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Assembly line balancing under uncertainty: Robust optimization models and exact solution method

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ABSTRACT

This research deals with line balancing under uncertainty and presents two robust optimization models. Interval uncertainty for operation times was assumed. The methods proposed generate line designs that are protected against this type of disruptions. A decomposition based algorithm was developed and combined with enhancement strategies to solve optimally large scale instances. The efficiency of this algorithm was tested and the experimental results were presented. The theoretical contribution of this paper lies in the novel models proposed and the decomposition based exact algorithm developed. Moreover, it is of practical interest since the production rate of the assembly lines designed with our algorithm will be more reliable as uncertainty is incorporated. Furthermore, this is a pioneering work on robust assembly line balancing and should serve as the basis for a decision support system on this subject.

1. Introduction

Assembly lines are production systems that contain serially located workstations in which operations are continuously performed. Parts move down the line until they are finished. They are commonly used in many industries as they produce large amounts of standardized products efficiently. In this respect, modeling and solving line balancing problems are increasingly gaining importance in light of industry's quest for efficiency.

Line balancing deals with assigning operations to workstations to optimize some predefined objective function(s). Precedence relations, which define the order of operations, are taken into account and capacity or cost-based objective functions are optimized.

Assembly lines can be classified into three categories with respect to (wrt.) the number of product models produced (Scholl, 1999): simple (SALBP), mixed (MALBP) and multi-models (MMALBP). Several versions of the same product are processed in mixed model lines and similar production processes are required for them. The lines where production processes differ significantly require set-ups and are called multi-model lines.

For SALBP on the whole, one type of homogeneous product is manufactured and there are two fundamental capacity oriented problems: minimizing the number of workstations given a required cycle time, which is defined by the maximum of the station times (SALBP 1), or minimizing the cycle time given the number of workstations (SALBP 2). The efficiency problem (SALBP E) which combines these two formulations and optimize the multiplication of the number of workstations and cycle time is also often studied (Wei and Chao, 2011).

In real life, assembly processes are subject to various sources of uncertainty, such as variability in operation times, resource uses or availabilities. These variations threaten assembly targets and to hedge against them is essential. Among these sources, variations in operation times could be significant, especially for lines that contain manual operations. In case of high variations, production management is costly (line stoppages, reassignment of workers, overtime, shortages, etc.). In this regard, this research focuses on prevention of these costs. For this purpose, we formulate the robust SALBP-2. In this problem, number of stations is assumed to be predetermined, hence variability affects the cycle time and hence production rates. An algorithm is developed to assign operations to workstations so that operations are most likely to be completed within the minimal cycle time defined. As a result, more reliable assembly systems, which have the ability to perform well even when confronted with unexpected events, will be designed.

We emphasize that this research contributes both to the theory and practice in assembly line design. Regarding theory, this is one of the first publications that apply robust optimization to model and hedge against disruptions in assembly lines. Moreover, Benders Decomposition is not commonly employed to solve balancing problems. In fact, a great majority of the studies use dynamic programming, branch and bound or heuristic methods.

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On the other hand, in practice, various enterprises in the automotive, mechanical and electronics industries might benefit from our models and algorithm in establishing reliable assembly lines. Moreover, our algorithm has the advantage of not requiring exhaustive historical data or probability distributions; reliable previous data might not exist to estimate probability distributions for operation times in many industries, especially for new lines.

The rest of the paper is organized as follows. The literature on related line balancing problems and methods that model and hedge against uncertainty are summarized in Section 2. Mathematical models are given for the deterministic and robust problems in Sections 3.1 and 3.2, respectively. To solve these problems, a decomposition algorithm is developed in Section 4. In Section 5, experimental analysis and computational results are presented. Finally, conclusions and future research perspectives are given in Section 6.

2. Related literature

To solve SALBP-2 to optimality, Klein and Scholl (1996) presented a branch and bound algorithm, while Uğurdağ et al. (1997) developed approximation algorithms. Goksen and Agpak (2006) followed a multi-criteria decision making approach and developed a goal programming model for U-type lines. However, Simaria and Vilarinho (2004) addressed mixed models, specifically MALBP-2, and produced approximate solutions with genetic algorithms. Ozcan and Toklu (2009) presented a mathematical model and a simulated annealing algorithm to balance two-sided lines. Dolgui et al. (2012) investigated a different extension of line balancing and incorporated equipment selection with minimum cost objective.

A classification and representation scheme for all these problems were presented by Boysen et al. (2007). We also refer the readers to the surveys of Scholl and Becker (2006), Boysen et al. (2008), Battaia and Dolgui (2013) for other relevant problems and models.

Note that the majority of these line balancing studies assume the complete knowledge of all data. But, today, integrating protection mechanisms against uncertainty sources is crucial to reach production goals. For this purpose, we can use robust optimization, which is one of the fundamental optimization approaches that model uncertainty and its effects as do stochastic programming, sensitivity analysis, parametric programming and fuzzy programming.

Among these approaches, stochastic programming is widely applied as it is a powerful modeling system to describe uncertain data using probability distributions. It has also been applied to line balancing (Cakir et al., 2011; Chiang and Urban, 2006; Erel et al., 2005; Guerriero and Miltenburg, 2003). However, we reemphasize that stochastic approach is only appropriate if an accurate probabilistic description is available.

Another alternative approach that has recently attracted the attention of many researchers is fuzzy programming. It uses fuzzy numbers and the constraints are defined by fuzzy sets with membership functions instead of random variables. Membership functions might allow some constraint violations and measure the degree of constraints satisfaction. It has been also applied to line balancing (Gen et al., 1996; Kara et al., 2009).

Sensitivity or stability analysis differs since it is reactive in nature and does not address uncertainty in the modeling phase. Sotskov et al. (2006) and Gurevsky et al. (2013) investigated the sensitivity of the solutions for line balancing problems and derived the necessary and sufficient conditions for a predefined solution to remain optimal with respect to small variations in processing times. They performed a post-optimality analysis, whereas we model the variability in processing times and generate the optimal solution(s) of the robust problem.

Robust optimization considers the worst-case performances and seeks for solutions that perform well under the worst-case scenarios (Ben-Tal and Nemirovski, 2000). The most common robust optimization models are minmax and minmax regret models. The minmax models minimize the maximum cost across all scenarios. Kouvelis and Yu (1997) discussed them comprehensively and applied them to a wide range of combinatorial optimization problems. Minmax regret models seek to minimize the maximum regret, which is the difference between the cost of the solution and optimal one, across all scenarios. They have been used to model robust versions of some combinatorial optimization problems such as the minimum spanning tree problem and some line balancing problems (Dolgui and Kovalev, 2012; Montemanni and Gambardella, 2005). Both minmax and minmax regret approaches are pessimistic, so they may perform poorly under many scenarios.

To avoid over pessimism, Bertsimas and Sim (2003) recommended a restricted uncertainty approach in which only a subset of coefficients (only Γ of them) get their upper bound values. Using this restricted uncertainty approach, Hazir et al. (2011) formulated optimization models for multi-mode project scheduling. Its applications in line balancing are quite recent: Al-e hashem et al. (2009) presented a formulation for mixed-model lines (MMALBP). Gurevsky et al. (2012) formulated the robust SALBP-1 and presented a branch and bound solution algorithm. Recently, Nazarian and Ko (2013) also investigated the relationship between the conservatism level of decision makers and manufacturing line design; differently, they concentrated on analysis of non-productive times in stations.

3. Problems and models

3.1. Deterministic SALBP-2

Consider an assembly system with K stations and n operations. The goal is to minimize the cycle time (Eq. (1)), which is defined by the maximum of the station times (station total execution times, Eq. (3)). A single station is assigned to each operation (Eq. (2)), and precedence constraints should not be violated (Eq. (4)).

$$\text{Min } C \tag{1}$$

$$\text{subject to } \sum_{k \in SI_j} x_{jk} = 1, \quad \text{for } j = 1, \ldots, n \tag{2}$$

$$\sum_{j \in M_k} t_j x_{jk} \leqslant C \quad \text{for } k = 1, \ldots, K \tag{3}$$

$$\sum_{k \in SI_i} k x_{ik} \leqslant \sum_{k \in SI_j} k x_{jk} \quad \forall (i,j) \in A, \quad LS_i \geqslant ES_j \tag{4}$$

$$x_{jk} \in \{0, 1\} \quad \text{for } j = 1, \ldots, n, \quad k \in SI_j \tag{5}$$

In the above formulation, binary decision variables x_{jk} assign operation j to station k (Eq. (5)). A graph, $G = (N, A)$, where N is the set of nodes and $A \subseteq N \times N$ is the set of arcs, models the precedence relations among operations. In addition, the following parameters are required to eliminate redundant precedence constraints: earliest and latest stations in which operation j could be performed (ES_j and LS_j), station interval ($SI_j = [ES_j, LS_j]$) and set of operations assignable to station k ($M_k = \{j: k \in SI_j\}$).

$$ES_j = \left\lceil \left(t_j + \sum_{l \in P_j^*} t_l \right) \Big/ \overline{C} \right\rceil, \quad LS_j = K + 1 - \left\lceil \left(t_j + \sum_{l \in F_j^*} t_l \right) \Big/ \overline{C} \right\rceil$$

Note that a derivation of these parameters requires defining the set of predecessors and successors (P_j^* and F_j^*) and an upper bound for the cycle time $\overline{C}$ (see Scholl, 1999 for details).