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MODELING THE OPERATION ALLOCATION AND MATERIAL HANDLING SYSTEM SELECTION IN FMS DESIGN: A GENETIC ALGORITHM-BASED APPROACH

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ABSTRACT

This paper considers the problem of simultaneously determining the operation allocation and material handling system selection in an FMS environment with multiple performance objectives. A multi-objective 0-1 integer programming model is developed which selects the machines, assigns the operations of the part types to the selected machines, and assigns the material handling equipment to transport the parts, as well as to handle the part at a given machine. The first objective function minimizes the total costs of the manufacturing operations, material handling operations, and machine setups; the second objective function maximizes the part–equipment “compatibility.” The “compatibility” is a measure which is computed as a function of the capabilities of the equipment, and the technological characteristics of the parts. A genetic algorithm-based solution approach is presented and the solution results are discussed. Some computational aspects of the model, which pertain to the design of the genetic algorithm, are also discussed.

1 INTRODUCTION

The key issue in manufacturing operations is how to produce high quality products at low costs to satisfy customer demands in the shortest time possible. Flexible manufacturing systems (FMS) are acclaimed for their ability to produce a diverse range of parts efficiently, and for their capability to respond quickly to changes in demand and resources (Gupta and Goyal, 1989). Therefore, the development of FMS is considered one of the most important developments in industrial automation in recent times.

Operation allocation (OA) in FMS refers to the assignment of operations of the part types to the machines according to the operation sequences prescribed by the process plans for each part type, and subject to constraints operating on the system. Considering the integrating function of material handling within manufacturing operations, this planning decision is related to the material handling operations in the FMS in as much as the requirements of part movement must be expressly addressed.

Material handling (MH) accounts for 30-75% of the total cost of a product, and an efficient material handling system (MHS) can potentially reduce the manufacturing operation costs by 15-30% (Sule, 1994). These figures underscore the importance of MH costs as an element in improving the cost structure of manufacturing operations. The determination of an MH system involves both the selection of suitable MH equipment and the assignment of MH operations to each individual piece of equipment. Hence, material handling system selection (MHSS) can be defined as the selection of MH equipment capable of performing the required MH operations within the constraints operating on the manufacturing system.

Given the significance of material handling in FMS, an inadequately designed MHS may indeed interfere severely with the overall performance of the system and lead to substantial losses in productivity and operational efficiency, and to longer lead times. Thus, to avoid such pitfalls, MHS design has to be integrated into the overall design of the manufacturing system.

The paper is organized as follows. Section 2 presents a brief review of the related literature. In Section 3, the mathematical model is presented. In section 4 a genetic algorithm-based solution procedure is proposed, a numerical example is given to demonstrate the application of the model, and the computational results are discussed. Finally, some observations and conclusions are summarized in section 5.

2 RELATED WORKS

This section contains a brief review of the recent literature pertaining to genetic algorithm-based approaches to operation allocation and material handling system selection problem.

Joines *et al*. (1996) used a genetic algorithm to solve an integer programming model of the design of a cellular manufacturing system. The formulation is a unique representation scheme since it reduces the size of the cell formation problem and increases the scale of the problem that can be solved. This approach also improves the design flexibility by allowing a variety of evaluations of functions to be employed and by incorporating design constraints during formation. Gravel *et al*. (1998) presented a genetic approach to find efficient solutions to the problem of forming manufacturing cells for products having multiple routings. The method seeks to generate an efficient set of solutions which the decision maker may choose by evaluating the consequences for each of the objectives.

Sinriech and Meir (1998) suggested a genetic algorithm solution approach to solve the process selection and part cell assignment problem. The study assumed a production environment where each part has several process plans, each manifested by a required set of tools. A mixed integer linear program was developed to minimize the production cost. Morad and Zalzala (1999) proposed a genetic algorithm to solve the integrated process planning and scheduling problem as a multi-objective weighted-sum optimization model intended to minimize makespan, the total rejects produced and the total cost of production. Kumar and Shanker (2000) used genetic algorithm to solve a mixed integer programming model of part type selection and machine loading problems in the production planning of flexible manufacturing systems. Tiwari and Vidyarthi (2000) developed a genetic algorithm-based heuristic to solve the machine loading problem of a random type FMS. The objectives of the loading problems were to minimize the system unbalance and to maximize the throughput satisfying the technological constraints on the system.

Rai *et al*. (2002) applied a fuzzy goal-programming concept to model the problem of machine-tool selection and operation allocation with the objective of minimizing the total cost of manufacturing operations, material handling and set-up. A genetic algorithm (GA)-based approach was used to solve this model. Moon et al. (2002) formulated a 0-1 integer programming model of an integrated machine tool selection and operation sequencing, and used a genetic algorithm approach to solve the model. The model determines machine visiting sequences for all part types, such that the total production time is minimized and the workloads among machine tools are balanced.

Yang and Wu (2002) developed a genetic algorithm-based method to obtain the solution to a mixed-integer programming model of the part type selection and machine loading problems by minimizing the difference between maximum and minimum workloads of all the machine resources.

Given the complexity of the MHSS problem, only a few researchers have addressed the material handling problem using GA-based algorithms. Lim (1997) considered the problem of determining cyclic schedules for a material handling hoist in the printed-circuit-board (PCB) electroplating line by using a genetic algorithm-based approach. The objective was to determine an optimal simple-cycle schedule of the hoist which maximizes the line throughput rate.

Sinriech and Samakh (1999) developed a genetic algorithm approach for the pickup/delivery station location problem in MH systems that have a segmented flow topology (SFT), considering the intradepartmental flows in the problem formulation.

Aiello *et al*. (2002) proposed an integrated approach to the facilities and MH system design, and used a genetic algorithm approach to find the solution which minimizes the MH cost.

Paulo *et al.* (2002) presented a new framework for the joint consideration of the operation allocation and the material handling system selection problems. Two 0-1 integer programming models were proposed, one for OA, and the second for MHSS, and solved sequentially. Lashkari *et al.* (2004) extended the work of Paulo *et al.* (2002) by developing modified 0-1 integer programming models that were solved iteratively to obtain a *locally optimal* solution. The current work extends and modifies the previous works by Paulo *et al.* (2002) and Lashkari *et al.* (2004), by integrating the OA and MHSS models into a unified model in an attempt to generate an overall optimal solution.

3 MATHEMATICAL MODEL

In this section, a single, integrated model of OA and MHSS is presented. The model extends and modifies the works of Paulo *et al.* (2002) and Lashkari *et al.* (2004). However, the structural changes introduced in the previous two models are substantial, resulting in a model which in fact represents a new formulation of the problem.

The complete statement of the 0-1 integer programming model is as follows:

P(OA-MHSS):

1) Minimize Total Cost

$$\sum_{i=1}^{n} d_i \sum_{p=1}^{P(i)} \sum_{s=1}^{S(ip)} \sum_{j \in J_{ips}} OC_{sj}(ip) Y_{sj}(ip) + \sum_{j=1}^{m} SC_j M_j +$$

$$\sum_{i=1}^{n} d_i \sum_{p=1}^{P(i)} \sum_{s=1}^{S(ip)} \sum_{j \in J_{ips}} \sum_{h=1}^{H} \sum_{\hat{h}=1}^{\hat{H}} \sum_{e \in E_{jh\hat{h}}} T_{ijh\hat{h}e} X_{sjh\hat{h}e}(ip) \quad (1)$$

2) Maximize Compatibility

$$\sum_{e=1}^{E} \sum_{h=1}^{H} \sum_{\hat{h}=1}^{\hat{H}} W_{h\hat{h}e} \sum_{i=1}^{n} C_{ei} \sum_{p=1}^{P(i)} \sum_{s=1}^{S(ip)} \sum_{j \in J_{ips}} X_{sjh\hat{h}e}(ip) \quad (2)$$

(where, $C_{ei} = 1 - \frac{\sum_{t=1}^{T} \left| W_{et} - \hat{W}_{it} \right|}{4T}$)

Subject to:

$$\sum_{p=1}^{P(i)} Z(ip) = 1 \qquad \forall i \qquad (3)$$

$$\sum_{j \in J_{ips}} Y_{sj}(ip) = Z(ip) \qquad \forall i,p,s \qquad (4)$$

$$Y_{sj}(ip) = A_{sjh\hat{h}}(ip) \qquad \forall i,p,s,j,h,\hat{h} \qquad (5)$$

$$\sum_{e \in E_{jh\hat{h}}} X_{sjh\hat{h}e}(ip) = A_{sjh\hat{h}}(ip) \qquad \forall i,p,s,j,h,\hat{h} \qquad (6)$$

$$\sum_{i=1}^{n} \sum_{p=1}^{P(i)} \sum_{s=1}^{S(ip)} \sum_{h=1}^{H} \sum_{\hat{h}=1}^{\hat{H}} \sum_{e \in E_{jh\hat{h}}} X_{sjh\hat{h}e}(ip) \geq M_j \qquad \forall j \qquad (7)$$

$$\sum_{i=1}^{n} d_i \sum_{p=1}^{P(i)} \sum_{s=1}^{S(ip)} \sum_{h=1}^{H} \sum_{\hat{h}=1}^{\hat{H}} \sum_{e \in E_{jh\hat{h}}} t_{sj}(ip) X_{sjh\hat{h}e}(ip) \leq b_j M_j \qquad \forall j \qquad (8)$$

$$D_e \leq D_{\hat{e}} \qquad \forall e,\hat{e} \qquad (9)$$

$$\sum_{i=1}^{n} \sum_{h=1}^{H} \sum_{\hat{h}=1}^{\hat{H}} \sum_{p=1}^{P(i)} \sum_{s=1}^{S(ip)} \sum_{j \in J_{ips}} X_{sjh\hat{h}e}(ip) \geq D_e \qquad \forall e \qquad (10)$$

$$\sum_{i=1}^{n} d_i \sum_{h=1}^{H} \sum_{\hat{h}=1}^{\hat{H}} \sum_{p=1}^{P(i)} \sum_{s=1}^{S(ip)} \sum_{j \in J_{ips}} l_{h\hat{h}e} X_{sjh\hat{h}e}(ip) \leq L_e D_e \qquad \forall e \qquad (11)$$

$$\left(X_{sjh\hat{h}e}(ip), A_{sjh\hat{h}}(ip), Y_{sj}(ip), Z(ip), M_j, D_e, D_{\hat{e}} \right) \in \{0,1\}$$
$$\forall (i,p,s,h,\hat{h},e \in E_{jh\hat{h}}, j \in J_{ips}) \qquad (12)$$

There are two objectives associated with the model: equation (1) minimizes the costs related to the manufacturing operations, set ups, and MH operations; equation (2) maximizes the “compatibility” of the part types and the MH equipment assigned to handle the parts.

The constraint equation (3) is to ensure that each part type is processed under a single process plan. The constraint equation (4) ensures that for a given *(ip)*, each operation of the selected process plan is assigned to only one of the available machines. The constraint equation (5) is to ensure that, once a machine is selected for operation *s* of *(ip)*, then all the MH operation- sub-operation combinations ($h\hat{h}$) corresponding to *(sj)* have to be performed. The MH operation- sub-operations ($h\hat{h}$) refer to the MH activities at a machine when the part arrives for a manufacturing operation. The operation *h* refers to the main MH operation in relation to the manufacturing operation *s*, whereas the operation $\hat{h}$ refers to a secondary MH operation that normally follows the main MH operation, depending on the characteristics of the part type in question. The MH operation- sub-operations are defined below:

Operations h	**Sub-operations $\hat{h}$**
L = loading/unloading	O = orientation change
H = handling/rehandling	P = position change
T = transportation	Q = quantity change
I = inspection	S = sequence change
S = storage/retrieval	T = time change
	N = no change

The constraint equation (6) states that each ($h\hat{h}$) combination corresponding to operation *s* of *(ip)*, to be performed at machine *j*, has to be assigned to only one piece of MH equipment which is available and able to perform that combination. The constraint equation (7) ensures that, if machine *j* is selected, then at least one operation has to be allocated to that machine. The constraint equation (8) guarantees that the allocated operations do not burden a selected machine beyond its capacity. The constraint equation (9) specifies that a piece of MH equipment *e* may be chosen only after another piece of equipment $\hat{e}$ has been selected. The constraint equation (10) is to ensure that once a piece of MH equipment is selected, then at least one MH combination ($h\hat{h}$) has to be assigned to it. The constraint equation (11) states that the allocated tasks do not load a selected piece of MH equipment beyond its capacity. Finally, The constraint equation (12) imposes the binary restrictions on the variables.

The parameter C_{ei} in the objective function equation (2) is proposed by Paulo *et al.* (2002) as a measure of the “compatibility” of a piece of MH equipment and a part type. The three rating factors ($W_{h\hat{h}e}$, W_{et} and $\hat{W}_{it}$) are largely subjective, and relate the key product variables, as proposed by Ayres (1988), to the MH equipment and the part type. For details, see Paulo *et al.* (2002).

4 EXPERIMENTS AND DISCUSSION

4.1 A numerical Example

The following numerical example is taken from Paulo *et al.* (2002), and is solved using genetic algorithm. Due to space limitation, however, only selected portions of the problem data are presented. The full set of data is available upon request.

It is assumed that, over the planning period, there are *i* = 1,…,14 part types to be processed on *j*=1,…,10 machines each with a capacity of 57,600 seconds. Table 1 presents the data for part type 7 which is used here as an example. Part type 7 has $P(7)$ = 2 process plans. The capabilities of the machines to perform the operations of this part type are as follows. Under process plan p = 1, this part type has $S(71)$ = 2 operations with the indices $s \in \{1,2\}$, whereas under process plan p = 2, it has $S(72)$ = 2 operations, with indices $s \in \{1,2\}$. Operation s = 1 of process plan p = 1 for part type 7 can be completed on any of the machines $j \in J_{711} = \{1,6,7,9,10\}$, and operation s = 2 on any of the machines $j \in J_{712} = \{3,7,8\}$. The demand for part type 7 as well as the machine setup costs are also listed in Table 1.

Table 1: Manufacturing operations time $t_{sj}(ip)$ and costs $OC_{sj}(ip)$, part type demands d_i and machine setup costs SC_j

Machine, j	Part Types, i				Machine Set-up Cost SC_j
	7				
	Process Plan, p				
	1		2		
	Operation, s		Operation, s		
	1	2	1	2	
1	10 $15			7 $11	120
2			11 $14		230
3		7 $3			450
4				9 $18	60
5					180
6	8 $11				220
7	5 $3	10 $6			310
8		11 $10		8 $7	90
9	9 $14		11 $18		260
10	9 $11		9 $11		550
Demand, d_i	90				

The MH requirements are derived from the data in Table 1, and they explain the sequence of MH operation-sub operations required when a part arrives at a machine for a manufacturing operation to be performed. For example, a part arriving at machine may need *(un)Load/None* and *Transportation/None*, implying that, at that machine, the part is loaded with no specific requirements, and is then transported to the next machine. The data also specify what MH equipment are capable of performing these MH combinations.

It is assumed that the information about the MH cost $T_{ijh\hat{h}e}$ for each part type, for various $(h\hat{h})$ combinations and for various MH equipment e with respect to each machine is available. The times needed by MH equipment to perform the various operation/sub-operation combinations are also available.

Table 2 shows the relative weight of the product variable t on all part types. From this table, it can be seen that each part has different ratings corresponding to its characteristics, with scales ranging from 1 to 5. For part type 7 for example, it is noted that the part is rated 1 on complexity and precision which means that this part exhibits a very low level of these two key variables. In other words, part type 7 comprises a low measure of the geometrical or dimensional information embodied in it and is not held to high tolerance in manufacture. The very high value for diversity indicates that the corresponding part family has a large number of parts. It also can be inferred that this part type is manufactured in large-size batches. The very low rating for mass/linear dimension indicates that the physical size or dimension of the part is small.

In this example, there are nine different types of MH equipment which are available to perform the MH operation/sub-operation combinations, each with a capacity of 57,600 seconds during the planning period. Table 3 shows the relative weight of the product variable t on material handling equipment e. The rating scales range from 0 to 5 for the material handling equipment against the choices of manufacturing technology.

Table 2: The $\hat{W}_{it}$ values for the numerical example

Part, i	Complexity	Precision	Diversity	Batch Size	Mass/linear Dimension
1	2	2	3	2	2
2	5	5	1	3	4
3	3	3	1	2	3
4	4	2	2	4	4
5	2	3	4	1	3
6	3	2	1	2	2
7	1	1	5	5	1
8	4	3	2	1	2
9	2	1	2	1	3
10	2	1	3	3	3
11	2	2	2	4	1
12	4	5	1	2	3
13	4	2	2	5	2
14	2	3	2	2	4

Table 3: The W_{et} values for the numerical example

Equipment, e	Complexity	Precision	Diversity	Batch Size	Mass/linear Dimension
1.Light-load robot	4	4	2	4	1
2.Heavy-load robot	4	4	2	4	4
3. Human	5	4	4	2	2
4. Powered hand truck	1	1	4	3	3
5.Forklift truck	1	1	4	4	5
6.Roller belt conveyor	2	2	4	3	4
7. Light belt conveyor	2	2	4	3	2
8. AGV	4	4	1	1	2
9. AS/RS	4	4	5	3	3

4.2 Multi-objective Genetic Algorithms (MOGA)

In this section, we present a multi-objective genetic algorithm for the solution of the mathematical model presented in section 3. The algorithm will generate the part-process plans, operation, machine and MH assignments for the model.

4.2.1 Real-coded MOGAs

MOGA codes the optimization problem in the model as a chromosome by using real number-coded strings having o's to 9's where each *gene* corresponds to an operation allocation and MH selection sequence possibility in which one part is assigned. The structure of the *gene* is represented in Table 4. The sequence denotes the formation of operation allocation and MH system selection. In this table, Seq. No. is the sequence number, O1 is manufacturing operation 1, and O2 is manufacturing operation 2. In the MH Selection section, the three characters refer to the MH operation h, the MH sub- operation $\hat{h}$, and the manufacturing operation s, respectively, as explained earlier. For example, LO2 denotes *load/unload-orientation change* for manufacturing operation s=2.

Table 4: Operation allocation and material handling system selection sequence possibility

Seq. No.	OA		MH Selection						
	O1	O2	LO1	TN1	IO1	LO2	TN2	IP2	SN2
1	1	3	1	4	3	1	4	3	9
2	1	3	1	4	3	1	4	6	9
. . . 24300									

The table shows a few of the possible sequences for operation allocation and material handling system selection for part 7. Sequence number 1 is taken as an example. The first manufacturing operation will be performed on machine 1 and the second operation on machine 3. The "loading/unloading-orientation" combination for manufacturing operation 1 will be carried out using MH equipment 1 (i.e., light-load robot). "Transportation-none" will be performed by MH equipment 4 (i.e., powered hand truck) and the "inspection-orientation" combination by MH equipment 3 (i.e., human.) "Loading/unloading-orientation" for manufacturing operation 2 is performed by light-load robot; "transportation" by powered hand truck; "inspection-position" by human; and "storage/retrieval" combination by AS/RS. Similar interpretations can be made for other sequences. Table 5 represents the number of possible sequences for each part type and the number of digits for the numerical example described in section 4.1

Figure 1 illustrates the chromosome design in MOGA for part type 7. The length of the chromosome is the sum of the digits required to represent the maximum number of sequences. Hence, the length of the chromosome for the numerical example is 80. Figure 1 only depicts the *genes* representation of part 7 corresponding to the operation allocation and material handling system selection sequence number 2; however, the general design of the structure is the same for other part types, and similar interpretations can be drawn for other gene representations.

Table 5: Number of possible sequences for f each part and number of digits

Part	Maximum Sequence Number	Number of Digits
1	309150	6
2	282150	6
3	316500	6
4	681075	6
5	372825	6
6	810000	6
7	24300	5
8	660825	6
9	28350	5
10	214650	6
11	168300	6
12	247725	6
13	810000	6
14	9450	4
TOTAL		80

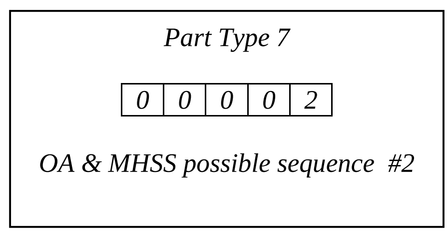

Figure 1: The chromosome representation for MOGA for part type 7

4.2.2 Fitness Function

Genetic algorithms have been largely applied to single-objective optimization problems. In order to apply genetic algorithms to a multi-objective optimization problem, the multiple objective functions may be combined into a single "fitness" function.

The weighted sum (WS) approach has been successfully applied to multi-objective GAs by Murata and Ishibuchi (1996), Gravel et al. (1998) and Morad and Zalzala (1999), and will be used her in order to obtain the set of solutions. This approach assigns weights to each objective function and combines the weighted objectives into a single objective function. Hence, the objective function of the model P(OA-MHSS) becomes:

$$\text{Min } f = w_1F_1 - w_2F_2 \qquad (13)$$

where:
w_i = weight i, i = 1, 2
$F1$ = objective function 1 (total costs)
$F2$ = objective function 2 (compatibility)

4.2.3 Constraints

Violation of constraints in a GA is handled in two ways. The first method prescribes the chromosomes to be designed in such a way that constraints are not violated when new solutions are generated. This method increases the computational time in generating new solutions but it always generates feasible solutions. The second method constructs a 'penalty function' to penalizes the fitness of a solution that violates a certain constraint. This method has been the most popular for constrained optimization by GA, but it increases the search time of the algorithm. Considering the structure of constraints (8) and (11) in our model, the penalty function method is the more suitable technique. These two constraints are converted into penalty functions and combined with the objective function, as explained below.

4.2.3.1 Machine Time Penalty Function (P1)

Machine time penalty comes into effect when operation allocation time on a machine exceeds the available time on that machine, i.e. when constraint (8) is violated. The penalty for machine time (P) is given by:

$$P1 = \begin{cases} 0 & \text{if } MA \geq ML \\ K\,(MA - ML) & \text{if } MA < ML \end{cases} \qquad (14)$$

where:
K = a positive constant
MA = machine availability
ML = machine load

4.2.3.2 Equipment Time Penalty Function (P2)

Equipment time penalty is the penalty for violating equation 11, i.e. when the total operation time of material handling equipment exceeds its capacity. The penalty for equipment time (P) is given by:

$$P2 = \begin{cases} 0 & \text{if } EA \geq EL \\ K\,(EA - EL) & \text{if } EA < EL \end{cases} \qquad (15)$$

where:
K = a positive constant
EA = machine availability
EL = machine load

Both penalty functions are merged with the main objective function to form the fitness function of a chromosome:

$$\text{Fitness} = f + P1 + P2 \qquad (16)$$

4.2.4 GA Operators

4.2.4.1 Selection Strategy

Reproduction is usually the first operator applied to a population. Reproduction selects good strings in a population and forms a mating pool. Both stochastic and deterministic sampling mechanisms are used in this study.

The best known stochastic method is Holland's proportionate selection or roulette wheel selection. The basic idea is to determine selection probability (also called survival probability) for each chromosome proportional to the fitness value. In addition, the elitist strategy is employed to specify that the best individual always survives intact into the next generation so as to enable the GA to converge faster. In the absence of such a strategy, it is possible for the best chromosome to disappear due to sampling error, crossover or mutation.

4.2.4.2 Crossover Operator

Blended crossover (BLX-α) is applied in this MOGA application. This operator produces offspring on a segment defined by two parents and a user specified parameter α as described below.

Offspring 1 = γ.Parent1 + (1-γ).Parent2
Offspring 2 = (1-γ).Parent1 + γ.Parent2
$\gamma = (1 + 2\alpha).\text{RAND1} - \alpha$

where offspring 1and offspring 2 denote encoded design variables of the offspring, members of the new population, and parent 1,2 denote the parents, a mated pair of the old generation. The random number, RAND1, is a uniform random number in the range [0-1].

4.2.4.3 Mutation Operator

The mutation operator alters the gene of a selected chromosome by a random change with a probability equal to the *mutation rate* (p_m). A number between 0 and 1 is generated at random. If the random number is less than equal to p_m, then the mutation occurs. The mutation operator simply replaces a gene (i.e., a real parameter value) in a chromosome with another number randomly chosen within the bounds of the parameter value.

4.2.5 GA Procedures

The algorithm operates by calling several procedures, which can be summarized as follows:

1. Procedure GENERATE: The initial population is randomly generated. The string for the population is described in Figure 2.

2. Procedure EVALUATION: The fitness value of each string recorded in the population is evaluated.

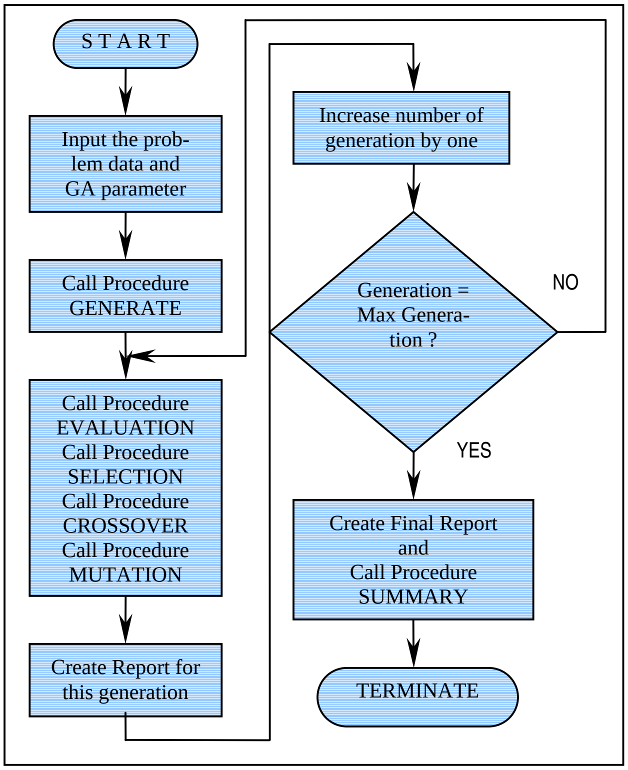

Figure 2: Flow chart of real coded GA

3. Procedure SELECTION/REPRODUCTION: A new population is created by selecting good strings among the old population and forming a mating pool.
4. Procedure CROSSOVER: Two new string records are created by randomly selecting two strings from the current population and mating their string structures.
5. Procedure MUTATION: A new string record is created by altering the value of gene or genes in one randomly selected string structure.

4.2.6 Computational Experience

The GA was coded in Java language program, and the computations were carried out using an Intel Pentium 4, 1.7 GHz computer, 256 MB RAM. The program contains about 1600 lines.

A summary of the results obtained by GA is shown in Table 6, and the portion of the results for part type 7 (corresponding to the case of W_1=1, W_2=2) is presented in Table 7. Part type 7 will be processed under process plan 1. Manufacturing operation 1 is assigned to machine 7, and manufacturing operation 2 is assigned to machine 3.

Table 6: Results obtained by GA using the weighted sum method

GA's General Parameters	W_1	W_2	Total Cost	Compatibility
	1	1	$ 15,007	322
Population Size: 220	1	20	$ 15,657	332
Crossover Probability: 0.95	1	40	$ 16,500	342.2
Mutation Probability: 0.2	1	60	$ 17,059	349.3
Maximum Generation: 100	1	80	$ 18,561	364
	1	100	$ 19,492	370.5

Table 7: The model solution corresponding to first experiment

Part Type 7				
Plan	**Manuf.. Operation**	**Machine**	**MH Operations**	**Equipment**
1	1	7	(un)Load/ None	Light-load robot
			Inspection / Orientation	Roller belt conveyor
			Transportation / Orientation	Light belt conveyor
	2	3	(un)Load/ Orientation	Human
			Inspection/ Position	Roller belt conveyor
			Transportation / None	Power hand truck
			S&R/None	AS/RS

During the first manufacturing operation, a *light-load robot* performs the MH operation *load/unload*; the part is then inspected, requiring an *orientation change* and using a *roller belt conveyor*. Next, the part is *transport*ed to the next machine, using a light belt conveyor, and its *orientation changed*. At machine 3 to perform the next manufacturing operation, the part requires the MH operation *load/unload,* using a human. It is then *inspect*ed and its *position chang*ed using a *roller belt conveyor*; next, the part is *transport*ed, on a power hand truck, to the storage area using the AS/RS equipment.

Figure 3 present the objective function values from GA. It should be noted that genetic algorithm-based heuristics do not guarantee truly optimal solutions, and the selection of a "best" solution is left to the decision maker to choose a solution, from among the set of Pareto- optimal solutions, that strikes an acceptable balance between the two objective function values. However, experience has shown that, in general, the computation of a well-diverse set of Pareto-optimal solutions is usually time consuming (Laumanns et al., 2002).

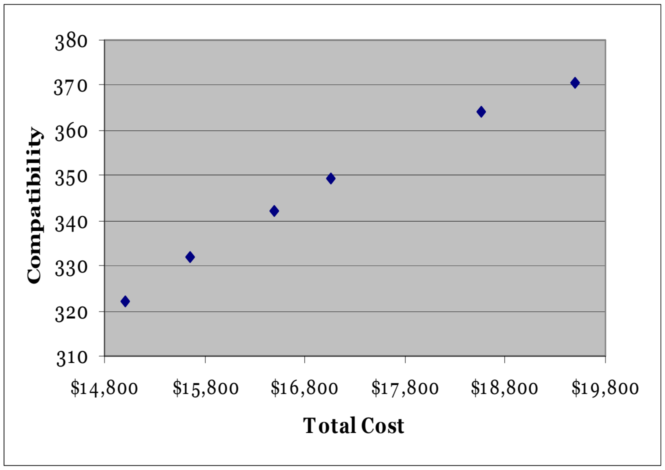

Figure 3: Solutions obtained using the weighted-sum method

5 CONCLUSIONS

In this paper, a mathematical model is developed to simultaneously solve the problems of operation allocation and material handling system selection. The purpose of this multi-objective model is to determine: (i) the allocation of the different operations of the part types to machines so as to minimize the total costs of operations, machine set-up and material handling; and (ii) the assignment of the MH equipment to the MH operation/sub-operations corresponding to the operation allocations (part, plan, operation, machine) so as to maximize the compatibility of MH equipment with part type. The solutions to the model are generated using a genetic algorithm-based approach. From the range of solutions generated by the algorithm, the decision maker may choose the one that achieves an acceptable balance between the two objective function values.

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APPENDIX: NOTATION

Indices and sets

$i \in \{1,2,\ldots,n\}$	part types
$p \in \{1,2,\ldots P(i)\}$	process plans for part type i
(ip)	a part type i, process plan p combination
$s \in \{1,2,\ldots S(ip)\}$	operations of part type i under process plan p
$h \in \{1,2,\ldots H\}$	major MH operations
$\hat{h} \in \{1,2,\ldots \hat{H}\}$	MH sub-operations
$(h\hat{h})$	a MH operation-sub operation combination
$e \in E_{jh\hat{h}}\{1,2,..,E\}$	set of MH equipment that can handle the combination $(h\hat{h})$ at machine j
$j \in J_{ips}\{1,2,..,m\}$	set of machines that can perform operation s of (ip)
(sj)	an operation s, machine j combination

Parameters

b_j	time available on machine j (units of time)
$OC_{sj}(ip)$	cost of performing operation s of (ip) on machine j ($)
d_i	demand for part type i (units)
SC_j	setup cost of machine j ($)
$t_{sj}(ip)$	time for performing operation s of (ip) on machine j (units of time)
$T_{ijh\hat{h}e}$	MH cost of performing the $(h\hat{h})$ combination for part type i on machine j using MH equipment e ($)
L_e	time available on MH equipment e (units of time)
$l_{h\hat{h}e}$	time for MH equipment e to perform the $(h\hat{h})$ combination (units of time)
$\hat{W}_{it}$	relative weight of the product variable t on part type i
W_{et}	relative weight of the product variable t on MH equipment e
$W_{h\hat{h}e}$	relative degree of the capability of MH equipment e to perform the $(h\hat{h})$ combination
C_{ei}	compatibility between MH equipment e and part type i

Decision Variables

$Z(ip) \varepsilon \{1,0\}$	= 1 if part type i is processed under process plan p; 0 otherwise
$Y_{sj}(ip) \varepsilon \{1,0\}$	= 1 if machine j is used to perform operation s of (ip); 0 otherwise
$A_{sjh\hat{h}}(ip) \varepsilon \{1,0\}$	= 1 if (ip) requires the combination $(h\hat{h})$ at machine j where manufacturing operation s is performed; 0 otherwise
$X_{sjh\hat{h}e}(ip) \varepsilon \{1,0\}$	= 1 if the combination $(h\hat{h})$ requires MH equipment e at machine j where manufacturing operation s of (ip) is performed; 0 otherwise
$M_j \varepsilon \{1,0\}$	= 1 if machine j is selected; 0 otherwise
$D_e \varepsilon \{1,0\}$	= 1 if MH equipment e is selected; 0 otherwise

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