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Technical Paper

A dynamic programming approach to GA-based heuristic for multi-period CF problems

Shahram Sharifi*, Satyaveer S. Chauhan, Nadia Bhuiyan

Concordia University, Canada

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ABSTRACT

In this paper we have introduced a multi-period cell formation (CF) model which is more computationally challenging than the most comprehensive CF models in the literature. A dynamic programming (DP) based approach coupled with GA-based heuristic is proposed to solve the multi-period problem. Since, the introduced dynamic programming is general and can be applied to any GA-based heuristic with full rejuvenation cycles to solve the multi-period part of the model, we focused only on the DP approach in this paper but have explained the interface with the GA-based heuristic. Illustrative example has been provided that clarifies the application of DP-heuristic. The performance of the DP-heuristic has been evaluated against LINGO and multi period GA-based heuristic.

1. Introduction

In situations where the sequence-dependent setup times frequently apply, the design of the cellular manufacturing system shall incorporate setup time in the cell formation procedure, in order to reduce the overall production cost even further by involving the setup cost in the cost minimization process. The integer programming model of such a problem is NP-complete in its strong sense. The presence of the sequence-dependent setup cost term leads to outburst of huge number of integer variables even for medium scale problem instances. Therefore exact optimization algorithms such as branch and bound and branch and cut methods may not provide "good" solutions in a reasonably short amount of time. Also the structure of the corresponding matrices is such that it does not accommodate special treatment to attain optimum solutions in acceptable time. In these situations, one has no way other than to turn to approximate methods for a "good enough solution". To address the impasse, a multi-period GA-based heuristic was developed. This heuristic was able to solve the single period problems of the mathematical programming model with acceptable accuracy in reasonably short amount of time as compared with commercial optimization software package. However, the multi-period solutions were not as satisfactory, mainly due to its contribution to the enlargement of the solution space which poses further computational burden.

In order to remedy this shortcoming, a supplementary approach was needed. A multi-stage solution approach was considered in the first stage of which the GA-based heuristic provides near optimal solution for single periods of the model and in the second stage of which, a dynamic programming based heuristic uses the single-period solutions provided by the GA-based heuristic to generate the multi-period solution.

The rest of this paper is organized as follows: Section 2 is the literature review relevant to this research. Section 3 introduces the mathematical model. Section 4 introduces the dynamic programming-based heuristic. Section 5 presents an illustrative numerical example. Section 6 compares the performance of the dynamic programming-based heuristic with those of LINGO and the multi-period GA. Finally Section 7 concludes this paper.

2. Literature review

Greene and Sadowski [10] presented a review of cellular manufacturing benefits. Kusiak and Chow [15] and Offodile et al. [18] presented a taxonomic review framework for cellular manufacturing. Kusiak [13,14] and Boctor [4] showed that mathematical programming approaches have the ability to incorporate a lot of production related data such as processing sequence, routing flexibility, etc. Rajamani et al. [20] considered a sequence-dependent setup time between pairs of parts notwithstanding the machine, in flow shop cells where various parts tend to go through identical production processes. Atmani [2] developed a mathematical programming model for production planning problem of determining optimal machine selection and operation allocation in flexible

* Corresponding author. Tel.: +1 4384951905.
E-mail address: ssharifi@encs.concordia.ca (S. Sharifi).

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manufacturing systems to minimize transportation and setup costs. Lashkari et al. [16] developed an operation allocation (OA) model which assigns a set of part types to a group of machines considering setup cost and provides information as an input to the material handling sub-system (MHSS) model.

Chan et al. [5] considered CF problem with both intercellular and intracellular movements. They adopted a two stage approach where a mathematical model obtains the machine cells and part families in the first phase, and then and another mathematical model optimizes the total intra-cell and inter-cell part movements and used a GA based heuristic to solve the model. Murugan and Selladurai [17] applied genetic algorithm to a cell formation problem that would reduce the setup time, however they used the group efficacy criteria approach rather than mathematical programming and the setup time, which, while not being sequence-dependent, were measured on two different machines as opposed to a common machine. Ghosh et al. [9] conducted a state-of-the- art generic review of application of various meta-heuristics in cellular manufacturing.

The concept of the dynamic cellular manufacturing system (DCMS) was first introduced by Rheault et al. [21]. Kannan and Ghosh [11] noted that cells can evolve and dissolve on a dynamic, real time basis, through applying scheduling mechanisms enabling them to respond more effectively to changes in workload and to shifts in the locations of bottlenecks. Chen [6] was among the first who emphasized the importance of cell reconfiguration in a dynamic environment. A decomposition technique was used to decompose the original multi-period integer programming model into several single-period models which he would solve optimally through a commercial optimization software package. A dynamic programming (DP) was then adopted to re-integrate the smaller single-period problem solutions to obtain the best feasible solution for the original multi-period problem. Defersha and Chen [7] developed a comprehensive mathematical programming model for cell formation which was a collection of nearly all major manufacturing features that had been sporadically used in various CF models before. They devised a problem specific GA-based heuristic to solve the model for real life manufacturing problems. Defersha and Chen [8] embedded a linear programming sub-model in their genetic algorithm based heuristic to solve a multi-period mixed integer programming comprehensive cell formation problem.

Ahmed et al. [1] conveyed a comparison among heuristic methods used for solving cellular manufacturing models in a dynamic environment. They considered a generic nonlinear mixed integer programming model for designing CMS in a dynamic environment and they solved the problem by the three well known meta-heuristics, namely genetic algorithm (GA), simulated annealing (SA) and Tabu search. Ohta and Nakumara [19] developed a genetic algorithm based heuristic to solve a cell formation problem including setup time as one of the factors in their similarity coefficient based model.

Balakrishnan and Cheng [3] conducted a comprehensive review of the research that had been done to address cellular manufacturing under conditions of multi-period planning horizons, with demand and resource uncertainties. Tavakkoli-Moghaddam et al. [25] and Safaei and Tavakkoli-Moghaddam [22] developed a multi-period cellular manufacturing system for dynamic environments. Koren and Shpitalni [12] studied the rationale of developing reconfigurable manufacturing systems. They discussed the core characteristics and design principles of reconfigurable manufacturing systems (RMS).

3. The problem

In closed job shop, a certain group of products with different batch sizes (product mix), is produced in repetitive cycles. In each cycle, when the batch of one part is completed, the part has to be interchanged with another one if they share the same machine or tool. If some or all changeover times between parts are sequence-dependent, our model comes into play in order to minimize the overall cost of production including that of the changeover time (setup time). Consider a part supplier to the automobile industry producing various component parts. The company has a policy for the first half of the year to provide a large number of a few products for the next six months while each of those products shall be delivered on a bi-weekly basis. This can be a result of a contractual obligation towards a specific car manufacturer or the auto industry as its whole market. This implies that the whole demand for the products shall be broken down to baskets of small batches of products which would be produced within repetitive cycles. The combination of all the repetitive cycles would meet the aggregate demand of the 6-month period. In the next 6-month period, the demand and the product mix would change, in a deterministic way, because of which we may need to reconfigure the manufacturing cells for the next planning horizon. Parts may have various operations on different machines and the operations of each part shall be processed in a pre-determined sequence, identified by their index numbers; thus the sequence of operations matters and shall be observed.

The processing order of the different parts in each cell and on each machine recommended by the solution of the model would minimize the amount of setup time and cost in each cycle together with other production related costs. The setup time is measured at the operation-level, that is, between every pair of different component parts in different operations. Each changeover from one part to another requires changing a set of adjustments which depends on not only the next part but also on the set of adjustments done for the previous part as well. The setup time between identical operations of a pair of identical parts is not considered as it is zero. The setup time between different operations of parts is obtained from the route sheets where other critical manufacturing information, such as sequence of operations, corresponding processing times, and machine types, is maintained.

Each machine has a limited capacity expressed in hours during each period. This implies that each machine type may have identical duplicates should it surpass its capacity limit in order to meet the corresponding demand. The objective is to design a cellular manufacturing system that simultaneously groups the machines and the component parts into cells so as to minimize the overall production cost including operation-level sequence-dependent setup time and cost, machine utilization cost, material handling (intercellular movement) cost and cell reconfiguration cost over the span of several time periods.

In achieving the aforementioned objective, there are several constraints and limitations that must be noted. Machine capacities cannot be exceeded and physical limitations shall be observed: cells can only include a certain range of machine types below or beyond which the cell is not viable. Furthermore, the model requires that operation j of any part shall precede operation $j+1$ of the same part on the same machine in the same cell for all j.

3.1. Mathematical formulation

Nomenclature

Indices
i: index of the component part $i = 1, \ldots, I$
j: index of the operation $j = 1, \ldots, J$
p: index of the sequential position of processing the operations of component parts on a machine type $p = 1, \ldots, P$
k: index of machine type $k = 1, \ldots, K$
l: index of the cell $l = 1, \ldots, L$