Chapter 11

ROBUST ASSEMBLY LINE BALANCING: STATE OF THE ART AND NEW RESEARCH PERSPECTIVES

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Abstract

This chapter scrutinizes problems, approaches, analytical models and solution algorithms on robust assembly line balancing problems and discourse about some possible research areas. The analysis and discussion could help identifying open problems and research topics that have broad industrial applications and require further investigation. Moreover, the conclusions derived might suggest a starting point to develop decision support systems (DSS) that aid production managers in planning and designing robust assembly line designs. These tools might aid product life cycle management (PLM) in various industries, especially automotive, home appliance and electronics.

Keywords: Line balancing, Robust optimization, Combinatorial optimization, Product life cycle management

AMS Subject Classification: 90B30, 90C27, 90C90.

1. Introduction

Today, severe international competition forces the companies to design, produce and market products rapidly as well as to achieve the product life cycle management (PLM) in an efficient manner. For that reason, modeling the effects of uncertainty, hedging against it and developing protection mechanisms in all phases of product life cycle has become imperative for profitability and competitiveness. Considering this tendency and need, in this chapter,
we focus on uncertainty and robustness in assembly systems and examine the mathematical models on robust line balancing.

Assembly lines contain serially located workstations and are widely used to produce large amounts of standardized products efficiently (mass production) in various industries like the automotive, home appliance and electronics. They can be categorized into three, with respect to (wrt.) the number of the product models assembled: simple (SALBP), mixed (MALBP) and multi-models (MMALBP) [41]. In simple model assembly lines, one type of homogeneous product is assembled; whereas, in mixed model assembly lines, several versions of a standardized product are processed. Nevertheless, similar production processes are required for mixed models and basic operations are usually the same, sequencing the models become a relevant optimization problem (see [13] for a comprehensive review of mixed model lines).

On the other hand, for the cases where assembly processes of the product differ significantly, when different models are launched, line equipments are usually needed to be reconfigured and workers are reoriented. These lines are called multi-model lines. In these lines, product changes require set-up operations, which are time-consuming and costly; therefore to optimize efficiency, batch sizing and scheduling should also be taken into account.

Line balancing problems fundamentally address assigning operations to work stations, while optimizing some predefined objective function(s). Precedence constraints, which associate the processing order of operations, are taken into account and capacity or cost-based optimization models are usually used. Capacity oriented ones such as minimizing the number of workstations given a required cycle time, which is defined by the maximum of the station times, (type 1) or minimizing the cycle time given the number of workstations (type 2) have been largely studied. Combining these two types of problems, the efficiency problem could be defined and it optimizes the multiplication of the number of workstations and cycle time.

We refer the readers to the surveys [4, 5, 12, 42] for a review of line balancing problems, modeling and solution approaches. Similar to the three division classification scheme that has been widely used in machine scheduling literature \( [\alpha/\beta/\gamma] \), Boysen et al. [11] proposed a nice comprehensive scheme for assembly line balancing problems. Divisions respectively define the precedence graph, station and line characteristics, and objectives.

We note that line balancing problems are NP-hard [41]. For solving small and moderate size problems to optimality, mostly branch and bound techniques have been used; however for large real life instances, approximate approaches are needed. Problem based heuristics, priority rule based algorithms or metaheuristics have been commonly applied.

Majority of the line balancing studies, which are mostly covered by the above mentioned survey papers, assumed deterministic environment; but, assembly systems face various sources of uncertainty, which define situations that we do not have complete information about processes and outcomes. In an assembly line, some operations might take more time than expected, there might be quality problems and need for rework or some resources might become unavailable due to reasons like machine breakdowns.

Hopp and Spearman [32] grouped causes of variability in production systems as “natural”, preemptive, nonpreemptive and recycle (quality problems). Natural variability refers to minor inherent variations. In preemptive ones like machine breakdowns, timing of occurrence could not be controlled; whereas in nonpreemptive cases like machine tool re-
placement, timing could be controlled to an extent. Quality problems and reworking might greatly increase effective processing times. All these sources of disruptions should be carefully examined, otherwise they could have considerable impacts on production plans and outputs.

In today’s competitive business environment, industry has been increasingly demanding for efficiency, flexibility and robustness [19]. To ensure the achievement of these goals, models and techniques of optimization under uncertainty, which is the branch of mathematical programming, have been used more and more to conceptualize and solve industrial problems. The benefits of these models and algorithms could be concretized by embedding them in computerized decision support tools. We refer to the discussion of Falkenauer [21] on the gap between the scope of current studies and industrial needs, and how optimization techniques could respond to these demands. Basically, less restrictive models and algorithms that produce high quality solutions quickly are in need, especially by the automotive industry.

In the next sections, we will briefly introduce the techniques of optimization under uncertainty, later, we will focus on robust optimization and present a model and some results regarding an assembly line balancing application.

2. Robust Optimization

Optimization under uncertainty, first questions how uncertain data could be represented: discrete or continuous. In the discrete case, scenarios referring to the realization of the uncertain variables are formulated. The scenario based description of data has been widely used in mathematical programming [40]. However, it is usually difficult to predefine the disruption scenarios and too many possibilities might be needed to taken into account. On the other hand, continuous data might be assumed to lie in some pre-specified intervals (interval uncertainty), in ellipsoidal or in convex sets. Secondly, a modeling approach is to be chosen: robust optimization, stochastic programming, fuzzy programming, parametric programming or sensitivity analysis.

Among these approaches, robust optimization aims to generate a plan that is insensitive to data uncertainty. Generally, the worst-case performance of the system is optimized, therefore, it includes some degree of conservatism [6, 46]. The most widely studied robust optimization models are minmax and minmax regret models [1, 37]. The minmax models minimize the maximum cost across all scenarios, whereas the regret based ones optimize the maximum regret across all scenarios. The regret of a solution in a given scenario refers to the difference between the cost of the solution and the optimal one for that scenario. Recently, these models have been successfully used to model robust versions of the well known combinatorial optimization problems [14] and applied to planning in various domains such as engineering, finance, logistics, network systems [8].

As an alternative framework, stochastic programming employs probabilistic models and describes the uncertainty using probability distributions. Two-stage stochastic recourse programming is a widely used technique in stochastic programming [10]. It is characterized by dividing the decision variables into two sets: the ones that are set before the realization of the uncertain events and the ones that are defined based on the first stage decisions and realized outcomes; this second set works to take corrective actions. If precise data is
available to estimate the distributions correctly, stochastic programming offers the benefit of using this relevant and useful information. However, in case of initial line investments and designs, it might not be always possible to have trustworthy data.

Among other modeling approaches fuzzy approach models uncertain parameters with fuzzy numbers; the constraints are modeled with using fuzzy sets and membership functions, which measure the level of constraint satisfaction. Fuzzy approach has been recently applied to various production planning problems (See [36] as an application in line balancing).

Sensitivity analysis examines the dependence of model output on input parameters and questions how optimality will be affected from parameter changes. Having reactive characteristics, it is different from stochastic programming and robust optimization. Sensitivity analysis and parametric programming are closely related and might be studied together; however, sensitivity analysis deals with discrete changes in problem parameters, whereas, parametric programming analyzes the continuous ones.

3. Robust Lines

In an assembly system, uncertainty could have significant effects on the line performance. We focus on variations in operation times and analyze their effects. These variations could be significant especially in lines that contain various manual operations. For automated systems uncertainty faced is relatively smaller, but still not absent [3]).

As a result of disruptions, cycle time gets larger and assembly output smaller, when compared to the completely known systems, which do not take into account the uncertainty at all. However, as variations are inevitable in many real life cases, assumption of complete knowledge becomes questionable. At this point, robust approach aims to mitigate the impacts of uncertainty, keep performance deviations as small as possible and produce results with lowest cycle times and largest output even under worst-cases.

Formally, we define robustness in assembly lines as the “insensitivity of line performance with respect to disruptions”. In other words, robust design aims to build line configurations so that performance measures (in our case cycle time) is affected as low as possible from disruptions, specifically operation time variations.

3.1. A Robust Optimization Model

We assume interval uncertainty for operation times. That is, uncertain times, $\tilde{t}_j$, lie in an interval between the nominal and upper bound values, i.e. $\tilde{t}_j \in [t_j, \overline{t}_j]$, $j = 1, \ldots, n$. It can be supposed that nominal values ($t_j$) are aggressive estimates, hence it is unlikely to observe values lower than them. Therefore, the deviation ($d_j = \overline{t}_j - t_j$) reflects the risk that could be faced for operation $j$. Recently, using interval operation times, [29] examined two robust versions of SALBP-2. An explanatory example, two versions of robust problems, optimization models and solution methods, and computational results were presented.

The first version assumes that uncertainty could be defined as a cardinality constrained set [9]; that is only a subset of coefficients (only $\Gamma$ of them) reach the worst case values. Robust SALBP-2 (SALBP-type 2 version) assuming cardinality constrained uncertainty is defined and formulated as follows:
Let us consider an assembly line with $K$ stations and $n$ operations. The decision problem in this system is to assign a single station to each operation so that cycle time (Eq. (1)) is minimized without violating the precedence constraints (Eq. (4)). Note that, cycle time is the maximum of the station times (station total execution times) and inversely related to throughput.

In case of disruptions, for instance, if some operations take more time than expected (especially on the bottleneck stations, the ones which define cycle time) assembly output can decrease considerably. Therefore, in formulating the robust problem, possible deviations in operation times need to be incorporated into cycle time calculations (Eq. (3)). In the below given formulation, maximal deviation in time for each station $k$ is set by integrating the function $g_k(x)$.

\[
\text{Min } C
\]

subject to

\[
\sum_{k \in SI_j} x_{jk} = 1, \quad \text{for } j = 1, \ldots, n
\]

\[
\sum_{j \in M_k} t_j x_{jk} + g_k(x) \leq C \quad \text{for } k = 1, \ldots, K
\]

\[
\sum_{k \in SI_i} k x_{ik} \leq \sum_{k \in SI_j} k x_{jk} \quad \forall (i, j) \in A, \quad LS_i \geq ES_j
\]

\[
g_k(x) = \text{Max} \left\{ \sum_{j \in M_k} d_j x_{jk} u_{jk} : \sum_{j \in M_k} u_{jk} \leq \Gamma, u_{jk} \in \{0, 1\} \right\}, \forall k
\]

\[
x_{jk} \in \{0, 1\} \quad \text{for } j = 1, \ldots, n, \quad k \in SI_j
\]

In the formulation, binary decision variables, $x_{jk}$, are used to assign operation $j$ to station $k$ (Eq. (6)). A graph, $G = (N, A)$, where $N$ is the set of nodes and $A \subseteq N \times N$ is the set of arcs, figures out the precedence relations. In addition, to eliminate the redundant precedence constraints, some parameters are defined: earliest and latest stations in which operation $j$ could be performed $(ES_j$ and $LS_j$), the station interval $(SI_j = [ES_j, LS_j])$ and the set of operations assignable to station $k$ ($M_k = \{j : k \in SI_j\}$).

The set of uncertain operations are set by the binary vector $u$, i.e. $\{j : u_{jk} = 1, \forall k\}$; these operations (at most $\Gamma$ operations) will be assigned processing times at upper bounds, the rest will take the nominal values. As a result of the integration of variables $\{u_{jk}$ and multiplication with $x_{jk}\$, the function $g_k(x)$ is non-linear, which makes the robust problem more complex than deterministic SALBP-2.

Note that if $\Gamma = 0$, the deterministic SALBP-2 is obtained, whereas high values of this parameter represent risk-averse decision making behavior and conservative line configurations will be produced. Note that containing the deterministic problem as a special case, robust problem is also NP-hard. Using the above defined approach [9], a mathematical formulation for mixed model lines (MMALBP) was formulated [2].
3.2. Solution Approach

For solving the robust problem, a tailored Benders Decomposition [7] algorithm was proposed [29], which is new for assembly line balancing; it has been widely used in various combinatorial optimization areas, especially in scheduling and network optimization [39]. Line balancing model presented above contains two optimization problems (the first one is SALBP-2, whereas the second one is to be solved to find out \( g(x) \) in Equation 5). Benders Decomposition iteratively solves these problems and generate the optimal results at the end. Convergence in the classical method could be slow [30], hence to speed up, it is crucial to integrate effective lower and upper bound calculation procedures so that search space could be bounded.

Computational effort depends on the parameter, \( \Gamma \). The effects of this parameter has been experimentally tested and illustrated. Figure 1 is plotted for a specific problem instance with \( n = 35 \) and \( K = 6 \); but it is illustrative, a similar shape is observed for all instances. As could be expected, with very small and and also large values of the parameter, the robust problem approaches to the deterministic problem; however, in between, more combinations, operation groups that take worst-case values, are required to be considered, hence the problem becomes more difficult to solve.

![Figure 1. The Impact of Pessimism Level on CPU on a specific test bed [29]](image)

One of the limiting assumption of the above defined model is that; at most \( \Gamma \) operations take the worst-case values on each station, whatever the operations assignment is. However, as a workstation processes more operations, it is more likely that the risk of deviations on this station is larger, because each operation involves some risk and transition between operations might not be as smooth as expected; as operations might require different tasks and movements, which require concentration and adjustment of workers. As a result, in many cases, the larger the number of operations assigned on a workstation, the more difficult to achieve expected station time. In this aspect, a new approach would be modeling the total processing time deviation to be dependent on the number of operations.
3.3. Another Robust Variant

In this version, differently, at most $\theta$ percent of the operations on a station will be assigned to values at the upper bounds [26]. This parameter could be defined both as station independent or dependent. Especially for the dependent case, each station should be analyzed and expert opinions are needed to define these parameters.

For the independent case, the function $g_k(x)$ is reformulated as:

$$g_k(x) = \max \left\{ \sum_{j \in M_k} d_j x_{jk} u_{jk} : \sum_{j \in M_k} u_{jk} \leq \theta \sum_{j \in M_k} x_{jk}, u_{jk} \in \{0, 1\} \right\}, \forall k \quad (7)$$

In the right hand side of the constraint, the total number of operations assigned to station $k$ is formulated and at most $\theta$ percent of them are considered. Basic advantage of this approach is that the variability of the distribution of the number of operations with respect to workstations will be implicitly reduced, because as a station contains more operations, it will be penalized by the function $g_k(x)$. However, solution of this new robust version is more difficult and further studies for improving computational efficiency are required [29].

Using this new restricted uncertainty approach, Gurevsky et al. [26] formulated the robust SALBP-1 and developed a branch and bound solution algorithm. In this case, robust approach creates a conservative solution in the sense that we might result in solutions with larger number of stations compared to the deterministic problem. The effect of conservatism level on line design was also investigated [20]; however, they followed a different approach and focused on non-productive times in stations.

For a more flexible assembly system, U-type line balancing, Hazir and Dolgui [28] formulated the robust problem. These line configurations offers more grouping options for the operations, a worker can work at multiple stations; at entrance and exit sides. However, a more difficult problem is to be solved. For this reason, a decomposition based approximate algorithm was developed and results on optimality gaps and solution time were presented. For this problem, other types of heuristics, especially problem specific ones could be developed and integrated to improve computational results for large scale instances.

As relevant studies, we cite two recent studies on min-max and min-max regret applications in line balancing [17, 18]: Both studies mainly focused on the definition, analysis of some robust line balancing problems and presentation of computational complexity results. Differently, a group of researchers [24, 25, 45, 44] concentrated on the sensitivity of solutions and investigated the conditions for a given line balance to stay optimal with respect to small variations in operation times. In these studies, absolute or relative perturbations could be modeled [38], in that sense two robustness variants discussed above correspond to these two approaches.

4. Conclusions and Future Research Directions

Robustness of production plans is increasingly attracting attention of researchers in operations research and practitioners in production management. In this chapter, we aimed to explore this field and applications on line balancing. We summarized some existing approaches and studies. Next, we enumerate some possible future research topics. Each item
refers to a specific topic and formulates a specific research question that needs to be further investigated.

1. Research to investigate model robust versions of more complicated assembly systems, such as flexible line configurations assembling multiple models might considerably serve to the needs of industry, i.e. modeling U-lines with mixed or multi-model production and/or settings with parallel workstations. However, as system size increases and models become less restrictive and solution becomes more difficult; in that sense algorithmic design, solution quality and computational efficiency become crucial.

2. Majority of line balancing studies optimize a single performance measure, such as the cycle time minimization. However, lines that are balanced using traditional single criterion approaches may result in poor performances in case of disruptions. Therefore, models that combine a capacity or cost based objective with a robustness criterion is a promising research areas and better adapted to the requirements of the industry. We also note that multi-criteria optimization has become a prominent field of study in operations research, and there exist various modeling and solution approaches.

3. In literature, capacity oriented models are much more investigated than cost or profit oriented ones (see the survey paper of Hazir et al. [27] for a comprehensive review on cost and profit based studies). However, optimizing capacity usage does not necessarily maximize profit. Related to this, another interesting research area is optimizing cost and profitability, and analysis of robustness with respect to these criteria. Main assembly line cost items could be grouped as: wages, material, inventory, equipment and maintenance expenses, set-up and idle time costs, delay penalties and cost of reconfiguring the line. Each category has its own special characteristics and should be investigated separately. Regarding robustness and cost optimization, Tolio and Urgo [47] experimentally showed that perturbations in manufacturing could significantly affect reconfiguration costs.

4. Line balancing has mainly focused on the variations in operation times. However, in assembly systems, machine breakdowns or absenteeism of experienced workers might significantly affect line performances and these disruption cases should also be taken into account in the line design phase. Therefore, variations in resource availability should also be analytically examined [34]. Furthermore, robustness regarding variations in product mix and volume is also important [33].

5. Minmax and minmax regret models have been increasingly studied to model robust versions of various combinatorial optimization problems in production planning. They might be further investigated in the domain of robust line balancing. At this point, for these models, considering the complexity of the approach and size of real life instances, developing efficient and high quality solution algorithms, particularly approximate ones is imperative.

6. As an alternative to traditional minmax approaches to robustness, some recent approaches are attractive. Two of them are bw [22] and Lexicographic $\alpha$ − robustness [35].
The first approach prevents to surpass an objective value, \( w \), in all scenarios (in a minimization problem), and obtains results below the target value of \( b \) as much as possible \( b < w \). The second one aims the diminish the dominating role of worst-case scenario and establishing tolerance in decision making by integrating the threshold level \( \alpha \). Not only the worst-case, second, third...largest cost scenarios are taken into account.

To the best of our knowledge, these approaches have not been applied in the domain of line balancing. However, in a recent study, similarly, a threshold level is imposed for the percentage of scenarios to be considered [48]. In all these robust approaches, developing efficient solution algorithms for large scale instances is challenging.

7. Note that parameters relating the pessimism level, \( \Gamma \) and \( \theta \) have been defined as station-independent. Using machine dependent parameters might assign different risk levels to stations and has practical implications. At this point, how to define these parameters becomes crucial. To analyze the impact of this parameter and approaches, one possibility is to perform a simulation study, other could be evaluation with case studies.

8. A relevant and important area for additional research is testing the robustness of line designs and comparison of balancing algorithms based on robustness [15]. For evaluating line designs, simulation could be used. We refer to the scheduling analysis [31] as an example study.

Simulation is a suitable approach due to the uncertain, complex and dynamic characteristics of the real life assembly systems (See two nice applications of for notebook computer and motorcycle assembly [16, 43]). However, at this point, developing scenarios for disruptions and estimating probability distributions that represent real instances correctly is crucial.

Consequently, two research topics could be integrated: developing mathematical models to generate robust lines and formulating measures to assess the robustness of a given line assignment so that candidate assignments might be evaluated based on robustness.

9. In order to achieve sustainable PLM, in addition to assembly design, planning the disassembly of products and reusing the components have recently been an important concern. Disassembly systems are different in the sense that the quality of returned products is a major concern and the reusability of these products and impact on operations and line design should be taken into account. Research studies on this topic have been rapidly increasing, one important direction could be quality risk analysis, modeling impacts on disassembly operations and investigating robustness in these specific systems.

10. Lastly, developing line balancing algorithms as a model base of a DSS to assist managers and embedding these DSS tools in a commercial software package will serve a lot to the industry. Although line balancing have been studied theoretically, usage of commercial software applications is not so wide; they are most frequently used by automotive industry (see OptiLine, Proplaner, Delmia...).
On the other hand, to solve robust optimization problems, software tools have been developed, i.e. ROME (Robust Optimization Made Easy [23]). These two streams of applications could be integrated to model and solve real-life optimization problems.

References


