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Design a Self Reliant Machine Cell Considering Alternative Routing Flexibility Using Genetic Algorithm Based Heuristic

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Abstract - **In this paper, genetic algorithm based heuristic is proposed to solve the self reliant machine cell formation problem. The proposed algorithm selects the optimum part route with fixed operation sequence before clustering the machines and part family. A heuristic is applied within the genetic algorithm to assign parts to independent cell. The proposed model exclusively takes in to accounts relevant production data such as production volume, alternative part process route and operation sequence. Conventional optimization method for the optimal cell formation problem requires substantial amount of time and large memory space. Hence a genetic algorithm based heuristic method has been developed for solving the proposed model. The results approve the effectiveness of the proposed method in designing the manufacturing cell.**

Keywords **-** Cellular Manufacturing System, Genetic Algorithm, Cell Formation Problem, Alternative Routing.

1. INTRODUCTION

A cellular manufacturing (CM) problem has captured a great deal of attention of many manufacturers and researchers. The variety and the uncertainty of demand, variety of characteristics of the product and manufacturing process are the reasons that motivated the request for flexibility. Manufacturing systems must be able to produce products with low production costs and high quality as quickly as possible in order to deliver the products to customers in time [14-20]. The traditional manufacturing systems, such as job shops and flow lines, are not capable of satisfying such requirements. The Cellular manufacturing (CM) is a hybrid system linking the advantage of both job shops (flexibility in producing a wide variety of product) and flow line (efficient flow and high production rate). The cellular manufacturing system (CMS) organized production process into smaller units called machine cells (MC). Each cell operates independently; the inter-cellular parts trade-off is minimized, i.e., parts do not move from one cell to another for processing. The implementation of CMS helps organization to achieve several benefits, such as simplified production planning, process control, reduced through put times, reduced work-in-process inventory, reduced set-up times and reduced material handling. Over the last three decades, a large number of clustering methods have been developed for identifying potential manufacturing cells [21-28].

2. LITERATURE REVIEW

Albadawia et al. [1] addressed an approach to solve cell formation problem, involves two phases. In the first phase, machine cells are identified by applying factor analysis to the matrix of similarity coefficients. In the second phase, an integer-programming model is used to assign parts to the identified machine cells. To evaluate its performance, the proposed approach is applied to a real life problem from a manufacturing plant.

Brown [3] develop a mathematical model that minimizes total costs of a CMS with intercellular transfer, machine duplication, and subcontracting while taking machine capacities into account to avoid capacity violations.

Iqbal [4] addressed an approach to balance the total inter-cell moves cost and total intra-cell moves cost and to minimize the sum of the two. A nonlinear mathematical model has been proposed. The case targets the conversion of an existing job shop, employs seven machines for manufacturing six different jobs, into a CMS. The solution to the case is verified by production simulation. The total inter-cell and intra-cell moves costs suggested by the algorithm are found in good agreement with the simulation results.

Jayaswal & Adil [12] developed a model and solution methodology for a problem of cell formation to minimize the sum of costs of inter-cell moves, machine investment and machine operating costs considering alternative routing.

Lozano et al. [5] investigate two sequence-based neural network approaches for cell formation. The objective function is the minimization of transportation costs (including both intra-cellular and inter-cellular movements). The problem is formulated mathematically and shown to be equivalent to a quadratic programming integer program that uses symmetric, sequence-based similarity coefficients between each pair of machines.

Mahdavi et al. [6] developed a mathematical model for the joint problem of the cell formation problem and the machine layout. The objective is to minimize the total cost of inter-cell and intra-cell movements and the investment cost of machines. This model has also considered the minimum utilization level of each cell to achieve the higher performance of cell utilization. Two examples from the literature are solved by the LINGO Software to validate and verify the proposed model.

Mahdavi et al. [7] addressed a cell formation problem. The objective is to group the machines and parts in dedicated manufacturing cells with minimize number of voids and exceptional elements in the cells. A genetic algorithm is proposed to solve the problem.

Mukattash et al. [8] addressed an algorithm for the formation of manufacturing cells with unbounded cell sizes, such that inter-cell movements are minimized. A closed interval for the solution is then specified with a lower bound of the minimum inter-cell movements for the initial conditions and an upper bound on the inter-cell movements of the last cell. A combinatorial proof is provided to show that there exists at least one solution starting from the initial conditions.

Shiyas & Pillai [9] proposed a genetic algorithm (GA) based solution procedure, applied for the mathematical model, provides best cell configuration. This GA is integrated with a part assignment rule to get both the cell and part family configurations. The GA is applied by using LINGO software.

Shiyas and Pillai [10] develop a genetic algorithm (GA) based solution methodology for the model which is also solved using an optimization package. This model provides the decision maker the flexibility of choosing a suitable cell design from different alternatives by considering the practical constraints

Solimanpur & Kamran [11] developed a mixed-integer and non-linear mathematical programming formulation to find the optimal solution. A technique is used to linearized the formulated non-linear model. A genetic algorithm is proposed to solve the linearized model. The effectiveness of the GA approach is evaluated with numerical examples.

The review of the research literature cited above reveals various techniques proposed for design of CMS. This paper presents a mathematical model to design the independent CMS considering alternative part route using GA based heuristic. The model is designed considering realistic industrial manufacturing vision.

2. PROBLEM FORMULATION

In the present work, the objective of cellular system design is to integrate it with the alternative part routings with fixed sequence of operations which yields a machine-part matrix with least machine operating time and minimum trade-off between the cells. A mixed integer formulation of the PF/MC formation problem is presented below. The following assumptions and notations are used to develop the mathematical representation of the objective function and design constraints.

2.1 Assumptions

1. The demand size for each part type is known.
2. Operating cost of each machine type per hour is known.
3. Each part type is processed by known sequence of operation.
4. The cell size is specified in advance.
5. The Operating times for all the part types on different machine types are known.
6. Each machine type can perform multiple operations. Likewise, each operation can be done on one or more machine types in different times.
7. The machine procurement cost of each machine type is known.
8. Setup times and inventory are not considered.

2.2 Notation

(a) ***Indicex set***

P {p=1, 2, 3, . . . , P} Part types. K {k= 1, 2, 3, ..., Op} Operation k for part type p.

M {m=1, 2, 3, ... M} Machine types. C {c=1, 2, 3, . . . … C} Manufacturing cells.

(b) Input Parameters

P = Number of part types. Op = Number of operation of part p.

M = Number of machine types. C = Maximum number of cells that can be formed.

DDp =Demand for part type p. μ_m = Operating cost per hour of machine type m.

δ_{intra} = Intra-cell material handling cost. σ_m = Procurement cost of machine of type m.

LB = Lower bound cell size. UB = Upper bound cell size.

T_{kpm} =Time required to perform operation i of part type p on machine type m.

$e_{kpm} = \begin{cases} 1, if\ operation\ \ k of\ \ part\, type\ \ p\, can be\, done on\, machine\, type\ m \\ 0, otherwise. \end{cases}$

(c) Decision Variables:-

U_{mc} = Number of machine types used in cell c.

$f_{kpmc} = \begin{cases} 1, if\ operation\, of\ \ part\, type\ \ p\, is\, done\, on\, machine\, type\ m\, in\, cell\ c. \\ 0, otherwise. \end{cases}$

2.2.1 Objective functions

The subsection presents a fixed integer-binary programming model that selects optimum part process route, minimize material handling and machine duplication. The model generates configuration of independent cells while taking into account the alternative routings with fixed sequence of operations of each part type.

$$Z_{\min} = \sum_{c=1}^{C}\sum_{m=1}^{M} U_{mc}\sigma_m + \sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{k=1}^{O_p} DD_P TR_{kpm} f_{kpmc}\mu_m + \sum_{p=1}^{P}[DD_p](\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{k=1}^{O_p-1}\gamma^{\text{intra}}[f_{k+1,pmc} - f_{kpmc}]) \quad (1)$$

The first term of the objective function Z presents the machine procurement cost. The second term presents processing cost for operations performed on machine type m and the last term imply material handling cost.

Subjected to:

$$\sum_{c=1}^{C}\sum_{m=1}^{M} e_{kpm} f_{kpmc} = 1 \quad (2) \qquad \sum_{m=1}^{M} U_{mc} \geq LB \quad (3)$$

$$\sum_{m=1}^{M} U_{mc} \leq UB \quad (4)$$

Equation (2) ensure that each part operation is assigned to one machine and one cell. Equation (3) & (4) specify the lower & upper bound.

3. GENETIC ALGORITHM BASED HEURISTIC SOLUTION PROCEDURE

A genetic algorithm based procedure is adopted for solution of design of CMS modeled in previous Section. An emblematic GA is based on the controlled growth of population, recombination operators and propagation over generations. The GA based solution procedure is presented in following sub-sections.

3.1 Chromosome Representation of solution

The chromosomal representation of solution applied to the proposed CMS model comprises of the following genes.

$$\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1R} \\ \vdots & & \dots & \vdots \\ x_{p1} & x_{p2} & \cdots & x_{pR} \end{bmatrix} \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1R} \\ \vdots & & \dots & \vdots \\ y_{p1} & y_{p2} & \cdots & y_{pR} \end{bmatrix}$$

Fig.1 Chromosome macroscopic structure

The matrix [X] indicates allocation of operation sequence of part type p to machines. The matrix [Y] implies row wise allocation of machines set in cells.

3.2 Initialization of the population

The initial population of preferred volume is generated randomly in steps. In first step, the segment [X] of the chromosome is generated randomly considering feasibility of performing part operation on machines. In second step segment [Y] of the chromosome is filled randomly. Solution for given problem is represented by the embedded segments (genes) structure known as chromosome.

3.3 Evaluations:

The fitness value is a decisive factor to measure the quality of a candidate solution or chromosome with reference to the designed objective function (Equation set 1) subjected to constraints (Equation set 2-4). The fitness values are used to select the parent solutions to obtain the next generation of solutions. The descendants or new solutions are selected with higher fitness value obtained by playing binary tournament between parent solutions.

The objective function of the CMS design problem is to minimize the total cost. However, genetic algorithm works with maximization functions. Thus necessary transformation from objective function to the fitness function is carried out in the following manner. [13]

$$Z_i = \frac{C_{\min}}{0.1 + C_i}$$

Z_i : fitness value of string *i*,
C_i : objective function value of the string *i*
$C_{\min}$: The smallest objective function value in the current generation.

If the smallest objective function value is equal to zero, its value is set equal to 0.1. Thus the maximization of the fitness value corresponds to the minimization of the objective function (total cost) value.

3.4 Genetic Operators

3.4.1 Reproduction or Parent Selection

After evaluating the fitness value of chromosomes in the population, better performing chromosomes (parents) are selected to produce the descendants. Chromosomes with higher fitness value have a higher chance of being selected more often, which is achieved by playing binary tournament between parent chromosomes according to their fitness value. Different selection schemes have been presented by Goldberg [14].

3.4.2 Crossover or Recombination

Crossover is performed between two selected parent solutions which create two new child solutions by exchanging segments of the parent solutions, thus child solutions retain partial properties of the parent solutions. Figure 2 depicts the chromosomes parent1 and parent 2 selected for crossover. There are two segments in the chromosome

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one each for machine and cell. For crossover, the selection of segments can be row-wise or column-wise following the matrix limits and the crossover probabilities.

3.4.3 Mutation

Mutation performs a secondary role in functioning of genetic algorithms. Even though crossover operator makes an effective search and recombines chromosome, yet it may cause loss of some useful genetic properties. The mutation operator safeguards against such an irretrievable defeat. The mutation operator performs local search with a low probability. The mutation operator can be implemented by inverting part of a gene in a parent chromosome to obtain child chromosome, as shown in Figure 3.

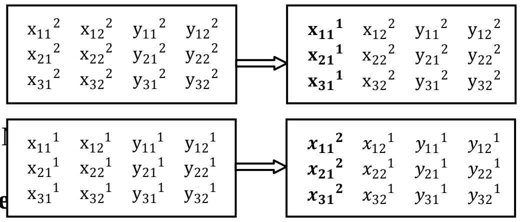

Fig. 2 Recombination or crossover

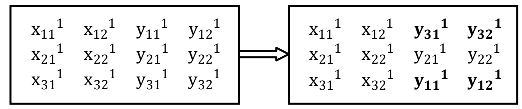

Fig. 3 [illegible]

3.4.4 Re[illegible]

The c[illegible]t chromosome structure so as to yield infeasible solutions i.e. ev[illegible]of machine type. The repair function is used to repair the distorted chromosome such that no machine type is left unassigned, and every cell gets minimum number of machines as per Equation (3-4).

3.4.5 Stopping Criterion:

The genetic algorithm continues to create population of child solutions until a criterion for termination is met. A single criterion or a set of criteria for termination can be adopted. In this case the termination criterion is the maximum number of generation, i.e. the algorithm stops functioning when a specified number of generations are reached.

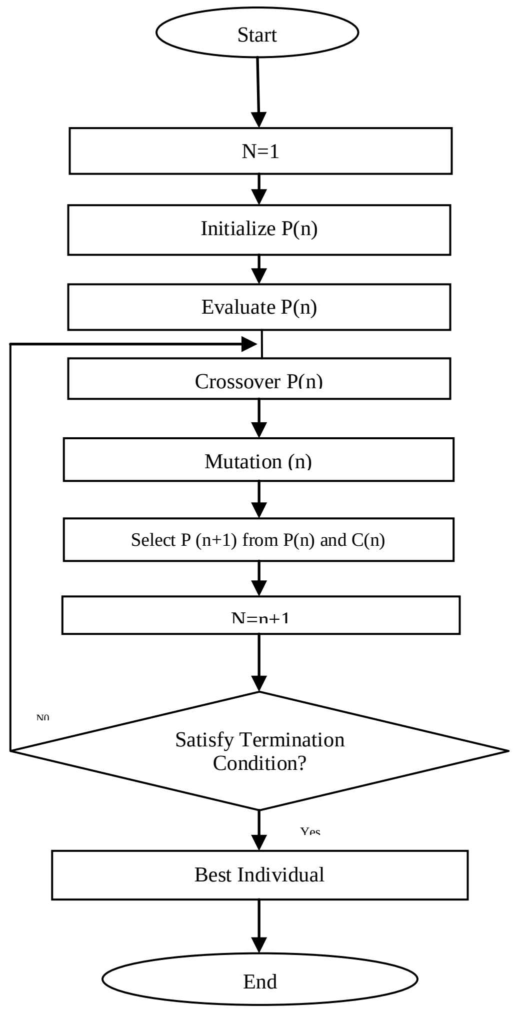

Fig. 4 Genetic Algorithm Flow chart

4. COMPUTATIONAL EXPERIENCE

To evaluate the computability of the proposed algorithm different problem scenario is adopted from the literature. Since the majority of cellular manufacturing systems operate with few cells and machines, the selected problem can provide a general perspective of the applicability of the proposed algorithm. The algorithm is coded in MATLAB-2009 and run on 2GHz Pentium-IV workstation with Windows 7. Based on the computational experience the following values are considered for the parameters: Pmut=0.025, Pcross=0.7, Pop Size=100 and Maxgen=50.

In order to verify the performance of the GA and computational capability, a total of fourteen problems have been solved by varying resolution parameters such as number of part type, cell size, and number of cells. A sample graph is also shown in Fig. No 5. The data set of the problem scenarios are randomly generated and time spent in seconds to obtain result depicted in table no 1.

5. CONCLUDING REMARKS

A mixed integer mathematical model considering alternative routings for each part type is presented. A heuristic algorithm is developed for unallied cell formation. The proposed algorithm generates a feasible solution by taking into consideration all the alternative routing of each operation & constraint on cell size.

The goal of this research is to develop a design methodology that minimizes the machine duplication, intra-cell material handling cost and operating cost by considering alternative routing. The proposed model generates machine cells and part families simultaneously and selects the best route instead of the user specifying predetermined routes.

Scenario No	No. of parts	No. of cells	No. of Operations	No. of machine	Time Elapsed (Sec.)
Scenario 1	11	3	2-4	10	5.5045
Scenario 2	12	3	3	8	5.5590
Scenario 3	12	3	2-4	12	5.7242
Scenario 4	12	3	3-6	12	5.9647
Scenario 5	14	3	2-5	14	6.3016
Scenario 6	15	3	2-4	15	6.3419
Scenario 7	20	6	2-3	11	6.3993
Scenario 8	20	5	2-3	11	6.7616
Scenario 9	20	3	2-3	11	6.7760
Scenario 10	12	3	4-8	12	6.8537
Scenario 11	20	3	2-4	15	6.9893
Scenario 12	30	5	2-4	15	7.6536
Scenario 13	30	7	2-4	15	7.5875
Scenario 14	30	3	2-4	15	7.6596

Table: 1. List of Problem Scenarios

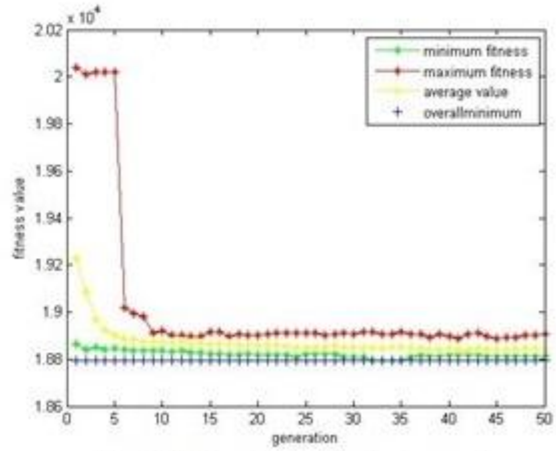

Fig. No 5 Sample graph of a Scenario

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