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Mixed-model assembly line balancing using a multi-objective ant colony optimization approach

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ABSTRACT

Mixed-model assembly lines are production systems at which two or more models are assembled sequentially at the same line. For optimal productivity and efficiency, during the design of these lines, the work to be done at stations must be well balanced satisfying the constraints such as time, space and location. This paper deals with the mixed-model assembly line balancing problem (MALBP). The most common objective for this problem is to minimize the number of stations for a given cycle time. However, the problem of capacity utilization and the discrepancies among station times due to operation time variations are of design concerns together with the number of stations, the line efficiency and the smooth production. A multi-objective ant colony optimization (MOACO) algorithm is proposed here to solve this problem. To prove the efficiency of the proposed algorithm, a number of test problems are solved. The results show that the MOACO algorithm is an efficient and effective algorithm which gives better results than other methods compared.

1. Introduction

Mixed-model assembly lines are needed for the assembly of products that are demanded in variety of models with comparatively lower prices. The assembly lines on which a mixed order of various models of similar products is produced sequentially, are called mixed-model assembly lines. Mixed-model assembly lines are commonly used for their flexibility with respect to model changes, for reducing the final product inventories and for a continuous flow of materials. However, ineffective use of the capacity of mixed-model assembly lines with reduction in productivity results in high unit costs due to higher initial investment costs. Therefore, in order for the mixed-model assembly lines to function properly and productively under the time, space and location constraints, the MALBP arises to distribute the work content evenly among the stations.

The MALBP types found in the literature are (Scholl, 1995):

1. MALBP-I: The number of stations is to be minimized for a given cycle time (i.e., production rate).
2. MALBP-II: The cycle time is to be minimized for a given number of stations.
3. MALBP-E: The cycle time and the number of stations are to be minimized at the same time.

In the literature, there exists numerous methods developed for assembly line balancing, but the majority of these are for the single-model assembly line balancing (SALBP). Since balancing problems are usually NP-hard, finding an optimal solution is hardly possible, therefore near optimal heuristic approaches are preferred. Thomopoulos (1967) is known to be the first to work on mixed-model assembly line balancing and sequencing. In his work, mixed-model line was treated as a single-model line. In a follow up work, Thomopoulos (1970) proposed smoothening for task assignments in mixed-model lines. It is suggested that all of the feasible solutions be searched for smoothening. In a work by Macaskill (1972), groups of tasks were assigned to stations in order to maximize the efficiency of the mixed-model lines but no smoothening was considered. Chakravarty and Shtub (1985) worked on balancing mixed-model lines with work-in-process inventory where labour, inventory and set-up costs are aimed at for minimization using algorithms which determine task assignments, cycle time, and the number of stations. In a following cost minimization work by Chakravarty and Shtub (1986) operation times are taken to be normally distributed rather than deterministic as compared to their previous work. Fokkert and Kok (1997) gave a review of the literature on the mixed-model and multi-model assembly line balancing problem and compared several heuristics based on the combined precedence diagram. Gokcen and Erel (1997, 1998) developed a goal programming model and a binary integer programming model for the mixed-model line balancing problem, respectively. Katayama (1998) presented a conventional algorithm to minimize the number of stations and an effective sequencing

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logic based on the original Target Chasing Method. Both of these algorithms are integrated in a two-stage hierarchical structure. Erel and Gokcen (1999) presented a shortest-route formulation for the mixed-model line balancing problem. Merengo, Nava, and Pozzetti (1999) presented a new balancing and production sequencing method for manual mixed-model assembly lines. The balancing method minimizes the number of station on the line; the sequencing method provides a uniform part usage. Kim, Kim, and Kim (2000) proposed a new method using a co-evolutionary algorithm that can simultaneously solve balancing and sequencing problems in mixed-model assembly lines. Karabati and Sayin (2003) formulated the MALBP with the objective of minimizing total cycle time by combining the cyclic sequencing information. They proposed a mathematical model and an alternative heuristic approach to minimize the maximum sub-cycle time. Bukchin and Rubinovitz (2006) developed a backtracking branch-and-bound algorithm to minimize stations and task duplication cost. Haq, Jayaprakash, and Rengarajan (2006) proposed a genetic algorithm to minimize the number of workstations. Recently, Xu and Xiao (2009) introduce robust optimization approaches to balance mixed model assembly lines with uncertain task times and daily model mix changes.

This work considers the mixed-model assembly line balancing problem to minimize the balance delay and the smoothness index for a given cycle time (MALBP-I). A multi-objective ant colony optimization algorithm is proposed to solve this problem. A comparison of the performance of the proposed algorithm given at this study shows that proposed algorithm is more effective than other methods compared.

The remainder of the paper is organized as follows. In Section 2, the basis of ACO is explained. In Section 3, MALBP-I is defined. The proposed algorithm (MOACO) for MALBP-I is given in Section 4. The algorithm is tested on problems of varying task numbers in order to examine the performance of the proposed approach in Section 5. Finally, conclusions and directions for future research are pointed out in Section 6.

2. Ant colony optimization

Ant colony optimization is proposed as a new metaheuristic approach for solving hard combinatorial optimization problems in the literature (e.g., Stützle & Dorigo, 2003). The basis mechanism of ACO metaheuristic is that a colony of artificial ants cooperates in finding good solutions to combinatorial optimization problems. An important and interesting behavior of ant colonies appears to be their foraging behavior. In particular, ants are capable of finding the shortest paths between food sources and their nest without using visual cues. While walking from food sources to the nest and vice versa, ants exploit on their ground a substance called pheromone. Ants can smell pheromone substance and, when choosing their way, they tend to choose, in probability, paths marked by strong pheromone concentrations. It has been shown experimentally that a colony of ants can find shortest path employing this pheromone trail with following behavior (see Dorigo & Di Caro, 1999).

The first example of such an algorithm is ant system (AS) proposed by Dorigo, Maniezzo, and Colorni (1991a, 1991b, 1996) and Colorni, Dorigo, and Maniezzo (1992a, 1992b) to solve the Traveling Salesman Problem (TSP). Then, further studies were done to improve the performance and, consequently, various other ACO algorithms are developed. Among them are ACS by Gambardella and Dorigo (1996), Ant-Q by Gambardella and Dorigo (1995), MMAS by Stützle and Hoos (1996, 1997), and rank based ant system by Bullnheimer, Hartl, and Strauss (1999). An extensive book concerned with ACO algorithms has been published by Dorigo and Stützle (2004).

3. The definition of the problem

In this section, we present a definition the MALBP. The MALBP is defined as to find a feasible assignment of tasks to an ordered sequence of stations such that the precedence relations of each model are satisfied and some performance measures are optimized for given M models with the set of tasks related to each model, the operation times of the tasks and their precedence relations. Compared to SALBP, MALBP is more complicated since the balance of station loads is needed to be done individually for each model. In order for the materials to flow continuously and for assembly equipment not to be duplicated, common tasks for models should be assigned to the same station. On the other side, these common tasks may require varying times for different models and the utility of a station may be considerably affected. In a mixed-model line, the cycle time is not an upper bound for station times, since it corresponds to an average production speed for which the station times for some models may exceed such an average value.

In MALBP, the precedence diagram of each model must be accounted for since not only the precedence relations but also the operation times may differ among models. The MALBP are usually solved by converting them into so-called single model lines. Fig. 1 shows a simple example to illustrate the process of constructing the joint precedence diagram.

The underlying properties and the assumptions for MALBP are as follows:

1. Demand is known for each model and the line works according to a "push" based production plan.
2. The operation times are deterministic for all tasks.
3. The precedence constraints are known and consistent among the models.

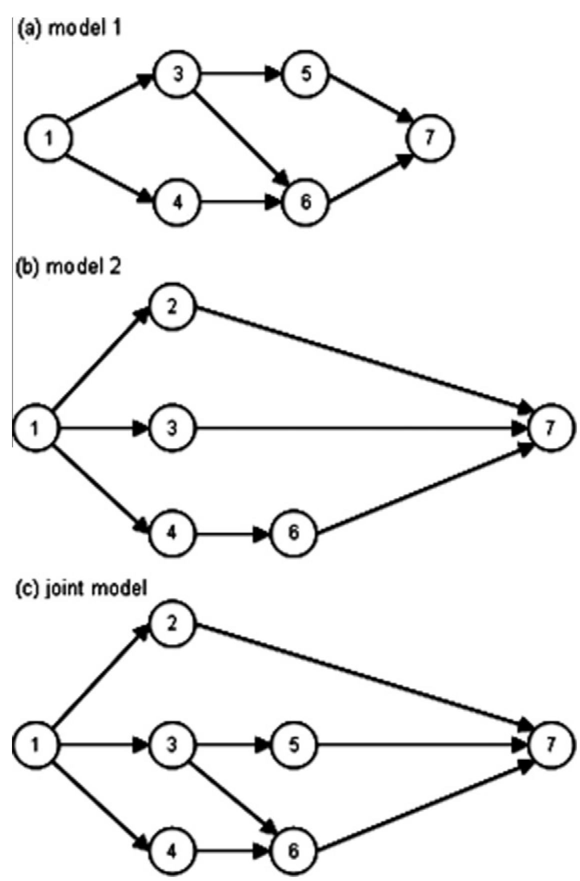

Fig. 1. Precedence diagram of model 1, model 2 and joint model.