Proceedings of the 2015 Winter Simulation Conference
L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, eds.

USING SIMULATION TO IMPROVE PLANNING DECISIONS IN MIXED-MODEL ASSEMBLY LINES

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ABSTRACT

In this paper, we discuss an optimization problem for mixed-model assembly lines in the aerospace industry. We minimize the total inventory and labor costs of an assembly line assuming a given job (airplane) sequence. A variable neighborhood search (VNS) approach is used to determine an appropriate number of workers for each station and processing times for jobs on stations. We are interested in executing the resulting plans in a stochastic simulation model to compute expected objective values in the face of uncertainty. An aggregated simulation model of the assembly line is described. Results of simulation experiments are presented that demonstrate that the proposed simulation-based approach leads to improved planning decisions.

1 INTRODUCTION

The aerospace industry is an example for large-scale assembly manufacturing that is characterized by a labor intensive low-volume production at a high customization level. Production planning and scheduling in aircraft manufacturing is mainly performed by human planners due to the high complexity, the very likely disturbances, and a large amount of customization. Optimization methods are only rarely used (cf. Heike et al. 2001 and Ríos et al. 2012). To fulfill a diverse customer demand, aircraft manufacturers have to be able to offer a wide range of products and produce them cost-efficiently. Consequently, aerospace companies develop different models within one airplane class. Mixed-model assembly lines are common where different product models within one class are assembled at the same line requiring different labor utilization during assembly.

In this paper, we discuss a planning problem with adjustments of processing times and number of workers assigned to a station of the assembly line. This class of problems is considered in the production planning framework of mixed-model assembly lines (cf. Boysen et al. 2009 for a recent review). A model problem for an airplane assembly line is researched. We assume that the jobs, i.e. the airplanes, are in a given sequence. While planning problems for mixed-model assembly lines in the automotive industry are discussed in the literature, this is not the case for aircraft manufacturing with the rare exception of (Heike et al. 2001). For the sake of completeness, we sketch a VNS-based solution approach for a deterministic planning problem similar to those discussed by Heike et al. (2001).

However, the main contribution of this paper is the design and the implementation of a simulation environment that allows for assessing plans under uncertainty by executing them. Such an environment is highly desirable since the planning model provides only a rough representation of the underlying manufacturing system and process. It is likely that disruptions occur due to inaccurate workload estimates, missing components, and missing resources. Therefore, the planning assumptions might be incorrect. Executing the plans using simulation allows for a more realistic assessment of the quality of the plans and therefore for better planning decisions.

The paper is organized as follows. We describe the planning problem in Section 2. This includes a discussion of plan execution under uncertainty. In addition, related work is reviewed in this section. The simulation environment is discussed in Section 3. The results of simulation experiments are presented and analyzed in Section 4.

2 PROBLEM SETTING

2.1 Planning Problem and Approach

We consider a flow line that contains m stations. Such a layout is quite common in aircraft manufacturing. The layout of such a flow line is shown in Figure 1.

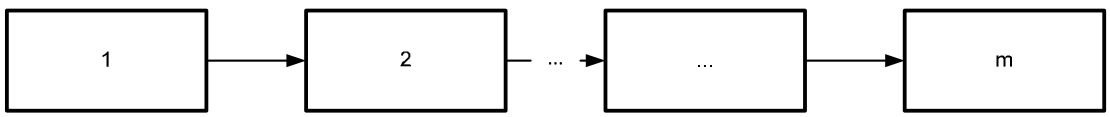

Figure 1: Layout of the flow line.

A set of n jobs $J = \{1,\ldots,n\}$ in a fixed job sequence is processed on the stations of the flow line. Each job i consists of m sets of tasks according to the number of stations that is also m. Such a set of tasks is called a work package. Station j of the assembly line has to process work package j of job i. The work load caused by work package j of i is L_{ij}. Each work package can only be assigned to exactly one station. Station j employs a crew of h_j workers. Each worker of this crew has r_{ij} days to work on job i. The start time for job i at station j is s_{ij}. It determines the completion time f_{ij}. For the sake of simplicity, load and unload times are not modeled. Buffer places are assigned to each station where we have a fixed value $b \in \{0,1,2\}$ for the number of buffer places at each station. Overtime hours are measured by the time to complete all work in excess of respective station's right border. We do not restrict the overtime hours. A work overload at a specific station leading to overtime has no impact on succeeding stations. Thus, we assume that the workload is compensated by additional shifts.

In addition to labor costs, inventory holding costs have to be taken into account. We differentiate between inventory within stations and between stations. We are interested in determining appropriate crew sizes, processing times, and start dates for each job and station such that the sum of the labor costs and inventory holding costs is minimized. There is a tradeoff between labor costs and inventory holding costs. Low labor costs increase the processing times. This results in a larger inventory.

Next, we present a non-linear integer programming formulation for the researched problem. In the remainder of this paper, the notation $x^+ := \max(x,0)$ is applied. We use the following sets and indices:

$i = 1,\ldots,n$: jobs
$j = 1,\ldots,m$: stations.

The following decision variables are considered:
s_{ij} : start date of job i on station j
r_{ij} : planned processing time of job i on station j
h_j : number of workers assigned to station j

f_{ij} : completion time of job i on station j.

The model is based on the following parameters:

L_{ij} : workload of job i on station j

A : regular hourly wage rate per worker

B : overtime hourly wage rate per worker

D_j : inventory holding cost per day at the station j

Y : regular hours available per day and worker

E_{lk} : inventory holding cost per day between station l and k

b : number of buffer places assigned to a single station, $b \in \{0,1,2\}$.

The model can be formulated as follows

$$\min\ (C_1 + C_2), \tag{1}$$

where

$$C_1 = \sum_{j=1}^{m}\left(AY\sum_{i=1}^{n} r_{ij} h_j + B\sum_{i=1}^{n}\left(L_{ij} - Y r_{ij} h_j\right)^+ \right), \tag{2}$$

$$C_2 = \sum_{j=1}^{m}\left(\sum_{i=2}^{n} AY\left(s_{ij} - \left(s_{i-1,j} + r_{i-1,j}\right)\right)h_j + \sum_{i=1}^{n} D_j\left(f_{ij} - s_{ij}\right)\right) + \sum_{i=1}^{n}\sum_{j=1}^{m-1} E_{j,j+1}\left(s_{i,j+1} - f_{ij}\right) \tag{3}$$

subject to

$$s_{ij} + r_{ij} \le s_{i,j+1}, \quad i = 1,\ldots,n,\ j = 1,\ldots,m-1, \tag{4}$$

$$s_{i-1,j} + r_{i-1,j} \le s_{ij}, \quad i = 2,\ldots,n,\ j = 1,\ldots,m, \tag{5}$$

$$f_{ij} = s_{ij} + r_{ij}, \quad i = 1,\ldots,n,\ j = 1,\ldots,m, \tag{6}$$

$$s_{i-1,j} \le s_{i+b,j-1}, i = 2,\ldots,n-b,\ j = 2,\ldots,m, \tag{7}$$

$$r_{ij}, h_j, s_{ij} \in \mathrm{N},\ f_{ij} \ge 0 \quad i = 1,\ldots,n,\ j = 1,\ldots,m. \tag{8}$$

The main decision variables are r_{ij}, h_j, and s_{ij}. The cost function (1) is defined as the sum of total labor and inventory costs. The C_1 part of the objective is nonlinear. It contains the costs for the regular working hours whereas the second term accounts for the overtime hours exceeding regular hours. Note that C_1 does not include s_{ij} decision variables. The first term of the C_2 expression (3) accounts for idle work between two consecutive jobs on the same station. The second term in expression (3) deals with inventory holding cost per station and per day, while the third term models inventory holding costs between two adjacent stations accounting for idle work-in-process (WIP) inventory. In case of $b=0$, only inventory costs at the stations appear since there is no buffer that allows for inventory between stations. Note that C_2 is linear in s_{ij} if the values of h_j and r_{ij} are already chosen. The constraints (4) ensure that a job i can only start at the downstream station $j+1$ if the processing is completed at the station j. The inter arrival time of two successive jobs at a given station is modeled by constraints (5). Equations (6) express the derived decision variables. The possible buffer places are modeled by constraints (7). The constraints (8) ensure that the decision variables are integer and non-negative.

Once the values of the decision variables h_j and r_{ij} are selected, the remaining optimization problem is an integer linear program (ILP) with objective C_2 and constraints (4)-(8). The non-linear optimization problem with objective C_1 is solved in a first phase (FP). An appropriate number of workers for each station and processing times for jobs on stations are determined. A VNS scheme is applied to deal with the FP. VNS is a fast local search-based metaheuristic (cf. Hansen and Mladenovic 2001). We apply neighborhood structures that change the entries of the vector $h := (h_j)$ and matrix $R := (r_{ij})$. However, due to space limitations we do not present the algorithmic details of the FP. Let (r_{ij}^*, h_j^*) be an optimal solution obtained in the FP. These values are used as input for the ILP that is solved in a second phase (SP) to determine optimal start dates s_{ij}^*.

2.2 Plan Execution under Uncertainty

The planning problem described in Subsection 2.1 is based on deterministic data. In a real-world assembly line, however, there are various sources of uncertainty. First of all, the processing time at the stations is highly uncertain because of a changing performance of workers, changes in the material and product characteristics, as well as a changing failure rate due to complex manual processes. The planned processing time might be exceeded. In addition, delays caused by logistics problems can postpone the planned start dates of jobs at stations. As a result, jobs can move to a successor station with a certain amount of uncompleted work. This again, might lead to increasing processing times on the successor station. Uncertain processing times will result in blockage and starvation of the assembly line.

We consider an asynchronous un-paced flow line. It allows for a station-specific processing time that depends on the workload. It is possible that a job on the successor station $j+1$ is not completed by that time and that additional buffers are not available. Thus, station j is blocked. Additional waiting time is the result. Blocked stations appear frequently in aircraft manufacturing flow lines (cf. Ríos et al. 2012, Tiacci 2015b). A station is blocked if the current job is not completed or the already completed job cannot be transferred to a downstream station. Similarly, station j can be starved after completing its job while waiting for a job from the predecessor station $j-1$.

Buffers can be placed in an assembly line to prevent starvation and blockage of stations. They are used to temporarily store jobs between stations. They are limited in size and capacity. Buffers help to compensate the variations in processing time, to increase throughput, and to reduce waiting time.

Independently from the buffers, there are two strategies to deal with processing time variations. The first strategy is based on the idea that each job is finished at a station without taking the planned processing time restriction into account. This strategy is called stop and fix. The second strategy ensures a given processing time that is obtained from the planned processing time by multiplying it with a safety factor $s \geq 1$. In case of a disruption, the job is moved to the successor station after exceeding the possible processing time. In this situation, the amount of uncompleted work from L_{ij} has to be transferred to one of the successive stations resulting in traveling work TW_i. Note that the stop and fix strategy is a special case of the traveling work strategy by choosing a very big value for the safety factor s.

Jobs cannot start earlier with processing on a station than the planned start time. This leads to idle time of the job. The notion of flow times is introduced next. The flow time w_{ij} of job i on station j is the time span that the job stays at the station. It consists of the realized processing time, waiting time because of logistics delays, and idle time because the job has to wait until it can start to process on the consecutive station.

We need to modify the objective when we are interested in assessing the performance of a plan executed in a stochastic environment. Therefore, we consider realizations of the processing times, start dates, and completion times of the jobs on the stations. We use the notation $\hat{X}$ if we refer to a concrete realization of a planned value X. A plan is executed within a certain horizon T. The horizon is chosen in such a way that we have $n^* < n$ for the number of jobs completed within T. End-of-horizon effects are reduced by this approach. Let $m^* < m$ be the last station where job n^*+1 is processed. We determine a modified workload by the following expression:

$$\widetilde{L}_{ij} := L_{ij} + Yh_j\left(\hat{r}_{ij} - r_{ij}\right). \tag{9}$$

We obtain for the realized cost $\hat{C} := \hat{C}_1 + \hat{C}_2 + \hat{C}_3$ where we have

$$\hat{C}_1 := \sum_{j=1}^{m}\left(AY\sum_{i=1}^{n^*}\hat{r}_{ij}h_j + B\sum_{i=1}^{n^*}\left(\widetilde{L}_{ij} - Y\hat{r}_{ij}h_j\right)^+ \right), \tag{10}$$

$$\hat{C}_2 = \sum_{j=1}^{m}\left(\sum_{i=2}^{n^*} AY\left(\hat{s}_{ij} - \left(\hat{s}_{i-1,j} + \hat{r}_{i-1,j}\right)\right)h_j + \sum_{i=1}^{n^*} D_j\left(\hat{f}_{ij} - \hat{s}_{ij}\right)\right) + \sum_{i=1}^{n^*}\sum_{j=1}^{m-1} E_{j,j+1}\left(\hat{s}_{i,j+1} - \hat{f}_{ij}\right), \tag{11}$$

$$\hat{C}_3 := \widetilde{A}\sum_{i=1}^{n^*} TW_i + BL_1 + BL_2\ , \tag{12}$$

$$\begin{aligned} BL_1 := &\sum_{j=1}^{m^*}\left(AY\hat{r}_{n^*+1,j}h_j + B\left(\widetilde{L}_{n^*+1,j} - Y\hat{r}_{n^*+1,j}h_j\right)^+ + AY\left(\hat{s}_{n^*+1,j} - \left(\hat{s}_{n^*j} + \hat{r}_{n^*j}\right)\right)h_j\right) + \\ &\sum_{j=1}^{m^*} D_j\left(\hat{s}_{n^*+1,j} - \hat{f}_{n^*+1,j}\right) + \sum_{j=2}^{m^*-1} E_{j,j+1}\left(\hat{s}_{n^*+1,j+1} - \hat{f}_{n^*+1,j}\right) + \widetilde{A}Y\sum_{j=m^*+1}^{m} L_{n^*+1,j} + \widetilde{A}TW_{n^*+1}\ , \end{aligned} \tag{13}$$

$$BL_2 := \widetilde{A}Y\sum_{i=n^*+2}^{n}\sum_{j=1}^{m} L_{ij}\ . \tag{14}$$

Note that $\hat{C}_3$ is a penalty term. The quantity $\widetilde{A}$ is a scaling factor. The term BL_1 collects the cost, the remaining workload, and the traveling work for job $n^* + 1$, while BL_2 represents the workload for the jobs $n^* + 1, \ldots, n$. Independent simulation replications are performed to calculate the sample mean as an unbiased estimator for the expected value of the total costs.

2.3 Discussion of Related Work

We discuss related work with respect to simulating mixed-model assembly lines and with respect to uncertainty in planning formulations for mixed-model assembly lines. Crew assignment, operation effectiveness, and cycle time constraints in aircraft assembly operations are discussed by Scott (1994). However, logistics processes and disruptions in manufacturing processes are not studied. A simulation model of an aircraft assembly line based on the simulation software Quest is presented by Lu et al. (2012). A specific simulator for the throughput determination in mixed-model assembly lines is recently proposed by Tiacci (2012). However, it seems that this simulator is not able to cope with the complexity found in low-volume assembly lines in aircraft manufacturing. Ziarnetzky et al. (2014) describe major building blocks of simulation models for low-volume mixed-model assembly lines in the aerospace industry. The simulation model discussed in the present paper is based on these building blocks.

Bukchin (1998) proposes several measures for throughput calculation in a mixed-model assembly line where the arrival sequence of items is randomly distributed. The results obtained by the measures are compared with those obtained from simulations. Measures based on the probability of a station to become a bottleneck yield results that are correlated with results from simulation. However, uncertain arrival times of the jobs are not important in our setting. A mixed-model assembly line balancing problem with stochastic task times and parallel workstations is considered in (Tiacci 2015a). A genetic algorithm is coupled with a discrete-event simulation tool to assess the performance of chromosomes. The similar approach is taken in (Tiacci 2015b) where balancing and buffer allocation decisions are made simultaneously. But our problem is different from the ones in (Tiacci 2015a, 2015b). It is based on a different objective function and is more aggregated. A robust approach is taken by Xu and Xiao (2009) to hedge against the risk of poor system performance in bad scenarios in a mixed-model assembly line with significant uncertainty. However, in our setting it is unclear how to obtain appropriate scenarios.

In the present paper, we extend the problem discussed by Heike et al. (2001) by proposing an efficient heuristic solution method and by designing and implementing a simulation environment for plan execution under uncertainty.

3 SIMULATION ENVIRONMENT

3.1 Requirements

We are interested in executing plans from a planning formulation that is based on deterministic data in a simulation model to compute expected objective values. The simulation model has to mimic the behavior of an existing flow line. The following requirements are important for the corresponding simulation model:

1. Since the planning formulation in Subsection 2.1 is based on the work package level rather than on the single task level, modeling a large number of tasks as common in the aircraft industry that are performed by individual workers with specific skills has to be avoided in the simulation model. Therefore, the modeling of work packages should be supported by the simulation environment. Workers are not modeled directly to keep the model as simple as possible. However, workers are implicitly represented by planning results.
2. A specific simulation model has to be generated for the solution of each planning instance to model the flow of jobs through the simulation model that is driven mainly by the job-specific workload at the stations, a planning parameter, and the start dates and the processing times of the jobs on the stations that are planning results.
3. Important sources of uncertainty like stochastic processing times and logistics delays have to be included in the simulation model. Realized processing times have to be modeled as stochastic perturbations of the planned processing times, while logistics delays are modeled by probability distributions.
4. The repair strategies discussed in Subsection 2.2 like stop and fix and traveling work have to be represented in the simulation model.

Simulation is required since the sophisticated material flow within the assembly line under uncertainty cannot be considered in an appropriate manner in the planning formulation. A simulation model that fulfills the derived requirements allows for coping with system behavior like blocking and starvation in conjunction with buffers under stochastic processing conditions.

3.2 Building Blocks of the Simulation Model and Implementation Issues

The simulation model is built using the simulation engine AutoSched AP. The physical line that consists of m stations and related buffers forms the static part of the model. The process flows are derived from a solution of a specific planning instance. The corresponding part of the model is created by taking into account the matrices $R=(r_{ij}), S=(s_{ij})$, the number of buffers b, and the number of workers $h=(h_j)$. However, workers are not modeled in a detailed manner. Only their number is of interest. It is assumed that the number of workers determined by the planning formulation is given. In the simulation model, jobs are the moving entities.

Simulation runs are performed to determine cost realizations $\hat{C}$ that are required to estimate the mean cost. When the traveling work strategy is applied, the realized work load $\tilde{L}_{ij}$ might differ from the original one. The overall situation is summarized in Figure 2.

Next, we describe how we incorporate uncertainty in the simulation model. We use triangularly distributed processing times, obtained from $\hat{r}_{ij} / r_{ij} \sim \text{triang}(a, b, 1)$ for $a \le 1 \le b$. Here we denote by

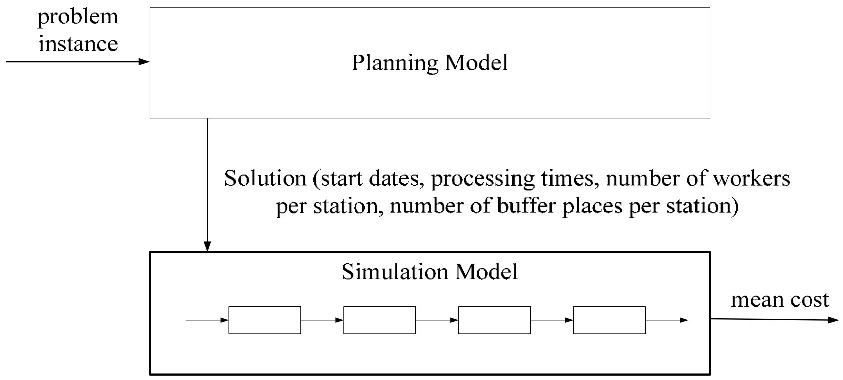

Figure 2: Architecture for simulation-based performance assessment of the planning approach.

$\text{triang}(a, b, m)$ triangularly distributed random variables with a, b, c being the minimum value, the maximum value, and the most likely value, respectively. Logistics delays d_{ij} are modeled as triangularly distributed random variables. Note that logistics delays might lead to postponed start dates.

When the traveling work strategy is applied and the generated realized processing time $\hat{r}_{ij}$ exceeds the maximum possible processing time sr_{ij} the additional amount of traveling work given by

$$(\hat{r}_{ij} - sr_{ij}) h_j Y P \tag{15}$$

appears where P is a penalty factor that accounts for the additional effort to transfer uncompleted work from one station to a subsequent one. If the generated realized processing time is smaller than sr_{ij} then the already collected traveling work at predecessor stations can be reduced by the amount

$$\widetilde{W}_{ij} := \min\left((sr_{ij} - \hat{r}_{ij}) h_j Y, TW_i\right). \tag{16}$$

At the same time, the realized processing time for job j at station i has to be increased by

$$\widetilde{W}_{ij} / (h_j Y). \tag{17}$$

This procedure is applied in an iterative manner to each job i at each station j.

The possible blocking time contributes to the flow time of a job at a station. The Kanban extension of AutoSched AP is applied to model this important behavior of real-world flow lines as proposed by Ziarnetzky et al. (2014). Kanban cards impose an artificial WIP capacity for certain operations.

We model the stations of the flow line in two steps within the simulation model to integrate the finite buffers. Logistics delays and the variable processing times are set in a first step, whereas possible idle and blockage time is assigned in a second step. All flow line stations have a capacity of one, i.e., at most one job can be processed on them at specific points in time. Therefore, each station has exactly one Kanban card linked to the current job processed at the station. If no buffers exist, i.e. b =0, Step 1 and Step 2 share the same single Kanban card. However, if $b>0$, b additional Kanban cards are assigned only to Step 2 to model the buffer. The resulting simulation model is validated by a domain expert.

4 SIMULATION EXPERIMENTS

4.1 Design of Experiments

We randomly generate problem instances similar to the problem description found in (Heike et al. 2001). The problem instances depend on the number of jobs *n*, the number of stations *m*, and the workload setting per station and job. We use $n = 60$ and $m = 7$ in all experiments. The values used for D_j and $E_{j,j+1}$ are provided in Table 1. The amount of workload can vary on a station for different aircraft models. The workload for the four different aircraft models A, B, C, and D is exemplified in Table 2. The regular hourly wage per worker is $A = 20$ units whereas the overtime wage is $B = 30$ units. Moreover, the setting $\widetilde{A} = 5A$ is used for the penalty term while the regular working hours per day Y is eight units.

Table 1: Values for inventory-related costs.

On station *j*	**1**	**2**	**3**	**4**	**5**	**6**	**7**
D_j	700	770	850	935	1029	1132	1245
Between station *j, j+1*	**0, 1**	**1, 2**	**2, 3**	**3, 4**	**4, 5**	**6, 7**	**7, 8**
$E_{j,j+1}$	-	400	440	484	532	585	-

Table 2: Workload L_{ij} for four different aircraft models.

Station	**1**	**2**	**3**	**4**	**5**	**6**	**7**
A	1539	1561	1149	1063	1204	1795	900
B	1247	1381	1382	1548	1561	1217	1590
C	1796	1122	915	1422	1173	1223	1123
D	1508	1465	1729	1401	1588	1240	941

The design of experiments is summarized in Table 3. We start from six factor combinations and generate three independent instances for each factor combination. This leads to 18 problem instances in total. The notation $DU[a,b]$ refers to a discrete uniform distribution over the set of integers $\{a,\dots,b\}$. Randomly generated job sequences are used in this research.

Table 3: Design of experiments for the planning formulation.

Factor	**Level**	**Count**
b	0,1,2	3
L_{ij}	$\sim DU[900,1800]$, $\sim DU[900,2700]$	2
	Number of independent problem instances per factor combination	3
	Total number of problem instances	18

The processing times are chosen as $r_{ij} = 6$ for the initial solution. The number of workers per station is randomly selected from $h_j \sim DU[15,40]$ in the initial solution. Since there are three possible values for b, we obtain three solutions per problem instance. The time horizon is $T = 300$ in all simulations. All problem instances are solved using the approach described in Subsection 2.1 with a computation time of ten minutes per instance.

The VNS algorithm of the FP is coded using the C++ programming language. The ILOG CPLEX 12.1 solver libraries are applied in the SP to solve the ILPs. All the experiments are performed on a PC with 3.0 GHz Intel Core(TM) i7-4610 CPU and 8GB RAM.

For a fixed planning scenario, simulation experiments are conducted. We expect that the performance of the planning approach under uncertainty depends on the safety factor, the penalty factor for traveling work, and the uncertainty of the logistics delays and the processing times. The design of experiments for the simulation-based performance assessment of plans is summarized in Table 4.

Table 4: Design of simulation experiments.

Factor	Level	Count
s	1.05,1.10,1.25, B	4
P	1.2,2.0,3.0	3
d_{ij}	$0: \equiv 0$ $1: \sim \text{triang}(0,4,0)$ $2: \sim \text{triang}(0,8,0)$	3
$\hat{r}_{ij} / r_{ij}$	$1: \sim \text{triang}(0.95,1.10,1.00)$ $2: \sim \text{triang}(0.90,1.50,1.00)$	2
	Number of independent simulation replications	10

Ten independent replications are performed for each simulation run to obtain statistically significant results. A single simulation run takes around 1.2 seconds. Realizations for n^* and $\hat{C}$ are obtained within each simulation replication. Instead of running the full design from Table 4, we consider only a partial design that is obtained by combining appropriate levels of processing time and logistics delay factors. The different scenarios are shown in Table 5.

Table 5: Simulation scenarios.

Scenario	Logistics Delays	Processing Time
1	1	1
2	2	2
3	0	2

4.2 Simulation Results

We start by considering the small penalty factor P=1.2 to assign uncompleted work to a successor station. When deterministic processing times and no logistics delays are assumed, the numbers of completed jobs n^* within the time horizon T are 44 and 43 for b=0 and b=1, respectively. The throughput n^* decreases as shown in Figure 3 due to the uncertainty in all scenarios. As expected, Scenario 2 causes the largest delays and leads therefore to the smallest throughput. The resulting throughput decreases by around 30%. The lowest n^* values are obtained when the stop and fix strategy is enforced and no buffers are available, i.e. b=0, s=B. The largest n^* values are achieved by applying the traveling work strategy with a safety factor of 1.05.

Table 6 shows the average realized costs for the setting P=1.2 relative to the costs that are obtained for throughput n^* when the planning instance with deterministic data is considered. As we can see from Table 6, the reduced throughput leads to higher costs caused by backlogs.

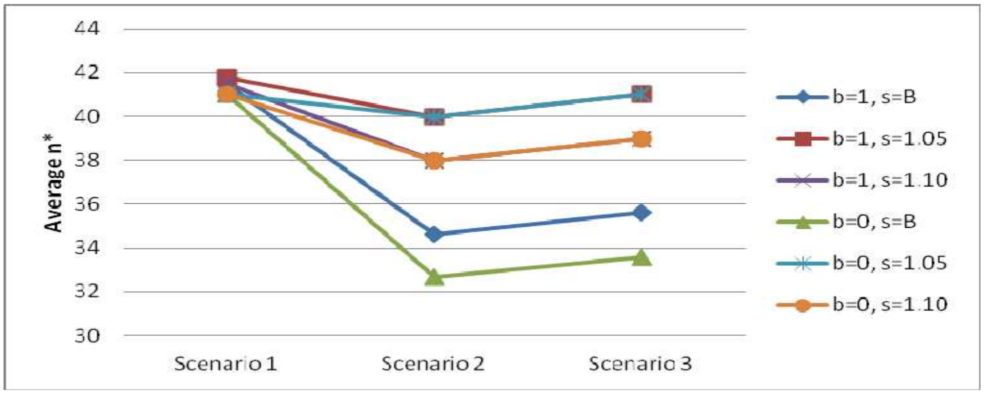

Figure 3: Average realized throughput for instances with $L_{ij} \sim DU[900,1800]$ and $P = 1.2$.

Applying Scenario 1 leads to additional costs of up to 20% whereas under Scenario 2 realized costs are almost doubled. Offering additional buffer capacity is beneficial. The costs are reduced by up to 20% compared to the setting $s = B$ with $b = 0$ and $b = 1$. The most efficient strategy is to combine $s = 1.10$ and *b*=1. Note that the cost improvement under Scenario 2 for $s = 1.10$ and *b*=0 compared to the setting with *b=1* is only 5%. The allocation of one buffer place is always superior to the allocation of two buffer places.

Table 6: Average realized costs for $P = 1.2$.

Scenario		**1**	**2**	**3**
b=0	$s = 1.05$	1.18	1.62	1.53
	$s = 1.10$	1.18	1.62	1.54
	$s = 1.25$	1.18	1.78	1.70
	$s = B$	1.18	1.85	1.78
b=1	$s = 1.05$	1.07	1.58	1.49
	$s = 1.10$	1.09	1.57	1.49
	$s = 1.25$	1.09	1.61	1.53
	$s = B$	1.09	1.64	1.56
b=2	$s = 1.05$	1.08	1.60	1.52
	$s = 1.10$	1.10	1.60	1.51
	$s = 1.25$	1.10	1.63	1.55
	$s = B$	1.10	1.67	1.58

When it takes a higher effort to transfer the planned workload from a station to its successor ones, the costs increase tremendously as shown in Table 7 where $P = 3.0$ is assumed. This means the effort to execute uncompleted work is three times higher than for the original work. In this case the stop and fix strategy (*s*=*B*) in combination with $b = 1$ outperforms all traveling work strategies. The costs increase only at most by 67% compared to all traveling work strategy settings where costs are at least doubled.

4.3 Analysis of the Results

The performance of executed plans in case of a low effort to reallocate uncompleted work ($P = 1.2$) and applying a safety factor of 1.05 and 1.10 is not influenced by the number of buffer places b. Therefore, the traveling work strategy can replace buffers as long as P is small. This is of particular interest in aircraft production with expensive, large-size subassemblies causing high inventory costs. In addition, the installation of buffers requires additional investments. In case of a larger reallocation effort, e.g. $P=3$, the assignment of buffers helps to compensate the variations in processing time to increase throughput and to reduce costs. Using two buffer places per station does not provide additional benefit with respect to throughput and costs. Moreover, applying safety factors larger than 1.10 is not beneficial for the problem instances analyzed in this paper. A small safety factor ensures a higher throughput. The application of the described repair strategies is beneficial to achieve small costs and a high throughput. Finally, the application of simulation leads to improved planning decisions under uncertainty, simply because a more realistic assessment of plans is possible.

Table 7: Average realized costs for $L_{ij} \sim DU[900,1800]$ and $P = 3.0$.

Scenario		1	2	3
b=0	$s = 1.05$	1.20	2.24	2.17
	$s = 1.10$	1.19	2.03	1.96
	s=B	1.19	1.87	1.80
b=1	$s = 1.05$	1.16	2.21	2.15
	$s = 1.10$	1.10	2.00	1.92
	s=B	1.10	1.67	1.58

5 CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

In this paper, we discussed the simulation-based assessment of plans that come from a planning formulation for mixed-model assembly lines. We described a deterministic planning problem that is motivated by real-world problems in the aerospace industry. A simulation environment is discussed that allows for executing the plans in a stochastic environment. Results of computational experiments demonstrate that the simulation-based assessment of plans is useful and leads to planning decisions that take the inherent uncertainty on the shop floor into account.

There are several directions for future research. First of all, we strive to replace the triangular distributions by more appropriate probability distributions. Moreover, we are interested in applying our planning algorithm in a rolling horizon setting. This allows for taking feedback from the shop floor into account. The second direction for future research consists in integrating the simulation approach with the VNS approach. Each move within the VNS approach requires the evaluation of the objective function. This can be achieved by simulating the corresponding plan as described in the present paper.

ACKNOWLEDGMENTS

The authors would like to thank Timm Ziarnetzky for setting up the simulation environment. The research is funded by European Commission Seventh Framework Program FP7/2007-2013 under the project ARUM, grant agreement no 314056. The authors gratefully acknowledge this financial support.

REFERENCES

Boysen, N., M. Fliedner, M., and A. Scholl. 2009. "Production Planning of Mixed-Model Assembly Lines: Overview and Extensions." *Production Planning and Control* 20(5):455-471.

Bukchin, J. 1998. "A Comparative Study of Performance Measures for Throughput of a Mixed Model Assembly Line in a JIT Environment." *International Journal of Production Research* 36(10):2669–2685.

Hansen, P., and N. Mladenovic. 2001. "Variable Neighborhood Search: Principles and Applications." *European Journal of Operational Research* 130:449–467.

Heike, G., M. Ramulu, E. Sorenson, P. Shanahan, and K. Moinzadeh. 2001. "Mixed Model Assembly Alternatives for Low-volume Manufacturing: The Case of the Aerospace Industry." *International Journal of Production Economics* 72:103-120.

Lu, H., X. Liu, W. Pang, W. Ye, and B. Wei. 2012. "Modeling and Simulation of Aircraft Assembly Line based on Quest." *Advanced Materials Research* 569:666–669.

Ríos, J., F. Mas, F., and J. L. Menendez. 2012. "Aircraft Final Assembly Line Balancing and Workload Smoothing: A Methodological Analysis." *Key Engineering Materials* 502:19-24.

Scott, H. A. 1994. "Modeling Aircraft Assembly Operations." In *Proceedings of the 1994 Winter Simulation Conference*, edited by J. D. Tew, S. Manivannan, D. A. Sadowski, and A. F. Seila, 920–927. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Tiacci, L. 2012. "Event and Object Oriented Simulation to Fast Evaluate Operational Objectives of Mixed Model Assembly Lines Problems." *Simulation Modelling Practice and Theory* 24:35–48.

Tiacci, L. 2015a. "Coupling a Genetic Algorithm Approach and a Discrete Event Simulator to Design Mixed-model Un-paced Assembly Lines with Parallel Workstations and Stochastic Task Times." *International Journal of Production Economics* 159:319-333.

Tiacci, L. 2015b. "Simultaneous Balancing and Buffer Allocation Decisions for the Design of Mixed-model Assembly Lines with Parallel Workstations and Stochastic Task Times." *International Journal of Production Economics* 162:201-215.

Xu, W., and T. Xiao. 2009. "Robust Balancing of Mixed Model Assembly Line." *COMPEL – The International Journal for Computation and Mathematics in Electrical and Electronic Engineering* 28(6):1489 – 1502.

Ziarnetzky, T., L. Mönch, and A. Biele. 2014. "Simulation of Low-Volume Mixed Model Assembly Lines: Modeling Aspects and Case Study." In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. D. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 2101–2112. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

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