A comprehensive study of Scheduling for cellular manufacturing system using Tabu Search Method

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Abstract: The main contribution of this work is to apply tabu search based algorithms for solution of scheduling of jobs in CMS environment. An attempt has been made in this work to vary the job sequencing so that optimal sequencing of jobs can be achieved. The idea behind this work is to perturb sequences in the search of better results. More the number of sequences higher will be the degree of the optimization of objective (COF). This algorithm is suitable to explore number of job sequences from a fixed job sequence and its ability to come out from local optima. The main objective, which is the combination of maximizing the machine utilization by keeping penalty cost nil is achieved by this method.

A scheduling procedure is developed for a specific FMS to maintain its flexibility and thereby the intended performance measures. The mechanism operates based on tabu search and optimizes two contradicting objectives simultaneously.

The problem in this research is considered as each processing step of job has a processing time with specific operation. Set up times of machines and intercellular movement times can be considered while solving the scheduling problem in future.

Introduction

Cellular manufacturing is an application of Group Technology in which machines or processes have been aggregated into cells, each of which is dedicated to production of a part or product family or limited group of families. Parts with similar processing requirements are identified; these are then placed into logical groups called part families and the equipment requirements for each part family are subsequently determined. A part family is a collection of parts which are similar either because of geometric shape and size or similar processing steps required in their manufacture. A manufacturing cell consists of several functionally dissimilar machines which are placed in close proximity to one another and dedicated to the manufacture of a part family. It utilizes the concept of divide and conquers i.e. to break up a complex manufacturing facility into several groups of machines (cells), each being dedicated to the processing of a part family. Therefore, each part type is ideally produced in a single cell. **Thus, material flow is simplified and scheduling task is made much easier.**

CM is a hybrid system (incorporates the flexibility of job shops and the high production rate of flow lines) in which machines are located in close proximity to one another (machine cell) and dedicated to a part family. This, cellular manufacturing is limited to two dimensions being part and machine.

The use of general-purpose machines and equipment in CM allows machines to be changed in order to handle new product designs and product demand with little efforts in terms of cost and time. So it provides great flexibility in producing a variety of products. In conclusion, CM is a manufacturing system that can produce medium volume/medium variety part types more economically than other types of manufacturing systems. In the last several decades, CM has become increasing popular among manufacturers.

Literature Review

Ching- Yuen, *et al.* [1999], reviews the development of CM, highlights some important factors that should be considered carefully while planning a CM process and supports these considerations with reference to the implementation of cellular manufacturing in China.

A. Sobhanallahi & E, Shan, [1998], Effect of cell based team work in productivity improvement at a manufacturing company, *Computers ind. Engng Vol.* 35, *Nos* 3-4, *pp.* 451-45, IRIS, Swinburne University of Technology, Melbourne, Victoria, Australia.

A. Garrido, M. A. Salido, F. Barber & M. A. Lopez, "Heuristic Methods for Solving *Job-Shop* Scheduling Problems" Dpto Sistemas Informáticos y Computación, Universidad Politécnica de Valencia, Camino de Vera s/n 46071, Spain Charlene A. Yauch & Harold J. Steudel, [2002], Cellular manufacturing for small businesses: key cultural factors that impact the conversion process, *Journal of Operations Management 20 (2002)* 593-617, Department of Industrial Engineering and Management, Oklahoma State University, USA.

B.Mahadevan, et al., [2000], Design of cellular manufacturing system for product oriented plant, Third International Conference on Operations & Quantitative Management, Sydney.

ROLE OF CMS

1. **Setup time is reduced**. A manufacturing cell is designed to handle parts having similar shapes and relatively similar sizes. For this reason, many of the parts can employ the same or similar holding devices (fixtures). Generic fixtures for the part family can be developed so that time required for changing fixtures and tools is decreased.

2. Lot sizes are reduced. Once setup times are greatly reduced in CM, small lots are possible and economical. Small lots also smooth production flow.

3. Work-in-process (WIP) and finished goods inventories are reduced.

With smaller lot sizes and reduced setup times, the amount of WIP can be reduced. Askin and Stand ridge showed that the WIP can be reduced by 50% when the setup time is cut in half. In addition to reduced setup times and WIP inventory, finished goods inventory is reduced. Instead of make-to-stock systems with parts either being run at long, fixed intervals or random intervals, the parts can be produced either just-in-time (JIT) in small lots or at fixed, short intervals.

4. **Material handling costs and time are reduced.** In CM, each part is processed completely within a single cell (where possible). Thus, part travel time and distance between cells is minimal.

5. A reduction in flow time is obtained. Reduced material handling time and reduced setup time greatly reduce flow time.

6. **Tool requirements are reduced**. Parts produced in a cell are of similar shape, size, and composition. Thus, they often have similar tooling requirements.

7. A reduction in space required. Reductions in WIP, finished goods inventories, and lot sizes lead to less space required.

8. **Throughput times are reduced**. In a job shop, parts are transferred between machines in batches. However, in CM each part is transferred immediately to the next machine after it has been processed. Thus, the waiting time is reduced substantially.

Design of Cellular Manufacturing Systems

The design of CMS's has been called cell formation (CF), part family/machine cell (PF/MC) formation, and manufacturing cell design. Given a set of part types, processing requirements, part type demand and available resources (machines, equipment, etc.,), the design of CMSs consists of the following three key steps:

- 1. Part families are formed according to their processing requirements.
- 2. Machines are grouped into manufacturing cells.
- 3. Part families are assigned to cells.

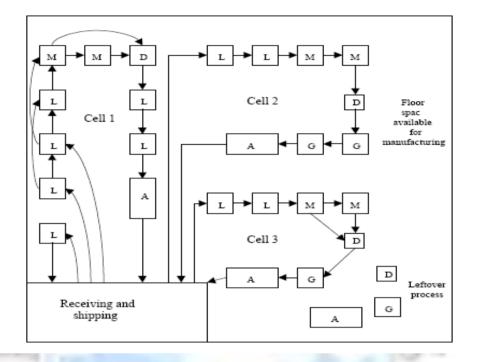
These three steps are not necessarily performed in the above order, or even sequentially. Part families and manufacturing cells can be formed simultaneously, along with the assignment of part families to the cells. After the design steps have been completed, a manufacturing cell configuration (or cell configuration, for short) is obtained. It is referred to as a cellular manufacturing system (CMS) which consists of a set of manufacturing cells; each cell is constituted of a group of machines and is dedicated to produce a part family.

The three solution strategies are. Part as follows:

1 family grouping technique: It is concerned with grouping parts into families and then machines are allocated to manufacture family of parts.

2. Machine grouping technique: In this technique, manufacturing cells are created first based on similarity in part routings, then the parts are allocated to the cells.

3. Machine-part grouping technique: In this technique, part families and manufacturing cells are formed simultaneously. This is the simultaneous machine-part grouping solution strategy. It is also known as machine-component group analysis and is based on PFA.



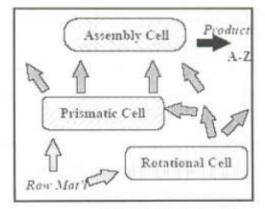
Cell formation approaches

1. Descriptive procedures

2. Cluster analysis

Descriptive procedures further classified into three major categories as:

a. Part family identification (PFI): PFI begins the cell formation process by identifying the families of parts first and then allocates machines to the families.



Part family focus cell

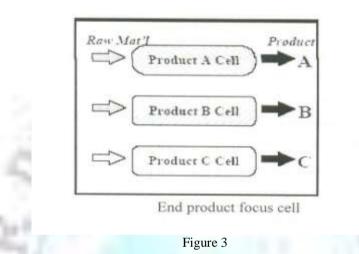


PFI methods can be sub-classified as:

- Eyeballing i.e. visual examination
- Parts classification and coding.

The role of group technology (GT) codes in the context of cellular manufacturing is primarily as an aid in identifying the part families to which production cells should be dedicated. Further analysis is required before a family of parts to be manufactured in a cell, and the machines which will comprise that cell, can be specified

b. Machine group identification (MGI): It is the reversal of PFI and involves first the identification of cluster of machines and then allocates the parts depending upon their common manufacturing features to the family of machines.



MGI procedures consider the CF problem as a two-stage process where in the first stage of their analysis, machines are grouped based on information available in part routings and then in the second stage, parts are allocated to machine groups.

c. Part families/machine grouping (PF/MG): - It involves the simultaneous identification of the part families and machine groups. Production Flow Analysis (PFA) is one of the PF/MG descriptive approaches for the cell formation. PFA (or nuclear synthesis) is basically an intuitive method and is relatively easy to implement. This method requires reliable and well documented route sheets.

Production Flow Analysis Algorithm

Step 1: Read the machine-component incidence matrix and compute the frequency of each machine. Frequency of machine refers to the number of parts requiring the machine for manufacturing.

Step 2: Choose the machine with the lowest non-zero frequency as the nucleus. Form the modules by indicating the components that require the nucleus machine and the other machines needed to make these components. This is known as nuclear synthesis.

Step 3: Repeat step 2 until no nucleus machine can be found.

Step 4: Merge modules if a machine set for one is a subset of another.

PFA method is not suitable for problem having more number of parts and machines however, K. Yasuda, Y. Yin, [2001] develops a large number of approaches to cope with: PFA difficulties which include part-oriented approach and process approach. Similarity coefficient methods are one of the techniques fall under process oriented approach. Process-oriented approach is based on manufacturing data such as, production methods, part routing information.

AREA OF RESEARCH STUDY

Presently, research pertaining to cell formation problem in CMS is in maturity phase of life cycle and the need of hour is that researchers realign their research objectives to the emerging business reality. CMS design research has not been able to adequately satisfy user requirements. There are many areas in which research in CMS can be done. **These**

include developing solution method lies that guarantees product focused cells and the use of more production information in solving the restructuring problems. Adopting a Focused Factory is a powerful approach for today's manufacturing enterprise as a focused factory can provide many benefits including; reduced inventories and cycle times, improved quality and operational efficiencies, better cash flow, greater customer satisfaction / loyalty and a happier more productive work force. The investigation of Stanley D. Stone [1998] introduces the basic concepts of Focused Factories including: Cellular Manufacturing, visual factory techniques in a case study format. It examined a small manufacturer of value added plastic components consisting primarily of control knobs for the aerospace, industrial and consumer markets and suggests one dozen ways to focus the factory to implement CM. This topic can also be extended as a research topic. One of the important research area is Scheduling of Cellular Manufacturing Systems. Initial investment in facilities grouped into CMS is very high so these systems must be scheduled in a manner to realize more utilization of all the facilities while meeting customer delivery schedule. Because of complexity of scheduling there are different views of it Problem Solving Perspective views the scheduling as an optimization problem. It is the formulation of scheduling as a combinatorial optimization problem isolated form the manufacturing planning and control system place. **Decision making Perspective** is the view that scheduling is a decision that a human must make. Schedulers perform a variety of tasks and use both formal and informal information to accomplish these. Schedulers must address uncertainty, manage bottlenecks, and anticipate the problems that people cause Organizational Perspective: is a systems-level view that scheduling is part of the complex flow of information and decision-making that forms the manufacturing planning and control system

SCHEDULING OF CMS

Scheduling is very important part in CMS, initial investment in facilities grouped into CMS is very high so these systems must be scheduled in a manner to realize more utilization of all the facilities while meeting customer delivery schedule. Scheduling concerns the allocation of limited resources to tasks over time. Production scheduling is concerned with the allocation of resources and the sequencing of tasks to produce goods and services. Although allocation and sequencing decisions are closely related, it is very difficult to model mathematically the interaction between them. However, by using a hierarchical approach, the allocation and the sequencing problems can be solved separately. The allocation problem is solved first and its results are supplied as inputs to the sequencing problem. The resource allocation problem can sometimes be solved using aggregate production planning techniques.

CONSTRAINTS IN SCHEDULING FOR CMS:

- Constraints associated with parts.
- Constraints associated with machines.
- Machine operability constraints.
- Machine availability constraints.
- Constraints associated to work orders.

OBJECTIVES FOR SCHEDULING IN CMS:

- Due dates fulfillment.
- End planning date fulfillment.
- Machine idle times reduction
- Cost reduction in manufacturing

VARIOUS APPROACHES USED FOR SCHEDULING CMS:

GENETIC ALGORITHMS:

- Genetic algorithms (GA) are an optimization methodology based on a direct analogy to Darwinian natural selection and mutations in biological reproduction. In principle, genetic algorithms encode a parallel search through concept space, with each process attempting coarse-grain hill climbing (Goldberg 1988). Instances of a concept correspond to individuals of a species. Induced changes and recombination of these concepts are tested against an evaluation function to see which ones will survive to the next generation. The use of genetic algorithms requires five components:
- 1. A way of encoding solutions to the problem -- fixed length string of symbols.
- 2. An evaluation function that returns a rating for each solution.
- 3. A way of initializing the population of solutions.
- 4. Operators that may be applied to parents when they reproduce to alter their genetic composition such as crossover (i.e., exchanging a randomly selected segment between parents), mutation (i.e., gene modification), and other domain specific operators.
- 5. Parameter setting for the algorithm, the operators, and so forth.

GENETIC A	LGORITHMS
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Year	Name of Researcher	Work done			
1992	Venugopal, V.	Applied GAs in solving a machine component-grouping problem			
	&Narendran, T.	with multiple objectives.			
1993	Starkweather et al.	Applied genetic algorithms to solve a dual -criteria job shop			
		scheduling problem in a real production facility.			
1998	R. Di Lorenzo,	Scheduling a Cellular manufacturing system with GA.			
	S.Fichera & V.				
	Grasso				
2004	H.Balasubramanin,L.	Applied GA in scheduling of parallel machines with incompatible			
	Monch	job families to minimize total weighted tardiness.			
2004	P.Vrat, R.Shankar	Applied multi-objective GA approach to design of CMS			
2005	K.L.Mak, X.X.Wang	Developed a Genetic scheduling methodology for VCM systems.			
2006	X. Wu, Y.Wang	Developed Concurrent design of CMS using GA.			
2006	F.T.S. Chan, S.H.	Applied GA in a distributed scheduling problem in FMS			
	Chung				

TABU SEARCH

The basic idea of Tabu search Glover [1989, 1990] is to explore the search space of all feasible scheduling solutions by a sequence of moves. Evaluating all candidates makes a move from one schedule to another schedule and choosing the best available, just like gradient-based techniques. Some moves are classified as tabu (i.e., they are forbidden) because they either trap the search at a local optimum, or they lead to cycling (repeating part of the search). These moves are put onto something called the Tabu List, which is built up from the history of moves used during the search. These tabu moves force exploration of the search space until the old solution area (e.g., local optimum) is left behind. Another key element is that of freeing the search by a short term memory function that provides "strategic forgetting". Tabu search methods have been evolving to more advanced frameworks that include longer term memory mechanisms. These advanced frameworks are sometimes referred as Adaptive Memory Programming (AMP), Glover [1996].

Year	Name of Researcher	Work done	
1994	Logendran, R	TS based heuristic for CMS's in the presence of Alternative	
		Process Plans.	
1995	T.duncan experiments	Compared tabu search algorithm with genetic algorithm for a	
		number of cases of traveling salesman problem	
1996	Nowiki & Smutnicki	Implemented tabu search methods for job shop and flow shop	
		scheduling problems.	
2000	Mungwatanna, A.	Guiding framework adopted in the proposed model	
2001	Jean paul Watson,	Made Dynamic model of Tabu search for Job shop scheduling	
	L.Darrell		
2003	K.Spiliopoulos &	Developed a TS algorithm for designing manufacturing cells.	
	S.Sofianopoulou		
2005	D.Lei & Z.Wu	Applied TS to multi-objective machine-part cell formation.	
2005	D.Lei & Z.Wu	Applied TS approach based on similarity coefficient approach	
		for Cell formation in GT.	

Table No. 3

PROCEDURE OF TABU SEARCH

STEP 1- Initialization

- A- Select a starting solution x-now ε X
- B- Set the history record H empty.
- C- Record the current best known solution by setting, x-best=x-now and define best cost=c (H, x-best)

STEP-2 (Choice and Termination)

Determine candidate-N (x-now) as a subset of N (H, x-now). Select x-next from

Candidate -N (x-now) to minimize c (H, x) over this set. (X-next is called a highest evaluation element of candidate -N (x-now). Terminate by a chosen iteration cut off rule.

STEP3- Update

Re –set x-now=x-next, and if c (h, x-now)<best-cost, perform step 1 (C).then return to Step-2 Update the history recor

In TS, each solution $x \in X$ has an associated set of neighbors (H,x) c X, called the neighborhood of x. Each solution x' \in N (x) can be reached directly from X by a move. History determines which solution s may be reached by a move from the current solution, selecting x-next from N (H, x-now). The essence of the method depends on how the history record H is defined and utilized, and on how the candidate neighborhood Candidate –N (x-now) and the evaluation function c (H, x) are determined.

COMPARISONS OF THE THREE APPROACHES

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FORMULATION OF THE PROBLEM

The combined objective function constitutes of two functions. These functions are related addresses the problem of scheduling jobs in a flexible job shop with the objective of minimizing total idleness of machine and maximizing the machine utilization. To achieve the objective of maximizing the machine utilization we use the minimization of total machine idle time. So the combined objective function (COF) becomes to minimize the machine idle time by keeping penalty cost zero. To attain our objective of keeping total penalty cost nil and maximizing the machine utilization, we have to minimize our Combined Objective Function (COF).

After every solution move in the TS procedure every solution in the neighborhood of the current solution will be evaluated for a Combined Objective Function (COF) of minimizing machine idle time and keeping penalty cost zero.

COMBINED OBJECTIVE FUNCTION (COF):

Minimize

 $COF = (W1) * [(Xp * C) \div MPP] + (W2)*(Xq \div TE)$ Where W1 = Weight age factor for Customer satisfaction.

TE = Total Elapsed (make span) Time.

Xp= Penalty cost incurred

W2= Weight age factor for machine utilization

C = Function of penalty cost if completion time CTi increases DDi due date for job, C becomes unity which means there will be some penalty cost which is not an acceptable condition. In such condition Tabu search moves will search the neighborhood network to get the required result that is value of Idleness and COF by keeping penalty cost zero.

1) X p= Total Penalty Cost incurred $Xp = \sum (CTi - DDi)*UPCi*BSi$ i= Job number CTi=Completion Time of job i DDi =Due Date for job i UPCi = Unit Penalty Cost for job i BSi = Batch size of job a) CTi = Processing time = (1/60*8) *Batch size = time in days b) TE= Total elapsed or Actual time= Processing time + Idle time c) Assuming MPP= 100 W2 =Weight age factor for Machine Utilization Xq =Total Machine idle Time of jth machine = $\sum MIj$

J=machine number MIj = Machine idle time of Jth machine = TE - \sum PTji Processing time of ith job with jth machine

The values of WI and W2 are weight age factors applied as per demand of the business situations such that W1 + W2 = 1In present situation in our problem we want penalty cost to be Nil so we have given weight age factor W1=0.1 and we want machine idle time to be minimized so have given weight age W2=0.9.

METHODOLOGY

Our primary objective is to maximize the utilization of the capital-intensive system. Also with the emerging trends towards customer orientation in the world of global market, the system can not afford to ignore objectives that have direct relation to customer satisfactions. So, both of the above objectives (maximizing the system utilization and keeping penalty cost nil) are considered for optimization.

Step I

An initial Job sequence (x_now) is selected at random among the flexible set of job sequence (X). The combined objective function value for the solution x_now is computed and defined as best cost. The history record H is initialized with empty record.

Step 2

A set of neighborhood solutions of x-now is generated: N(x-now) and all the solutions

stored in H are identified in N(x_now) and removed to form the set of movable solutions: Candidate-N(x_now). Step 3

The COF values of all the solutions in the Candidate (x_now) are calculated and the one

(*x*-*next*) with the minimum value c (H, *x_next*) is chosen. Step 4

If c (H, x_next)<= best-cost then a move performed, best cost is replaced with c(H, x_next) and the history record H is appended with the swapped pairs of sequence number. Otherwise the history record H is browsed and solution satisfying the aspiration criteria is chosen as x_next . The H is also updated. Step 5

If the term ination criteria are not met, step 2 to step 5 is repeated otherwise the procedure is stopped.

RESULTS

1. Several combinations of job sequencing are to be evaluated by perturbing sequencing obtained from fixed job sequence.

2. Corresponding to each job sequence, the operation-machine-allocation are carried out to achieve the combined objective function of minimizing total tardiness and maximizing the machine utilization by satisfying the system constraints (Available machining time at different machine for each job and penalty after due date).

We have run the software to get the optimal solution for the problem given in Example 4.3 and compared the results with other scheduling rules. The results are shown in table:

Case Name	Sequence of parts	Penalty	Idleness	COF
Tabu Search	23; 38; 35; 36; 31; 26; 42; 40; 16; 3; 11; 1; 7; 34; 25; 24; 15; 41; 19; 28; 37; 12; 18;32; 39; 5; 14; 17; 29; 9; 2; 43;33 21; 30; 4; 20; 13; 22; 27; 6; 10; 8	0.0000	0.3986	0.3587

TABLE 5: Comparison of Results

The results show in Tabu search methods the value of penalty is lowest for maximizing machine utilization. Our Combined objective function is also minimum in case of Tabu search method. Hence it can be said that minimizing penalty and maximizing the machine utilization of job sequences are observed here. This corroborates the performance of this algorithm is better as compared to other algorithms.

CONCLUSION

The main contribution of this work is to apply tabu search based algorithms for solution of scheduling of jobs in CMS environment. An attempt has been made in this work to vary the job sequencing so that optimal sequencing of jobs can be achieved. The idea behind this work is to perturb sequences in the search of better results. More the number of sequences higher will be the degree of the optimization of objective (COF). This algorithm is suitable to explore number of job sequences from a fixed job sequence and its ability to come out from local optima. The main objective, which is the combination of maximizing the machine utilization by keeping penalty cost nil is achieved by this method. A scheduling procedure is developed for a specific FMS to maintain its flexibility and thereby the intended performance measures. The mechanism operates based on tabu search and optimizes two contradicting objectives simultaneously. The schedule obtained by tabu search is compared with the solutions obtained by different scheduling rules i.e. SPT, HPT, EDD etc

After comparing the results it can be concluded that tabu search method is by far superior to other scheduling rules, as it gives optimal value for penalty. idleness and combined objective function (COF). Thus the optimization of scheduling problem can be achieved up to greater degree by utilizing tabu search method.

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