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AIRCRAFT ASSEMBLY RAMP-UP PLANNING USING A HYBRID SIMULATION-OPTIMIZATION APPROACH

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ABSTRACT

Assembly processes have the most influencing and long-term impact on the production volume and cost in the aerospace industry. One of the most crucial factors in aircraft assembly lines design during the conceptual design phase is ramp-up planning that synchronizes the production rates at the globally dispersed facilities. Inspired by a pilot study performed with an aerospace company, this paper introduces a hybrid simulation-optimization approach for addressing an assembly production chain ramp-up problem that takes into account: (1) the interdependencies of the ramp-up profiles between final assembly lines and its upstream lines; (2) workforce planning with various learning curves; (3) inter-plant buffer and lead-time optimization, in the problem formulation. The approach supports the optimization of the ramp-up profile that minimizes the times the aircraft assemblies stay in the buffers and simultaneously attains zero backlog. It also generates the required simulation-optimization data for supporting the decision-making activities in the industrialization projects.

1 INTRODUCTION

Industrialization projects of a manufacturing supply chain involve many complex decisions over various phases in order to satisfy the strategic objectives of the company. These design decisions include equipment sizing, layout, level of automation, workload allocations, internal and external logistics planning, to name but a few. For the industrialization projects in the aerospace industry, the assembly processes have the most influencing, long-term impact on both the production volume and cost – nearly 30% of the overall production cost is estimated to be spent on assembly and up to 80% of final aircraft cost is determined during the conceptual design phase (Mas et al. 2013).

For the industrialization engineers, their works during the conceptual design phase involve the splitting of the conceptual assembly definition into a logistics plan, assembly lines design, layout planning, and their evaluations. In a global supply chain network, since the logistic plan represents a large proportion of the total cost, how workloads can be optimally allocated to the geographically dispersed facilities has to be carried out in the early phase. But in the later design phase, after the assembly processes are well-defined for different lines in a production network, more focus will be put to the calculations of the workforce to achieve the capacity required to fulfill the demand. This is particularly important to the labor-intensive aircraft industry in which most of the assembly operations are performed by human workers so that the total cost of the required workforce will contribute to a significant percentage in the total manufacturing cost.

For the workforce calculations, especially in high-tech, complex processes like aircraft assembly, their special skills, and learning factors must be considered already in the conceptual design phase. Notably, the learning curve of the assembly workers represents the impact of their experience on the production costs, product quality as well as productivity. For the last, when their experience is gained through repetitive tasks, the quantity produced per period can be gradually increased until the targeted steady-state production rate can be reached. This is called production ramp-up, which is very commonly applied in industries that involve complex manual assembly tasks for making automotive or aircraft. And particularly for these industries where productions take place at their globally dispersed facilities, involving long-haul transportations of semi-assemblies from upstream to downstream plants, *ramp-up planning must take into account the interdependencies between the ramp-ups in the distributed plants* (Becker et al. 2016).

Instead of some continuously ascending production ramp-ups, plateau or staircase-like ramp-up curves are planned so that the production capacity is increased stepwise for multiple periods, whereas in each period, the output level is constant before the capacity is increased in the next “ramp-up”. This is an important characteristic because learning occurs during ramp-ups, which leads to the improvement of not only productivity but also product quality, i.e., reduction in errors (Glock and Grosse 2015). In a study for the ramp-up planning for new product introductions in the automotive industry, Wochner et al. (2016) identified the lack of appropriate quantitative decision support in ramp-up management except for a few optimization-based models, e.g., (Becker et al. 2016). In their systematic review of decision-support models for production ramp-up phase that apply mathematical optimization or simulation approaches, Glock and Grosse (2015) have found various decision-support methods that consider learning effects and increasing customer demand rates in time, but decision-support models for worker assignment and work-flow management during ramp-ups are rare. Their analysis also revealed that most of the studies developed analytical models to support decision-making during ramp-ups, and that works that employed simulation approaches are very few. They concluded that there is “a significant potential for future research to develop comprehensive simulation studies of ramp-up processes,” especially in generating further insights into the complexities of production ramp-ups.

The importance of developing conceptual simulation models of complex manufacturing systems for evaluations of alternative designs and decision-making support, rather than relying on experience, have been emphasized in the simulation literature (Fowler and Rose 2004; Moris et al. 2008; Ng et al. 2011; Vasudevan and Devikar 2011). In a recent WSC article, Allen et al. (2018) presented a hybrid simulation and analytical modeling approach to capture the impact of increasing demand and capacity constraints on the operational and financial performance of an aerospace supply chain. But, traditionally, the conceptual design phase for aircraft industrialization projects has not been supported by knowledge-based and predictive technologies like modeling, simulation, and optimization to the same extent when compared to the other aspects of aircraft development (Mas et al. 2013). To the knowledge of the present authors, studying the production ramp-ups using any simulation-optimization approaches, especially for aircraft manufacturing, has not been found in the literature. This can be supported by a recent student project conducted for an aerospace company in Sweden (Blom and Svensson 2019), which reported that papers on ramp-up, from both a production and an aerospace perspective, are virtually non-exist, and, therefore, identified as a research gap.

Inspired by a pilot study carried out with a major European aircraft manufacturer, this paper introduces a hybrid simulation-optimization approach for addressing an aircraft assembly production chain ramp-up problem that takes into account: (1) the interdependencies of the ramp-up profiles between a final assembly line (FAL) and the Pre-FAL lines; (2) workforce planning with various learning curves; (3) inter-plant buffer optimization and lead-time optimization, in the problem formulation. After this introductory section, the rest of the paper is organized as follows. Section 2 gives some concepts from Supply Chain Science for a generic supply chain model and relevant objectives to the aerospace industry. Section 3 details our proposed hybrid simulation-optimization approach for generating the Pre-FAL ramp-up profile and its related simulation output data for supporting decision making. The simulation-based optimization results of finding the minimum inter-plant buffer capacity with the consideration of variability like breakdown and repair in the lines to make the study more generalized are presented in Section 4. Finally, conclusions and future work are included in Section 5.

2 SUPPLY CHAIN SCIENCE

In supply chain science (Hopp 2008), a manufacturing supply chain is defined as a goal-oriented network of production processes and stocks used to deliver goods to customers. As illustrated in Figure 1, a stock point represents the inter-plant storage that stores the products at the end of a plant to fulfill the demand from a down-stream customer within a serial supply chain. Despite the apparent simplicity of using only a few entities, such kind of demand-stock-production (DSP) networks can be used to represent any complex manufacturing value chains (Pound et al. 2014).

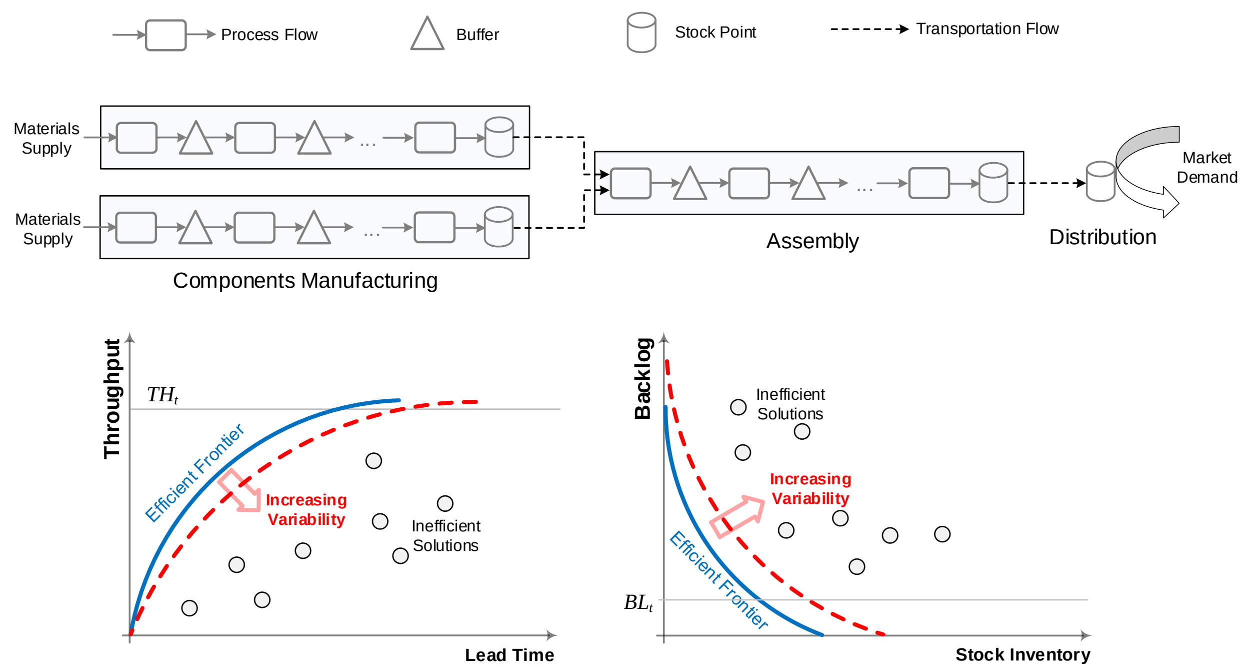

Figure 1: A demand-stock-production network and trade-offs among its design/operating objectives.

In such a DSP network, trade-offs among several key performance objectives like throughput, lead-time, stock inventory and backlog (i.e., total no. of tardy jobs after due-dates) can be related in the form of efficient frontier (EFs) as illustrated in Figure 1. While it is solely a strategic decision for manufacturing executives/managers to decide where they want to be to achieve the business objectives suitable for their company, e.g., absolutely minimum inventory cost versus highly responsive with no backlog using an EF, the task of obtaining one is far from trivial. First, they need an input-output model to predict the performance of their supply-chain network under different inventory settings. Second, but maybe even more challenging, is when a large number of stock points and different sources of variability in the network are involved, the generation of such an EF is intractable for most of the analytical modeling and optimization methods so that some more advanced technologies are needed. As argued in previous studies, we advocate the use of some combinations of simulations, either discrete-event simulations (Ng et al. 2011) or system dynamics (Bandaru et al. 2015), and multi-objective optimization, as an efficient way to address such a non-trivial task of generating EF curves for supporting the design (Ng et al. 2016) and/or improvement (Pehrsson et al. 2016) of complex manufacturing networks. As a matter of fact, Pound et al. (2014) have suggested that a high-level modeling program like discrete-event simulation is needed when the manager is facing the complexity of demand and product variations that cannot be handled by the mathematics introduced in Factory Physics.

One of the most important principles emphasized in the Factory Physics framework is the corrupting influence of variability. Expressed as the “variability law”, increasing variability always degrades the performance of a manufacturing system. In a production line, variability can be caused by machine breakdown (availability issues), quality problems (scrap and rework), setups due to technological or logistic constraints, as well as natural work-task variations by human workers (manual assembly processes), to name a few. In a supply chain network, these production-level variations can contribute to the variability like material shortages and delays. The advantage of using simulation-based multi-objective optimization (SMO) is that the corrupting effect on the EFs can be visualized graphically (see Figure 1). A more comprehensive review of using SMO for supply chain systems design can be found in (Aslam et al. 2011).

3 AIRCRAFT ASSEMBLY RAMP-UP PLANNING

3.1 An Aircraft Assembly Production Network

With the same entity conventions used in Figure 1, Figure 2 depicts the flow between the Pre-FALs and the FAL as a DSP network. In comparison to a generic supply chain network, there are certain noticeable differences. First, there are no inter-station buffers in the modeled plants because FALs are mostly designed as synchronous, meaning that all the workstations have the same cycle time or takt (Ríos et al. 2012). Second, the end of the line is called “end buffer”, instead of a stock point, because, in principle, it is an area that the aircraft assemblies are waiting, if needed, to be transported to FAL. In the pilot study, we considered the deterministic case in which there is no variability in the assembly plants. This is a reasonable assumption when considering the aerospace industry usually employs the capacity buffer (Pound et al. 2014) management strategy to ensure the 100% on-time delivery (OTD), or equivalently, zero backlog. On the other hand, any waiting of the finished aircraft assemblies at a stock point or buffer is too costly, so that an optimization approach that can determine the minimum waiting time in the buffers, but without causing delayed deliveries to the customers (i.e., zero backlog), is necessary.

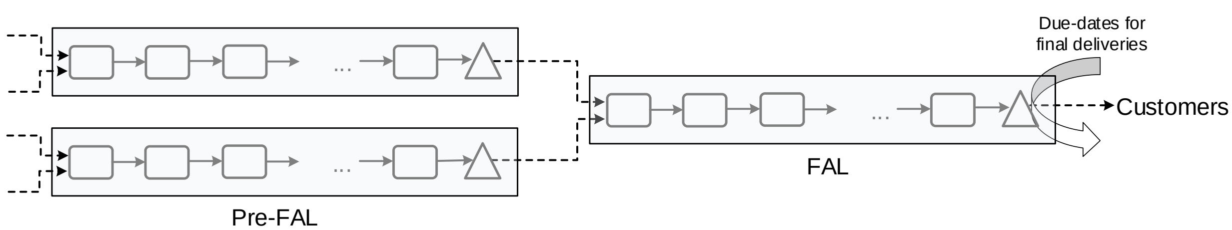

Figure 2: Aircraft assembly as a DSP network.

The IDEF0 diagram in Figure 3 outlines our proposed hybrid simulation-optimization approach. It includes the following linked activities which will be further described in the subsequent sub-sections:

1. Using the desired start date at the FAL, pre-determined FAL ramp-up profile, and the different industrial calendars, a recursive Mixed-Integer Linear Programming (MILP) model has been developed to determine the optimal Pre-FAL ramp-up profile to minimize the times that the aircraft assemblies stay in their end buffers (see Section 3.2 for more details).
2. Based on optimized ramp-up profiles and the assembly line design, run deterministic simulations using FACTS Analyzer that is chosen for its tightly integrated simulation and optimization functions (Ng et al. 2011).

3. Using the simulation output data to generate the report with the information needed to support the decision-making activities of the industrial engineers/managers (Section 3.3, Figures 6-9).
4. SMO for generating the EF with respect to multiple objectives like backlog, buffer sizes, and lead times when variability must be considered and fine-tune the ramp-up profiles (Section 4).

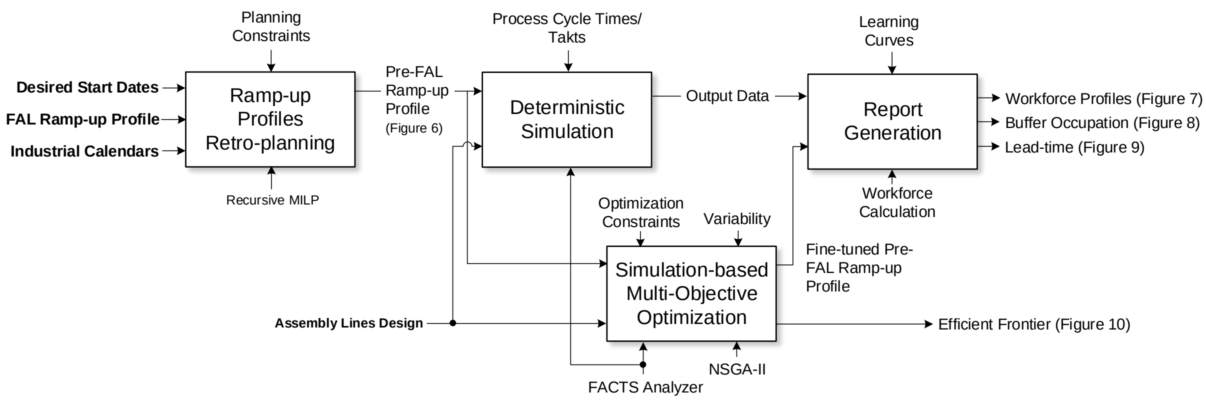

Figure 3: The hybrid simulation-optimization methodology represented in an IDEF0 diagram.

3.2 Pre-FAL Ramp-up Profile Optimization

As mentioned, a supply chain that involves productions on globally dispersed facilities has to consider different industrial calendars for the precise planning and control of the production at each site to effectively utilize their resources. Commonly, companies need the most downstream facility to work at a certain pace in order to be able to meet the demands of their customers. When new complex products are to be produced that involves a stepwise ramp-up profile of the production pace at the most downstream facility, this problem becomes even harder. Due to differences in the industrial calendars, e.g., holidays not occurring simultaneously at different sites, upstream sites need their own ramp-up profile that shortens lead-times and minimizes the required inventories, while still being able to supply the downstream site on time. An example with only two transportation linked facilities with two different industrial calendars is shown in Figure 4.

The downstream site should follow a ramp-up profile that increases the rate of production in three steps. Knowing these production rates and when the production of the first job should start, it is possible to go upstream for every job (1, 2, …), considering available production hours in both calendars and the transportation time, and calculate when the individual jobs should be ready for transport. Figure 5 presents an example of where blue dots represent the times when each individual job needs to be ready for transport, and red segments represent production rates. The irregularities among the blue dots clearly illustrate the effects different calendars have on the input rate profile of the downstream site when the retro-planning is done. Therefore, the problem then amounts to finding the set of production rates (red lines) that minimizes the sum of the vertical distance between each blue dot and the red segments while at all times keeping the blue dots below the red segments; otherwise, jobs can be late for transport.

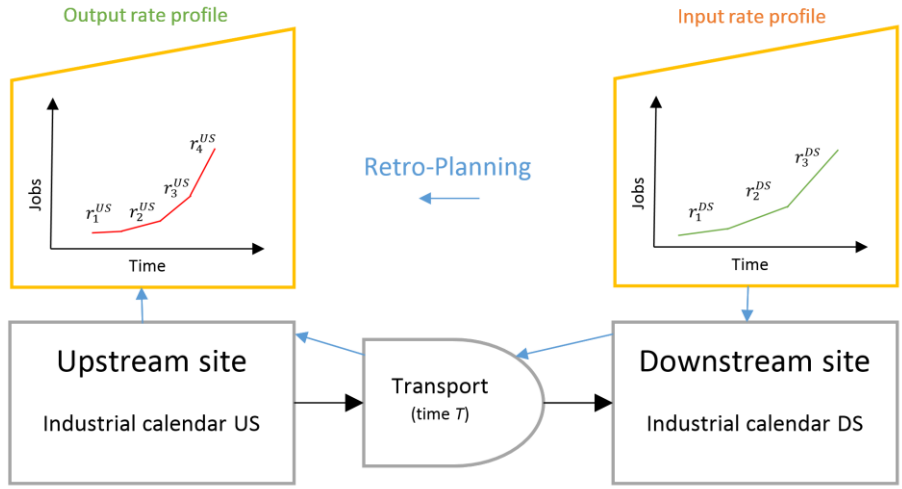

Figure 4: Schematic illustrations of the retro-planning between two facilities.

In addition, any valid solutions to the problem should meet the following requirements:

- Production rate changes need to happen at the start of a new job, e.g., a job cannot be processed halfway with one rate and then the remainder with a different rate at a certain station.
- Production rates should always increase; i.e., it is not allowed to change from one rate to a lower one.
- Two production rate changes cannot happen too close to each other; there needs to be a minimal time G between any two consecutive rate changes.

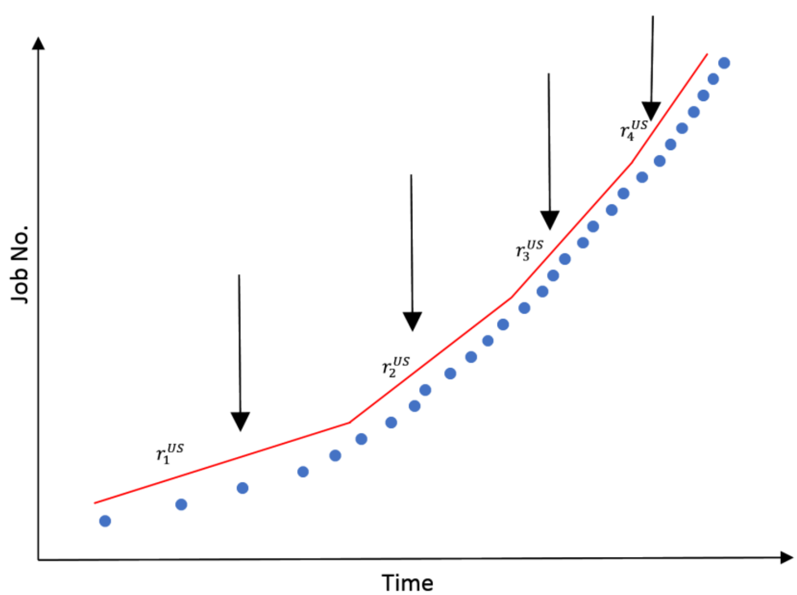

Figure 5: Illustration of how to find production rates (red lines) from the job due-dates for transport/delivery (blue dots).

The problem can easily be formulated into a MILP-problem when it is known at which jobs the production rate change should occur. However, that is not the case here where those are among the desired outputs. Hence, a regression analysis method, known as multivariate adaptive regression splines (MARS), introduced by Friedman (1991), is being resorted to optimize the number of production rate increase stages and when, i.e., at which jobs, these rate increases should happen. MARS is used to construct a model of a function:

$$y = f(x_1, \dots, x_n) + \epsilon$$

where y represents the response variable, $\{x_i\}_1^n \in \mathbb{D} \subset \mathbb{R}^n$ the predictor variables and ϵ a stochastic component with expected mean 0 that represent relationships not captured by any of the predictor variables. The constructed MARS model is mathematically expressed as:

$$\hat{f}(\boldsymbol{x}) = \sum_{m=1}^{M} a_m B_m(\boldsymbol{x})$$

where, $\{a_j\}_1^M$ are the coefficients for the basis functions B_m in the following form:

$$B_m(\boldsymbol{x}) = \prod_{k=1}^{K_m} \left[s_{km} \cdot \left(x_{v(k,m)} - t_{km} \right) \right]_+$$

where, K_m represent the number of splits for B_m, $s_{km} = \pm 1$ the direction of the step function $[\quad]_+$, $v(k,m)$ the index of the split predictor variable and t_{km} the value of the predictor variable at the split (also referred to as the knot location). MARS is divided into a forward and a backward phase. In very general terms, the forward phases search for the best knot locations in a recursive manner, like:

Algorithm 1

1. Let $\mathbb{C}$ be the set of all candidate knot locations and M_{max} the maximum number of basis functions.
2. Evaluate each knot location in $\mathbb{C}$ by computing the basis function coefficients that minimize a lack-of-fit (LOF) function (usually the squared error loss).
3. Keep the best knot location and exclude it from $\mathbb{C}$.
4. Terminate if M_{max} is reached.
5. Go to 2.

In order not to end up with an over-fitted and unnecessarily complex model, the backward (pruning) phase will remove any introduced knots that do not significantly worsen the fit of the model, even if they are removed, in a stepwise manner. What constitutes a significant reduction in the accuracy of the model is decided by a modified form of the generalized cross-validation criterion by Craven and Wahba (1979). For a more in-depth description of MARS the interested reader is referred to the excellent and in-depth description found in (Friedman 1991).

The input to our problem consists of a sequence of shipping times $\mathbb{S} = \{s_1, \dots, s_p\}$ when individual jobs $\mathbb{P} = \{1, \dots, p\}$ should be ready for transportation. In terms of MARS this represents a function with a single predictor variable ($n = 1, K_m = 1$). Now, by letting the response variable y be the shipping times and the job number be our predictor variable x the MARS procedure will ensure that rate changes only happen at the change from one job to the next, fulfilling the first requirement. Using the squared error loss as the LOF

will not work for our problem since it will not prevent jobs from being late for transport. Instead, we formulate our LOF function as a MILP-problem that computes the basis function coefficients that minimize the total distance between our model $\hat{f}(x), x \in \mathbb{P}$ and $\mathbb{S}$ while enforcing that no jobs are late for transport:

$$\begin{aligned} & minimize \qquad \sum_{j=1}^{p} (s_j - \hat{f}(j)) \\ & s.t. \quad \hat{f}(j) - s_j < 0, \qquad \forall j \in \mathbb{P} \end{aligned} \tag{1}$$

Finally, when considering the required monotonically increasing production rates, using the fact that the slopes of our piecewise linear model $\hat{f}(\boldsymbol{x})$ actually represent the production rates, it can be expressed as in Equation (2) and added as an additional constraint to Equation (1):

$$\frac{\hat{f}(j+2) - \hat{f}(j+1)}{j+2-(j+1)} - \frac{\hat{f}(j+1) - \hat{f}(j)}{j+1-j} =$$

$$\hat{f}(j+2) - 2\hat{f}(j+1) + \hat{f}(j) < 0, \forall j \in \{1, \dots, p-2\} \tag{2}$$

Actually, this represents decreasing slopes (<0). But, considering our choice of the response variable and predictor variable, the axes in Figure 5 are swapped; this corresponds to increasing production rates.

3.3 Simulation Results

Figures 6-9 show some of the major simulation output data plots generated for supporting decision-making activities. Figure 6 is the main output from retro-planning, showing the production rate increased in several ramp-up stages, determined by the recursive MILP algorithm. The main plot in Figure 7 superimposes a learning curve example (the sub-plot in the same figure) tested on the stepwise increased production rates over the simulated horizon to plot the calculated workforce required for the Pre-FAL and FAL lines during the simulated period. It is important to note the dataset presented here, consisted of 9 Pre-FAL stations and 5 FAL stations, is a hypothetical one which did not come from any real company and the calendar in the past as the simulated period (i.e., 1970-1975) is deliberately chosen to avoid revealing the time scale of the studied aerospace problem.

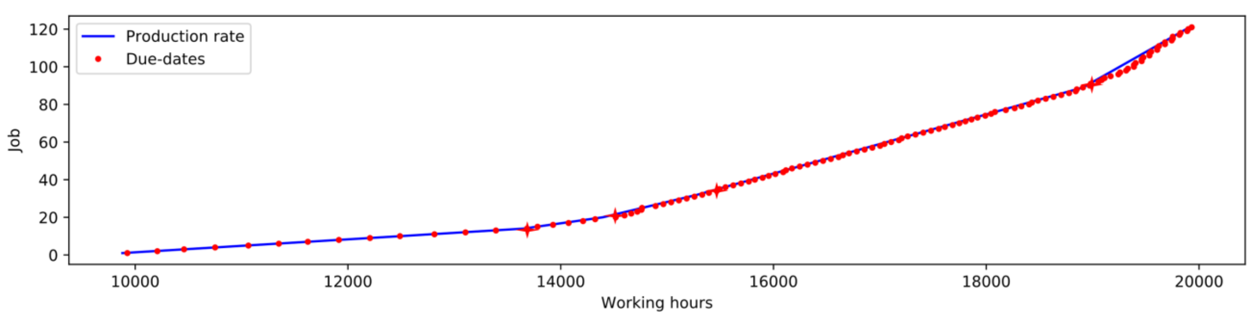

Figure 6: Production rate increased in five ramp-up stages (segments), meeting all the Pre-FAL due-dates.

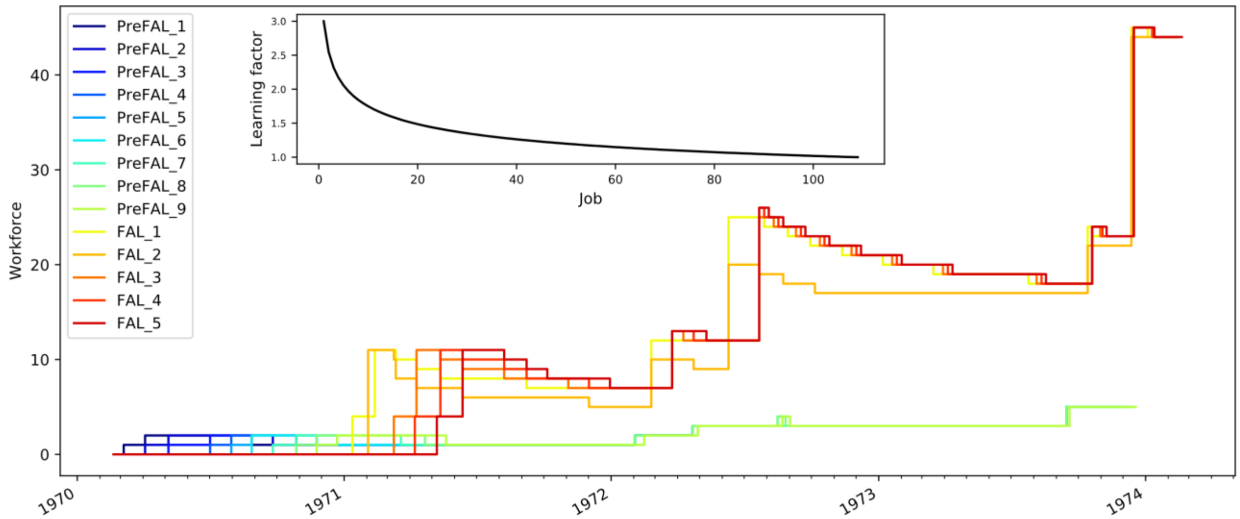

Figure 7: Calculation of the required workforce by considering the learning factor in the sub-plot on the ramp-ups at the PreFALs and FALs.

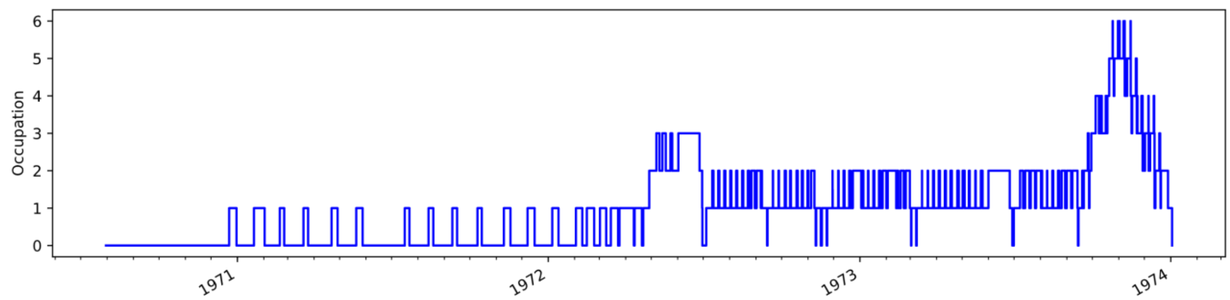

Figure 8: Occupation rate of the inter-plant buffer (number of occupied end buffers) during the entire simulated horizon.

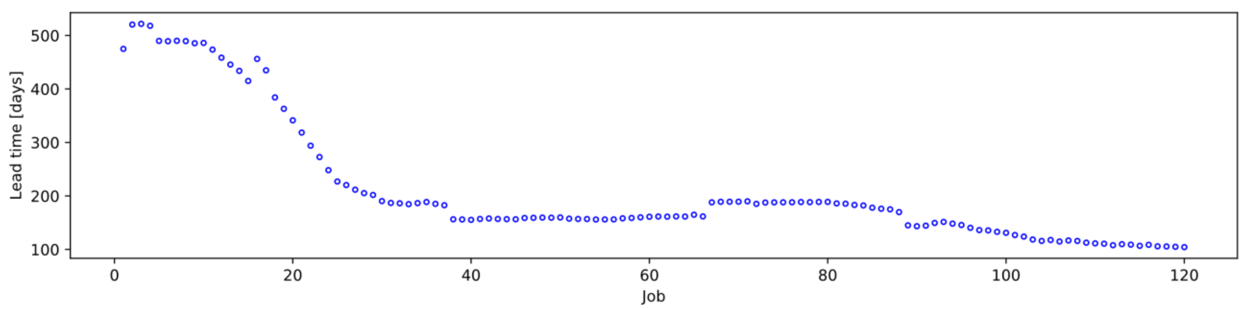

Figure 9: Lead-times of the jobs, decreased over the simulation horizon due to the stepwise increase of the production rate.

The buffer occupation level (Figure 8) plotted with the simulation output data has been found to be very useful for the engineers to see not only how many end buffers are needed, but more importantly, when they are used. Note that with this dataset, six end buffers will be needed, especially to cope with the waiting finished aircraft assemblies near the end of the simulated period, if zero backlog is desired (see also SMO results in Figure 10). Finally, lead-times (in days) of the jobs are displayed from the simulation output. Notably, lead-times of the jobs are declined over time due to the stepwise increase of the production rate.

4 SIMULATION-BASED MULTI-OBJECTIVE OPTIMIZATION

Finally, we include the SMO results using the same model with two different settings to illustrate the corrupting effect of increasing variability. The SMO was carried out with the NSGA-II algorithm (Deb et al. 2002) in FACTS Analyzer using the same simulation model developed for the pilot study. We considered two sources of correlated variability to the simulation model: availability and repair time, in two configurations: (1) availability 99%, and (2) 95%, both with a mean time to repair (MTTR) = 5 hr. in two separate SMO runs. The SMO problem was formulated with three objectives: {Min(Backlog), Min(Buffer), Min(Lead-time)}, using the parameters of the five segments in the ramp-up profile presented in Figure 6 as the decision variables expressed in the equations below:

$$\acute{T}_i = T_i * p_i, \text{where } T_i \text{ is the original takt; } p_i \in [0.1,1]; \ \forall\, i \in \{1, \dots, 5\}$$
$$\acute{C}_i = C_i + \delta_{C_i}, \text{where } C_i \text{ is original takt change; } \delta_{C_i} \in [-15, \dots, 15]; \ \forall\, i \in \{1, \dots, 4\}$$
$$\acute{O} = O + \delta_{O_i}, \text{where } O \text{ is original start offset; } \delta_O \in [0,10000]$$

The SMO results, in the form of EF plots in Figure 10, are anticipated based on the theory about the corrupting influence of variability discussed in Section 2 (see also Figure 1). Specifically, as shown in the two plots, the reduction of availability (i.e., higher variability), in this case from 99% to 95%, has led to the consequence that a larger buffer size and longer lead-time are needed to attain zero backlog (i.e., no tardy jobs). It is interesting to point out the end buffer size to attain zero backlogs is 5 for the availability 99% case when compared with six are required in the deterministic simulation presented in Section 3.3, specifically indicated in Figure 8, simply because the SMO has further fine-tuned the optimization results (Figure 6) from using the MARS approach depicted in Section 3.2. Nevertheless, it is over the scope of the paper to reveal further details of the difference between the solutions after the fine-tuning.

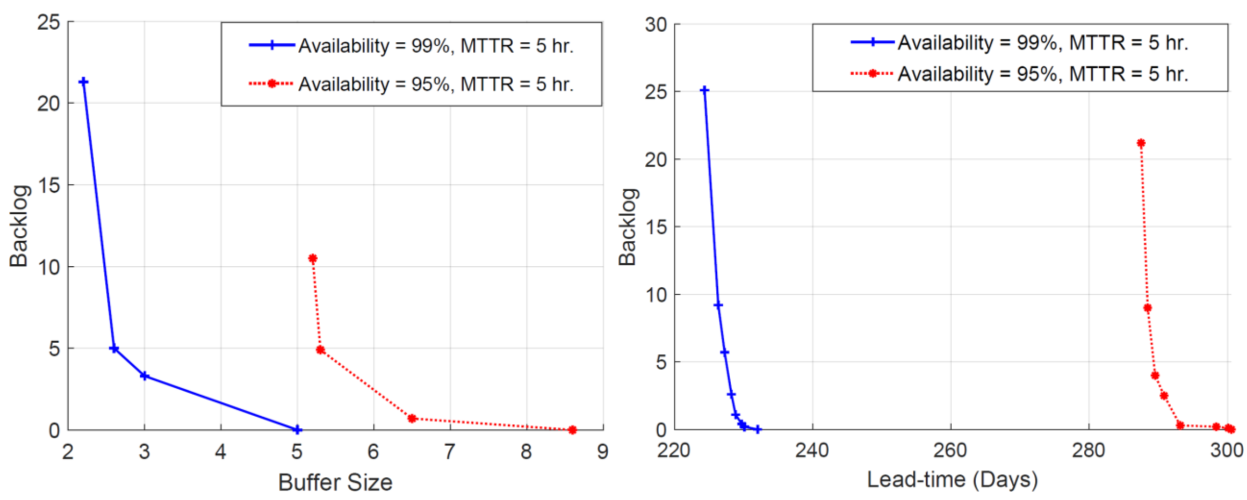

Figure 10: SMO results in EF plots, Buffer-Backlog on the left, and Lead-time vs. Backlog on the right, showing the corrupting effect of increasing variability.

5 CONCLUSIONS AND OUTLOOK

Through the integration of simulation and optimization models, metaheuristics, and analytical ones like MILP, decision variables in the conceptual design phase of aircraft assembly lines can be optimized with multiple conflicting objectives. This paper has presented such an application study to an aircraft assembly ramp-up planning problem that invoked the need for a hybrid simulation-optimization approach, combining discrete-event simulation, recursive MILP, and NSGA-II.

Although the developed toolset/solution and the generated results have considered many specificities related to the ramp-up planning in the aerospace industry, the approach is by itself generic to consider more design factors in the industrialization project, which have not been covered in this paper. Another crucial aspect of supporting decision-making, namely, the analysis of any patterns of the ramp-up profiles that constituent the optimal solutions in different regions of the EF plots – a concept we discussed extensively in previous publications (Ng et al. 2016; Bandaru et al. 2017), is being planned to be carried out shortly. When combined as a complete optimization-based decision-making support methodology, we believe they provide a general framework for solving some other industrial supply-chain network optimization problems.

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