traditional facility layout.

In this paper, the developed genetic algorithm considers the quantitative aspects of facility layout in the flexible manufacturing system. The efficacy of the algorithm is testified on the problems of distinct size reported in the literature. The computational results provided for all the test problems signify that the developed heuristic outperforms in speed and quality of solution. The results evaluated on the benchmark problems reported in literature approve the proposed algorithm as an alternative solution strategy for the facility layout design in FMS.

In addition, more realistic facility layout can be modelled including the qualitative aspects; pickup/drop-off location, aisle designing for safety purpose considering the clearance space between the facilities, and specified machine adjacency requirement as a decision variable for the developed genetic algorithm.

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