Research Journal of Applied Sciences, Engineering and Technology 7(1): 165-168, 2014
DOI:10.19026/rjaset.7.235
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: May 08, 2013 Accepted: June 06, 2013 Published: January 01, 2014

Research Article
Optimization of Inter Cellular Movement of Parts in Cellular Manufacturing System Using Genetic Algorithm

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Abstract: In the modern manufacturing environment, Cellular Manufacturing Systems (CMS) have gained greater importance in job shop or batch-type production to gain economic advantage similar to those of mass production. Successful implementation of CMS highly depends on the determination of part families; machine cells and minimizing inter cellular movement. This study considers machine component grouping problems namely inter-cellular movement and cell load variation by developing a mathematical model and optimizing the solution using Genetic Algorithm to arrive at a cell formation to minimize the inter-cellular movement and cell load variation. The results are presented with a numerical example.

Keywords: Cell formation, cellular manufacturing, genetic algorithm, optimization

INTRODUCTION

Modern manufacturing environment is characterized by competitive market, larger product variety, fast changing customer needs and shorter product life cycles. This leads to efficient resource utilization and attempts to preempt a competitive response. This brings into the picture the technique of Cellular Manufacturing Systems (CMS) which has received considerable attention among researchers in providing a cell formation method such that the resources are utilized to the maximum extent with minimization of cost, maximizing the output and to over all control of the production process.

Cellular manufacturing systems acts as a compromise between flow line production and job shop production. These are the result of direct application of Group Technology (GT) philosophy. In GT, parts that have similar processing requirements such as machines, tools, routes and geometrical shapes are classified into part families (Javadian *et al*., 2010).

Machine cells contain groups of functionally dissimilar machine types such that each machine cell processes one or more part families. Reorganization of functional shop processes leads to several benefits such as reduction in production costs, setup and throughput times, work-in process inventories, material handling as well as improvements in machine utilization.

A bi-criteria mathematical model is proposed for a machine cell formation problem and solution approach using Genetic algorithm (Venugopal and Narendran, 1992). A simultaneous solution of the machine grouping and cell layout problem is modeled using simulated annealing technique (Attahiru *et al*., 1992). A machine cell component problem is modeled and solution approach with a genetic algorithm (Onwubolu and Mutingi, 2001). A competitive study of simulated annealing; genetic algorithm and Tabu search is made for designing CMS (Ahemed *et al*., 2004).

A methodology for forming manufacturing cells is developed (Genwook, 2006) using a new similarity coefficient and solution using Genetic algorithm. A mathematical model is considered to identify machine groups and part families using an efficient simulated annealing (Abdelmole and Taboun, 1999). A comparative study of Tabu search procedures is made (Jeffery, 2005) for the cell formation problem with four other procedures that generate heuristic solutions. A mathematical model is developed (Poornachandra and Vira, 2005) and used Kusiak's method, in design of CMS with assembly considerations, for finding out similarity coefficient. Recently, an optimization algorithm for cell load variation was developed (Hossein and Tang, 2013). A hybrid algorithm for design of incremental cellular manufacturing systems was developed using Genetic algorithm and neural network (Rezaeian *et al*., 2011).

Intercellular movement value corresponds to the total number of inter-cellular moves of all the parts in a particular machine-cell cluster or machine cell arrangement. Inter-cell movement is one of the important variables for cellular manufacturing design. The value of the inter-cell movement changes with machine-arrangement. Optimization of inter-cell movements leads to minimizing the transportation cost between cells, which results in reducing manufacturing cost. Cell load variation is also another important criterion in design of CMS. Minimization of cell load is

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ideal where balancing work load with in cell is the design criteria or where there is restriction on the available working time period.

Genetic Algorithm (GA) is heuristic technique used to find best solutions to optimization and search problems. These are a part of evolutionary algorithms that use techniques like inheritance, mutation, selection and cross over. This algorithm is an iterative process which ends once the termination condition is satisfied. Here in this study, a cell formation problem is solved using bi-criteria mathematical model subjected to constraints and the results are optimized using genetic algorithm technique to obtain a cell configuration such that inter-cellular movements and cello load variations are minimized. The Genetic algorithm codes for given problem statement is written and simulated in MATLAB 7 and results are explained with a case study. The system requirements to simulate algorithm are windows operating system, minimum of 256MB RAM and 2000MB free space on hard disk.

PROBLEM FORMULATION

In this study, a machine component grouping problem with two main objectives is considered .A fifteen parts ten machines problem is considered to find out the best possible cellular grouping of machines and parts to minimize cellular movement. The objectives considered are minimization of inter cell movements and minimization of cell load variations.

Indices and parameters:

- r = Part of the product 1, 2, 3…n
- n = Total number of parts
- p = Machine cells 1, 2....k
- k = Total number of cells
- m = Total number of machines
- i = Machine index 1, 2…m
- t_{ir} = Processing time (hour/piece) of component r on machine i
- T_i = Available time on machine I in a given period of time
- Nr = Production requirement of component r in a given period of time
- W = $[w_{ir}]$ is an m×n machine-component incidence matrix where
- w_{ir} = Workload on machine i induced by part
- r = $(t_{ir} \times Nr)/ T_i$
- X = $[x_{ip}]$ is an m×k cell membership matrix where
- x_{ip} = 1if i-th machine is in cell p = 0 otherwise
- M = $[m_{pr}]$ is a k×n matrix of average cell load where
- m_{pr} = $(\sum_{i=1}^{m} x_{ip} w_{ir})/(\sum_{i=1}^{m} x_{ip})$
- E = $[e_{ri}]$ is an n×m matrix where
- e_{ri} = 1 if t_{ir}>0 = 0 otherwise
- y_{rp} = 1 if $\sum_{i=1}^{m} (e_{ri} x_{ip}) > 0$ = 0 otherwise

Objective function:

- Minimization of Intercellular Movement:

$$F_1=\sum_{r=1}^{n} Nr \left[\sum_{p=1}^{k} (y_{rp}-1)\right]$$

- Minimization of cell load variation:

$$F_2=\sum_{i=1}^{m} \sum_{p=1}^{k} x_{ip} \sum_{r=1}^{n} (w_{ir}- m_{pr})^2$$

Constraints:

- Unique assignment of machines to cells

$$\sum_{p=1}^{k} x_{ip} = 1 \text{ for } i=1,2,3\ldots m$$

- Number of machines in a particular cell(cell size)

$$\sum_{i=1}^{m} x_{ip} > 2 \text{ for } p=1,2,3\ldots k$$

IMPLEMENTED ALGORITHM

This section gives the sequence of steps followed in generating genetic algorithm and finally with the given input data, its performance is calculated.

Initialization and evaluation: Randomly generate initial population P1 by input values of population size, number of cells, number of generations, probability of crossover and probability of mutation. Constraints should be looked after while generating population.

Reproduction/selection: Strings are selected stochastically from parent population P1 to form two pools, OP1 and OP2 that is being recombined. Evaluate the string by calculating the objective function values F1 and F2 for parent population P1.

Crossover/recombination: Two candidates for crossover are selected randomly one from pool OP1 and other from pool OP2 and multiple crossover operators is applied to selected strings with a probability of crossover given in the input values. Also apply mutation to sub-sequent strings with a probability of mutation. Now, test for constraints for generated new off spring population after crossover and mutation and if violated, apply mutation until constraints are satisfied. Evaluate objective function values for offspring population and sort them in the increasing order of their function values.

Replacement strategy: Compare the sorted strings functional values in offspring's with parent population P1 functional values and chose the best of out for next generation. For other off springs, a random selection is made with a particular probability.

Table 1: Machine-part time matrix

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15
M1	0.0	0.0	0.3	0.0	0.0	0.6	0.6	0.2	0.2	0.5	0.7	0.0	0.0	0.0	0.0
M2	0.4	0.0	0.5	0.0	0.0	0.7	0.3	0.4	0.3	0.6	0.8	0.0	0.0	0.0	0.0
M3	0.6	0.0	0.7	0.3	0.0	0.2	0.4	0.9	0.6	0.2	0.2	0.0	0.0	0.0	0.0
M4	0.0	0.2	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.7	0.5
M5	0.0	0.2	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.5	0.0
M6	0.0	0.8	0.0	0.0	0.9	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.7	0.0
M7	0.8	0.0	0.9	0.0	0.0	0.3	0.5	0.5	0.7	0.3	0.5	0.0	0.0	0.0	0.0
M8	0.0	1.1	0.0	0.0	1.2	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.8	0.0
M9	0.0	0.4	0.0	0.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.9	0.0
M10	0.6	0.0	0.2	0.0	0.0	0.3	0.9	0.2	0.3	0.4	0.5	0.0	0.0	0.0	0.0

Table 2: Machine part index matrix

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15
M1	0	0	1	0	0	1	1	1	1	1	1	0	0	0	0
M2	1	0	1	0	0	1	1	1	1	1	1	0	0	0	0
M3	1	0	1	1	0	1	1	1	1	1	1	0	0	0	0
M4	0	1	0	0	1	0	0	0	0	0	0	0	1	1	1
M5	0	1	0	0	1	0	0	0	0	0	0	1	0	1	0
M6	0	1	0	0	1	0	0	0	0	0	0	1	0	1	0
M7	1	0	1	0	0	1	1	1	1	1	1	0	0	0	0
M8	0	1	0	0	1	0	0	0	0	0	0	1	0	1	0
M9	0	1	0	0	1	0	0	0	0	0	0	1	0	1	0
M10	1	0	1	0	0	1	1	1	1	1	1	0	0	0	0

Table 3: Total time available on the machine

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
Time	8	8.6	8.5	9	7.9	7.7	8.3	8.5	8.7	8

Table 4: Lot size of part types being manufactured

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15
Nr	155	150	148	160	144	158	152	155	164	148	140	144	145	162	170

New generation: New generation is generated if the value of the current generation is less than the value of number of generation values given in the input. If generation is less, then current population becomes old population and the process is repeated. Otherwise stop. The optimal solution would be one string that stands out with lower objective functional values in the final population.

RESULTS AND DISCUSSION

Genetic algorithm is applied to the input data given below and is run for 100 iterations. The final machine cell formation with minimum inter-cell movement was found and part families are created and assigned to the cells.

Input: Input data for the problem is shown in Table 1 to 4. Table 1 shows time required for part on machine to do the machining, Table 2 shows machine part index matrix which implies whether or not a part gets machined on particular machine, Table 3 shows total machine time available, Table 4 shows the lot size of part types that needs to be manufactured. This input data is taken for simulating the algorithm and output is shown below.

Output: The following results are obtained after 100 iterations. The string is the representation of cells. The string (2 2 2 1 3 1 2 3 1 2) denotes that 1st, 2nd, 3rd 7th , 10th machine should be in 2nd cell,4th,6th,9th should be in 1st cell and 4th, 5th ,8th machine should be in 3rd cell.

Cell 1 = (M4, M6, M9)
Cell 2 = (M1, M2, M3, M7, M10)
Cell 3 = (M5, M8)

Intercellular Movement values, Cell load values obtained and corresponding machine cell string are as follows:

F1 = [1820 600 2420 2420 1665 3040 600 600 3485]
F2 = [3263.7 2612.8 1347.4, 1347.4 3207.2 3561.9 3114.7 2746.4 3373.6]
Cell String = (2 2 2 1 3 1 2 3 1 2)

Table 5: Final selected 10 populations after 100 iterations

3	2	1	1	1	3	1	3	2	2
2	1	1	2	3	3	2	2	2	1
3	3	2	3	3	1	2	1	2	1
2	1	3	3	3	1	2	3	2	1
2	1	3	1	2	3	3	2	2	1
3	2	1	3	1	3	1	2	1	1
1	1	2	1	1	1	3	3	2	1
3	3	1	1	3	2	3	1	2	1
3	1	2	3	1	1	3	2	1	2
2	2	2	1	3	1	3	2	3	1

Table 5 shows the final selected 10 populations after 100 iterations. The results obtained shows that

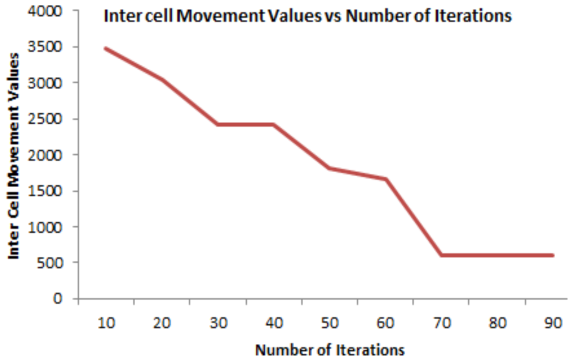

Fig. 1: Inter cell movement values vs. number of iterations

intercellular movement and cell load minimum values are 600 and 1347.4 respectively for the given ten machines -fifteen parts arrangement. From the Fig. 1, it is shown that the solution of genetic algorithm converges to a low values as the number of iteration increases and hence the inter cell movement is decreased in the system.

CONCLUSION

Implementing cellular manufacturing is effective in grouping the clustering machines and parts according to similar operation characteristics and assigning the part families basis of inter-cell movement and cell load. Exceptional elements can also be minimized which in turn leads to minimization of transportation cost between cells and also manufacturing cost. Minimization of cell load is ideal where balancing work load with in cell design or when there is restriction on the available working time period. This method allows specifying the number of cells. With such a facility, the manufacturing system designers will be able to arrive at an optimum machine allocation to the cell. Genetic algorithm optimization technique used in this study gave better results and but there also exists several other optimization techniques which can be applied to cellular manufacturing systems. Thus implementation of cellular manufacturing systems in any organization with specific objectives gives competitive edge in the modern technology over other organizations.

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