Proceedings of the 2016 Winter Simulation Conference
T. M. K. Roeder, P. I. Frazier, R. Szechtman, E. Zhou, T. Huschka, and S. E. Chick, eds.

TARGETED INCREMENTAL DEBOTTLENECKING OF BATCH PROCESS PLANTS

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ABSTRACT

This paper provides analysis and debottlenecking strategies for batch process plants. Operational characteristics like shared resources, multiple products and product lines, and process step variability can make debottlenecking choices complex. A disciplined methodology for debottlenecking helps an improvement team to sift through options efficiently to find cost-effective recommendations that meet the desired improvement goals but avoid wasteful or excessive investment.

We take into consideration these challenges and provide a practical methodology for the systematic debottlenecking of batch processes through the use of statistical, discrete-event simulation, and optimization tools. The analysis and methodology we propose is applicable quite generally to parallel, sequential, as well as sequential-parallel multi-product batch plant configurations.

1 INTRODUCTION

1.1 Motivation

Increasing process throughout (debottlenecking) is certainly a familiar subject in industrial engineering and previous WinterSim conferences have many fine papers on the topic. However, for chemical batch processes, operational characteristics like shared resources, multiple products and product lines, and process step variability can make debottlenecking choices complex. We sought to develop a disciplined methodology for debottlenecking to aid improvement teams as they sift through options efficiently to find cost-effective recommendations that meet the desired improvement goals but avoid wasteful or excessive investment. Regardless of the throughput increase, the improvement must be able to meet the minimum economic return on investment (ROI) set by the company.

Market forces like increasing demand and market expansion often push required production beyond current capability. Increasing throughput may also have operational and supply chain benefits leading to increased profitability. Increases in plant throughput enable ramping up production to keep pace with demand, and can help drive top line growth. Increases in throughput may also lead to flexible production schedules or reduce production makespans and consequently reduce operating costs to improve bottom line performance in lower demand periods. Differentiated high-value products are often associated with seasonal demands with high variability (Cachon and Terwiesch 2012) so a debottlenecked plant can have a positive effect on inventory and delivery lead times, and is responsive and robust to fluctuations in market conditions.

In what follows we present our approach to successfully debottlenecking a chemical batch plant to meet the increased production target, meet the required ROI and capture supply chain synergies.

1.2 Literature Review

In the process engineering literature, debottlenecking opportunities for continuous process plants are discussed by Litzen and Bravo (1999) and Litzen and Flanegan (2016). Their work uses a simulation-based approach to rank unit operations in terms of their distance from target throughput. The unique feature with process plants is that unit operations that exceed the target throughput may be modified by leveraging reflux ratios, heat duties, column pressures, etc. to afford greater throughput in bottleneck unit operations. Several case studies are presented. Other papers take an optimization-based approach (e.g., Diaz et al. 1995; Voudouris 1996; Zhang, Zhu, and Towler 2001).

Koulouris, Calandranis, and Petrides (2000) provide systematic analysis for batch plants. They use processing times and utilizations to define a number of metrics that are useful for characterizing bottlenecks. Different equipment are classified based on the relationship between their capacities and their uptime. The fundamental premise is that overall throughput improvements can be made by increasing batch sizes. Depending on what class the equipment bottleneck belongs to, one may be able to increase batch sizes by (1) introducing more cycles per batch for the relevant equipment; (2) reassigning larger equipment to bottleneck tasks; or (3) introducing new equipment. The paper considers a single-product plant, and the methodology does not incorporate processing time variability.

Several other papers in the literature (Tan et al. 2007; Alshekhli et al. 2011) use similar principles for different debottlenecking applications.

1.3 Approach

Over the last few decades, batch process plants have become prevalent for the production of specialty chemicals and other low-volume/high-margin products (Rippin 1993). One advantage of batch approach is that multiple products can be produced just by changing the batch recipe. Recipes specify the rations of raw materials, operating conditions, feeding sequences, processing times, etc. A consequence of having a multi-product plant is that there is not a single product that represents the average performance of the plant and the sequence and relative demand of the different products must be considered in the debottlenecking analysis.

In manufacturing plants the personnel, product mix, operations and state of equipment change frequently and having an updated understanding of how these affect current plant capacity can help technical teams not only operate better, but respond quickly to calls for production capacity increases. Mathematical models of plant operation are often the easiest and best way to describe current operations. These are typically categorized as either simulation models or optimization models. Each has its pros and cons, and our experience suggests that they are best used in a complementary manner; simulation models enable high fidelity descriptions of operations, rules, and variability, while optimization models effectively manipulate high-dimensional degrees of freedom over abridged model representations. Our debottlenecking strategy incorporates an optimization sub-step, as described in later sections.

Production systems with significant variability in processing times are modeled easily in discrete-event simulation environments. A debottlenecking case study using discrete-event simulation, and involving a sequential-parallel multi-product production process is presented in Sharda and Bury (2010). The work performed bottleneck analysis within the DMAIC (define, measure, analyze, improve, control) framework of Six Sigma project management system (Breyfoggle III 1999). In this paper we build and expand upon that approach.

Within the 'define' phase of the project, market conditions are analyzed to set new production targets, the available improvement budget and the current understanding of operations can determine how much improvement in throughput is required and theoretically possible. The updated knowledge of operations would also be part of the 'control' phase, once improvements have been made. The 'measure', 'analyze', and 'improve' phases are part of the iterative debottlenecking scheme we propose in this paper.

The methodology we present eliminates bottlenecks in a systematic manner with consideration of costs and practical improvement constraints; considers variability in processing times; is applicable to multi-product batch plants with general configurations – sequential, parallel, or sequential-parallel; and combines the relative advantages of discrete-event simulation and mathematical optimization. The method may also be extended to be applicable to both flowshop and jobshop plants.

Section 2 defines the problem we consider, including the scope and pre-analysis of data; Section 3 outlines the analysis and debottlenecking method that we propose; and Sections 4 and 5 illustrate and discuss results on an example case study at The Dow Chemical Company.

2 PROBLEM DEFINITION AND PREPROCESSING

2.1 Process Description

The plant layout for the case study we consider is shown in Figure 1. The four production trains are shown. Each train is a sequential sequence of operations and each train may be in a different state. The blue boxes indicate the major processing equipment. The grey boxes are shared resources between the trains. Arrows indicate direction of material transfer. As this is a batch process, the material flows occur at discrete time intervals. As products are recipe-based, raw material tanks are resources that are shared among the trains. Manpower and other mechanical operations may also be shared among the trains.

Raw materials are loaded sequentially onto a particular train, and can also be loaded simultaneously on the four trains. In addition, required resources may be captured by a train making them unavailable and causing a delay in the other trains. This adds to the overall processing times. The equipment is not identical in size or throughput across trains, and this is taken into consideration while allocating batches to trains in the batch scheduling phase.

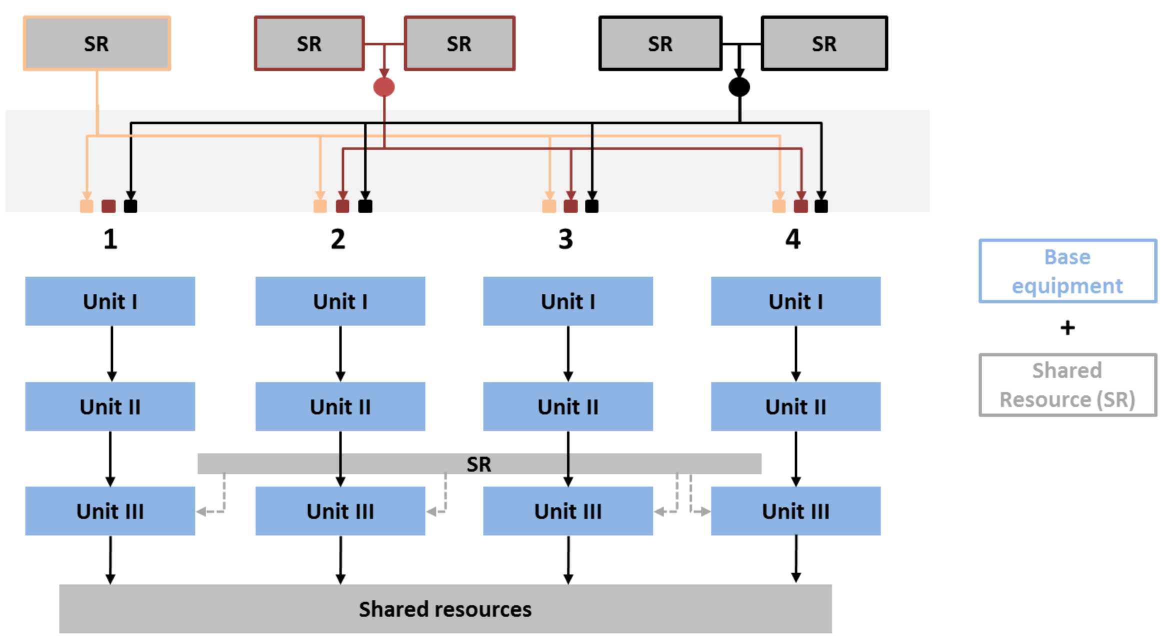

Figure 1: Four parallel production trains are shown (1, 2, 3, 4). Blue boxes are processing equipment, and grey boxes denote shared resources (equipment or manpower).

2.2 Schedule Conversion

We use a high-fidelity simulation that has the operational logic and fitted probability distributions to analyze scenarios that will deliver the required production capacity increase. The first step is to translate this monthly production target into a form that can be used in the simulation. Given an improvement target in the form of an absolute annual throughput goal, or a percentage increase from current production levels, we scale this for one month's worth of production as in Figure 2.

As illustrated in Figure 2, the production plan target (step 1) may be divided into the fractions that represent a forecast of the relative production volumes of the different products—a product wheel (step 2). We then divide these volumes into individual batch sizes (step 3), assign these batches to different trains (four, in our case), and specify a batch/campaign sequence (step 4). At this point the makespan will exceed 30 days because of current production bottlenecks. We can then complete step 4 by examining a proposed set of improvements (debottlenecking) to reduce the makespan to 30 days on all trains.

The division of volume into batches is really more involved, as batch size will depend on the equipment used to process it or the train it is assigned to—this will be discussed in more detail in the next section. We assume that we have already determined maximal batch sizes for each product on each train/set of processing equipment (through, say, a similar method to that proposed in Koulouris, Calandranis, and Petrides (2000)), and focus on improvements beyond batch size increases.

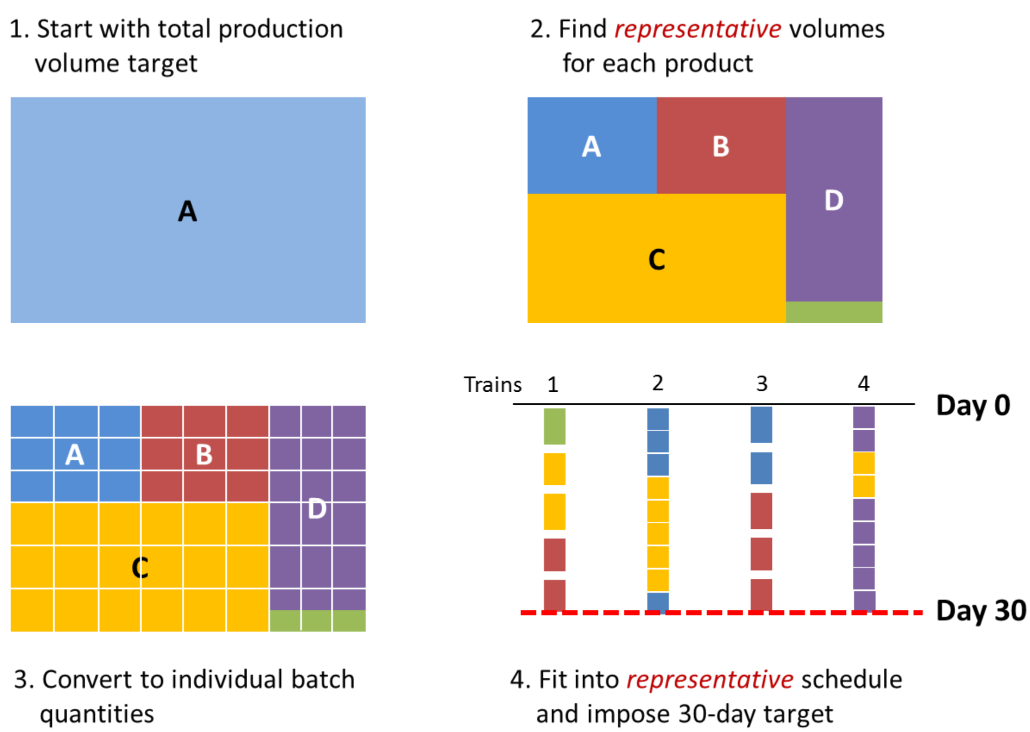

Figure 2: Translation of a monthly production target to simulation input in the form of a monthly production schedule.

2.3 Data Analysis and Key Metrics

Process monitoring systems are often set up to capture individual step times in a batch process. From a simulation point of view, it is important to segregate the independent data from the dependent data to avoid double counting. We may only need to consider certain processing times; some wait times may only be a consequence of the processing times.

Next, we collect relevant historical data in order to understand the nature, distribution, and correlations in the data. As mentioned earlier, the plant operation may constantly be changing, and it is important to use data that bests represents both current operation and future product mix. The understanding of step time variability is improved by extracting data from periods of operation where (1) the product mix is representative of forecasted demand; (2) the step times are not time-varying; (3) there is no process idling. Of course, best practices for data analysis such as removal of outliers, use of appropriate product substitutes in case of limited historical data, and use of empirical distributions when no parametric distribution is appropriate should be employed. We use the JMP statistical software (SAS Institute 1989-2015) for visualization and analysis of data and the ExpertFit® distribution fitting software (Law 2006) to fit the data as it provides output in the syntax of the simulation software specified.

Further, it may be helpful to narrow the scope to portions of the production process that are going to impact the analysis. For instance, an auxiliary production process that produces a precursor to the plant under consideration may be left out if, historically, there has never been lack of supply—it will not affect the bottleneck analysis. With an understanding of the processing logic, relevant scope, and the relevant step time distributions, a discrete-event simulation can be built; we use the ExtendSim® software (Imagine That Inc. 2013) for this.

To validate the simulation, a comparison of inter-batch start times, overall production times, queue lengths, and individual processing and wait times may be useful. If the match is not satisfactory, a review of the simulation setup and details of operations and data must be done. Gaining confidence in the simulation and its ability to reproduce historical data is often a time-consuming step.

From a debottlenecking point of view, it is useful to aggregate individual step time data to compute equipment utilizations. The equipment utilization point of view is useful, as it makes it easier to identify bottlenecks in the system. A piece of equipment that is used all of the time (100% utilization) is clearly the rate-limiting step, and therefore is a bottleneck in the process. Reducing the time in this equipment speeds up the overall process, and increases the utilizations in the other pieces of equipment as well. This pre-processing of data forms part of the measure/analyze step in the Six Sigma DMAIC process.

3 DEBOTTLENECKING STRATEGY

A multi-product, sequential-parallel production scheme provides for flexible manufacturing operation is harder to analyze than a single batch train. In a sequential-parallel process plant, multiple trains or processing steps may involve shared resources. For instance, a step may involve the injection of a polymer into the vessel. This polymer may come from a common reservoir that can service only one vessel at a time. As this is an activity common to multiple parallel processes, an improvement in the injection time may affect all parallel processing trains. Another factor in process plants is the nature of material flows between equipment. If a viscous liquid or solid is involved, multiple pieces of equipment may be involved in the same processing step. Similarly, if operating protocol says that a batch has to wait for a downstream vessel as it prepares for material transfer, both vessels are being utilized at the same time. Again, an improvement in this step could positively impact utilizations in both pieces of equipment.

For a multi-product plant, it may not be straightforward to determine what the bottleneck is, let along the extent to which the bottleneck process must be improved, as is illustrated in Figure 3. In Trains 1 and 3, the utilizations in Units II and III (which are a combination of load, process, and unload operations) are in the high 90s, indicating that they represent the bottleneck, although not all of the time. In Trains 2 and 4, this is less clear. This is due to both processing time variability as well as product mix, and warrants a closer look. Variability in processing times further confounds production and bottleneck analysis, and a product-wise look at equipment utilization times is required (Figure 4).

The figure shows the processing time spent by all products in each of the major equipment units on Train 1. Error bars show the variability across batches. The products, along with the number of batches in parenthesis is shown on the horizontal axis. This serves to further explain what we see in Figure 3, where the bottleneck seems to be Unit III. Product B has most number of batches, and, on average, spends most processing time in Unit III. However, Unit I spends most time processing Product A and, even in the case of Product B, some batches may spend more processing time in Unit I due to variability (as indicated by the overlapping error bars).

In this case, most impact would be made if we focused on Product B as it is the most-produced product by far. In order to remove the bottleneck for Product B, we improved the processing time in Unit III by 45 minutes, so that Product B would take as much time in Unit III as in the other Units.

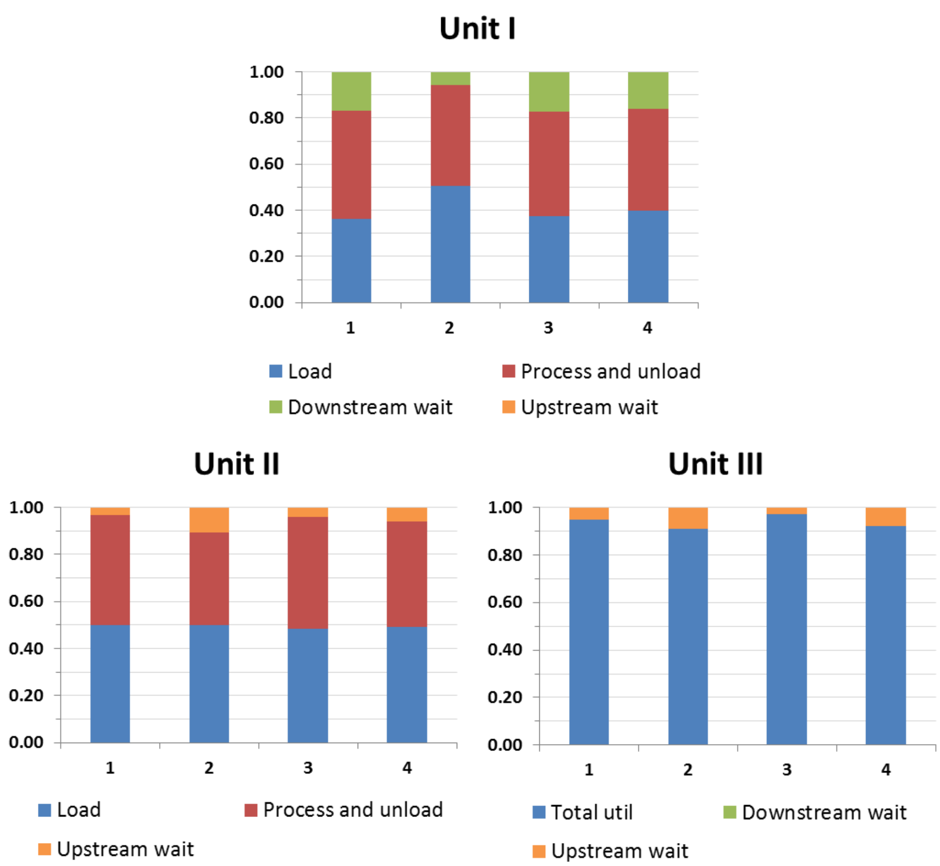

Figure 3: Illustrative example of utilizations in the major equipment on each train.

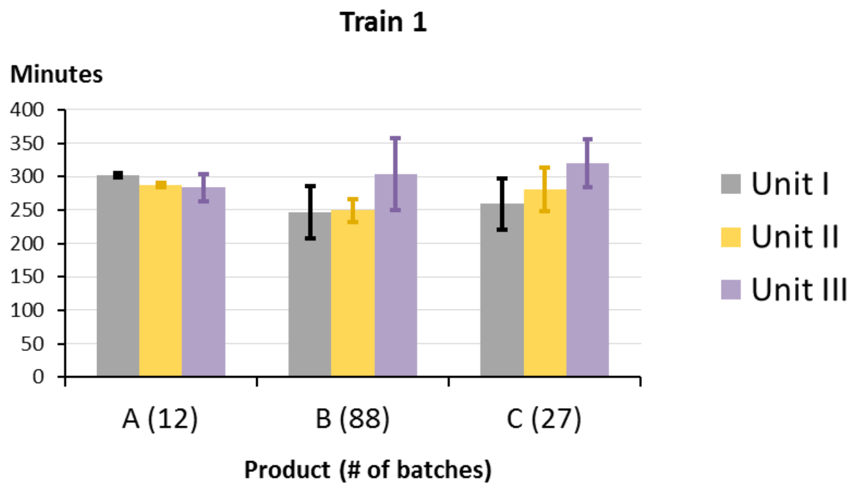

Figure 4: Time utilized by major equipment units in processing each product on Train 1.

3.1 Classification of Process Improvement Options

Improvements may be classified as: Type 1—operational improvements by removing slack and uncovering hidden capacity with current infrastructure; Type 2—upgrades to current equipment, planning and scheduling improvements and improvements in operating discipline; Type 3—fundamental improvements in operating policies; and Type 4—investment in new pieces of equipment/trains. This classification represents the relative ease with which these improvements may be implemented, with Type 1 being the easiest, and Type 4 being most difficult, as it involves significant capital investment.

Type 1 improvements are low-hanging fruit that should become apparent with a close look at step time data. Unnecessary wait times for downstream equipment that are coded in to plant control logic are an example of this.

Examples of Type 3 improvements may involve combining two steps in a piece of equipment by carrying them out simultaneously, or modifying the recipe to add ingredients in a different sequence, or changing ingredient loading operation to complete loading a batch on one train before moving to the next (conversion from parallel to sequential operation in the loading sub-process). These changes may require a more involved study by the research or operations teams before they can be implemented.

Type 4 improvements involve the most capital expenditure, and involve investment in entirely new pieces of equipment (e.g., larger processing vessel, intermediate storage), or in entirely new trains. This type of improvement is less common, and takes place only when there is a need to significantly increase capacity.

Type 2 improvements will be the focus of this work. Upgrades to equipment may include, for example, replacing an existing pump with one that can pump at a higher rate, or introducing an online measurement device to avoid having to do a manual sampling step. Planning and scheduling improvement opportunities can be discovered through the use of mathematical programming models. The models could be used, for instance, to determine the number and size of batches, their train allocation in order to balance overall processing times across trains, and the processing sequence that minimizes average wait times, product changeovers and cleaning rinses between campaigns. In our case study, transitions and cleaning add significant processing time, and the focus is on minimizing these. These recommendations may be brought back to the simulation environment for rigorous analysis. Improvements in operating discipline involve reducing the variability around manual tasks by implementing training programs or updating work processes.

Prior to debottlenecking, it is important to distinguish between improvements that can *guarantee* a certain improvement in processing time (e.g. Type 1, Type 2 (equipment upgrades), Type 4), and those that can improve a certain processing time *in theory* (e.g. Type 2 (operating discipline, planning and scheduling), Type 3). The extent of operating discipline improvements is inherently hard to guarantee, as they involve imperfect human involvement. The precise magnitude of planning and scheduling improvements may also be difficult to guarantee due to a certain supply chain or inventory policy in place, or due to changing product mix that will change batch-train allocation.

It is also important to specify the maximum speed-up that is technically possible with the improvements that can guarantee processing time reduction. When going after a certain production target in the debottlenecking process, we stack *guaranteed* improvements while respecting this technical constraint, and then implement *theoretical* improvements on top of these. Different *theoretical* improvement scenarios can be analyzed by appropriately rolling back the guaranteed improvements.

3.2 Debottlenecking Decision Sequence

The approach we propose is to first see whether these improvements are enough to achieve the target. If they are, then we need to specify which improvements will achieve the target exactly. By doing this, in combination with targeted debottlenecking study, we ensure that (1) the investments or improvements we propose are most effective and not wasteful; and (2) we do not invest excessively by overshooting our target. The debottlenecking procedure includes iterated measure, analyze, and improve steps of the Six Sigma DMAIC process.

The debottlenecking strategy is as follows:

Step 1. **Analyze operations –** Run simulation to obtain step times by product and by train (as in Figure 4).
Step 2. **Identify improvement opportunities –** Determine the average gap between largest and smallest step times on high volume products on each train. If *guaranteed* improvement (Phase I) opportunities have been exhausted, consider *theoretical* improvements (Phase II).
Step 3. **Determine improvement scenarios –** With consideration of feasibility, narrow down on a specific cycle time improvement or change in operations on each train, and choose the most economical investment option that delivers this improvement. If budget is already exhausted, elmininate improvement options that involve capital.
Step 4. **Implement improvement –** Code in improvements in the simulation, and if all improvement opportunities are not exhausted return to **Step 1** to investigate a new improvement scenario; else proceed.
Step 5. **Target progress check –** If production targets are not achieved, deem it infeasible and **exit**, reporting the best possible improvement, cost, and shortfall.
Step 6. **Backtrack –** Roll back most recent set of cycle time improvements in simulation.
Step 7. **Simulate –** Simulate; if production targets are still achieved, return to **Step 6**, else proceed.
Step 8. **Meet target –** Use a binary search to converge to precise cycle time improvement recommendations for each train. Ensure that the 30-day target is met with high probability.

For each of the simulation scenarios, we compute the number of replications required (Law and Kelton 2000) through

$$n(\beta) = \min\left\{ i \geq n_0 \;\middle|\; t_{i-1,1-\alpha/2}\sqrt{\frac{S^2(n_0)}{i}} \leq \beta \right\},$$

where β is the absolute error desired, and α is the confidence level. $S(n_0)$ is the standard deviation obtained using $n_0$initial replications.

The reason this 'incremental improvement followed by backtracking' strategy shines is that when we backtrack, we have a roadmap as to which improvements to be more conservative about at each backtracking step. Once we have done Phase I, different Phase II scenarios can be tested on top of these. Once plant personnel narrow down on the specific Phase II (thoeretical) scenario that they feel is most realistic, we now have a method to roll back Phase I improvements to determine the precise set of cost-effective cycle time improvements that we need to invest in.

4 CASE STUDY AND RESULTS

The iterations of the algorithm described in the previous section result in the waterfall step times shown in Figure 5. Iterations 1—5 represent *guaranteed* improvements. The cycle time improvements in these five iterations are shown at the top of Figure 6.

Iteration 6 represents improvements in operating discipline, and Iterations 7 and 8 represent balancing of batches on trains and rescheduling to minimize transitions and rinses between campaign respectively. Iteration 9 is the final backtracking step which we implement when we see that the implemented improvements overshoot the target production level in Figure 5.

At the outset, it was given that it is not feasible to improve cycle times in Units II and III beyond 45 minutes. An example of bottleneck improvement hitting a constraint is in Iteration 3 at the top of Figure 6. In Iteration 3, Unit III is still the main bottleneck in Train 1. However, the 45 min improvement limit has been hit in Iteration 2, so Unit II is improved instead. This still delivers a 1 day overall time improvement as can be seen in Figure 5.

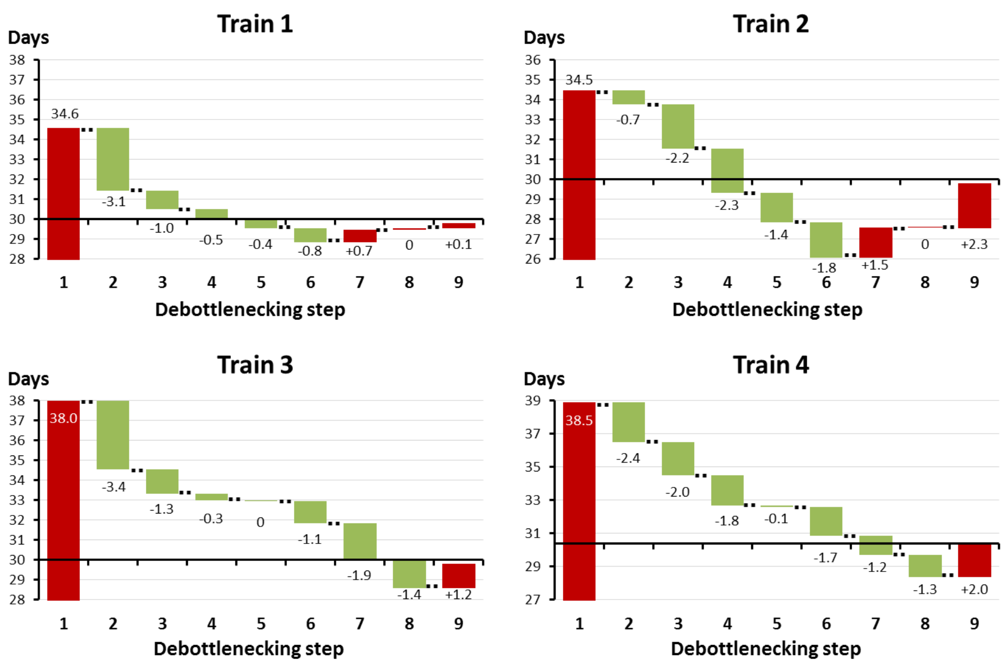

Figure 5: Total production times for all trains after Phases I and II (Avg. = 29.9 days).

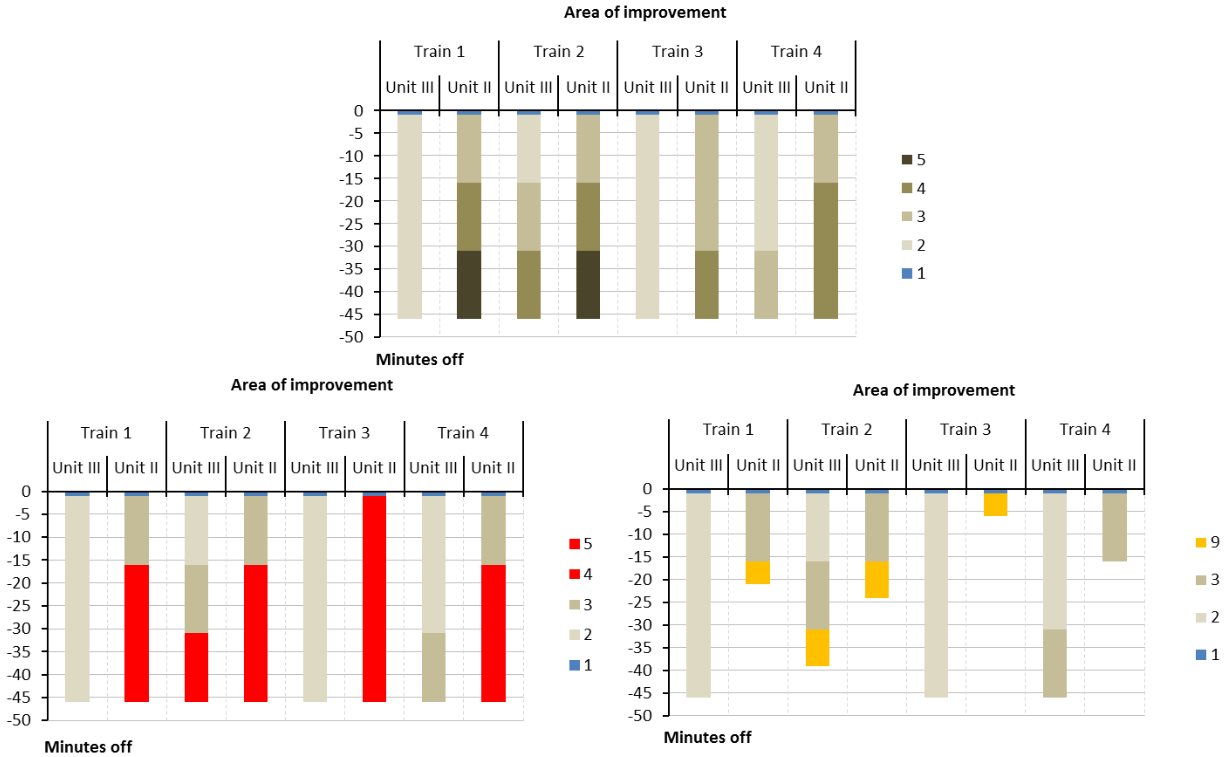

Figure 6: Cycle-time improvements for debottlenecking iterations (top and bottom right figures). Bottom left figure shows extent of roll back.

5 CONCLUSIONS

The debottlenecking method we propose is very generally applicable. Given an target throughput and a set of improvement options, the decision sequence sifts through a set of improvement options efficiently. It considers costs, process time variability, and feasibility of improvements to cost-effectively improve capacity in a multi-product sequential-parallel batch process plant.

The classification of process improvement types, the use of mathematical optimization as a sub-step, and the backtracking method facilitate the recommendation of specific improvements while avoiding wasteful expenditure. The method is illustrated through a sequential-parallel batch plant case study.

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