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CONTRIBUTORS TO LEAD TIME IN CONSTRUCTION SUPPLY CHAINS: CASE OF PIPE SUPPORTS USED IN POWER PLANTS

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ABSTRACT

This paper describes process models that characterize the design phase in the supply chain of pipe supports used in power plants. The models are used to study how production system design factors such as batching, uncertainty, and multitasking throughout this phase hamper supply chain performance. These factors all cause an increase in lead time. The models build on the STROBOSCOPE discrete-event simulation engine and illustrate several deterministic and probabilistic simulation scenarios including different batch sizes, uncertainty levels, and allocation percentages of shared resources. Based on the analysis of the simulation results, this paper recommends performance improvement opportunities that apply not only to the supply chain of pipe supports but generally to the delivery of capital projects.

1 MOTIVATION

This paper presents process models and discrete-event simulation results to highlight factors that contribute to lead time in the delivery of capital projects. The models specifically represent one part of the design phase in the supply chain of pipe supports used in power plants. Today's practices characteristically have lead times that are very long relative to the modest amount of value-added time that is needed to execute each single task or a sequence of tasks that make up a process in the supply chain. This study is to help project managers quantify lead times in current practice and identify opportunities for lead time reduction.

2 IMPORTANCE OF PROCESS SIMULATION

Simulation is an important tool in process optimization. It may be used either to sharpen intuition about 'the expected' or to discover 'the unexpected' before the real process has started or during its execution. Through the use of simulation, people can gain insight into one or several processes that constitute a complex system so that they may identify missing parameters and predict the behavior of that system under varying conditions. Furthermore, simulation helps them to design and analyze a production system, to determine ordering and restocking policies for materials inventory, to design communications patterns, to study transportation alternatives, to analyze financial implications, and all this, with the possibility of evaluating different process design alternatives.

3 SUPPLY CHAIN MODELING

Supply chains are linked chains or networks of interrelated tasks designed to best satisfy end-customer needs while rewarding all members of the chain. Supply chains therefore lend themselves to being mapped to process models for use in simulation, as is described here.

4 DESIGN PROCESS FOR PIPE SUPPORTS

Figure 1 illustrates a process in the form of a value stream map (after Rother and Shook 1998) that characterizes one part of the design phase in the supply chain for pipe supports (Arbulu 2002, Arbulu and Tommelein 2002a, b). Rectangles illustrate so-called value-added or conversion tasks. Triangles illustrate holding places or buffers between the value-adding tasks. The map focuses on routing pipe, locating pipe supports, and conducting a pipe stress analysis and reflects data collected on power plant projects. Each of the tasks, respectively, takes about 2-to-2.5 man-hours (mh), 0.5 mh, and 1.8-to-2.3 mh per support. These durations add up to a total of about 4.3-to-5.3 mh of value-added time per support to be processed. In practice, however, any one support usually takes 8 weeks of so-called lead time to go through this three-task process. The ratio of value-added time over lead time thus is a mere 1-to-2%! The presented simulation model seeks to provide a rationale for this incongruity.

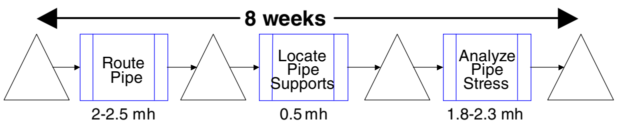

Figure 1: Excerpt of Design Process for Pipe Supports

Three potential explanations for this incongruity are (1) batching, (2) variability in task durations, and (3) multitasking throughout this three-task process. Batching means that outputs from one task are released to the next task, not in a unit quantity (which, in this case, would mean one support at a time), but in sets that follow certain grouping criteria. Variability in task duration stems from factors such as complexity of support designs, engineering skill levels, tooling requirements, etc. Multitasking means that a resource is not dedicated exclusively to performing one task at a time, but instead alternates working on several tasks before completing any one of them. In combination, these three factors may result in significant increases in supply chain lead time relative to time needed to perform each and every value added task in the chain.

5 DESIGN PROCESS MODEL IN STROBOSCOPE

The models in this paper build on the STROBOSCOPE discrete-event simulation engine (Martinez 1996) and illustrate deterministic and probabilistic simulation scenarios including different combinations of batch sizes, uncertainty levels, and shared resources. All models were run in STROBOSCOPE (version 1,2,2,0) on a Pentium 566-Mhz computer with Windows® 98 second edition.

Figure 2 depicts the STROBOSCOPE process model of the tasks 'route pipe,' 'locate pipe supports,' and 'analyze pipe stress,' corresponding to the rectangles in the value stream map shown in Figure 1. Modeling assumptions were made to be consistent with the aim of this study, which was to highlight supply chain problems located at the interfaces between processes, rather than to realistically model any specific value-added task in the supply chain. The most relevant modeling assumptions are the following:

1. The process model includes (1) a primary chain (surrounded by a blue, solid box in Figure 2) with RoutePipe1, Locate1, and AnalyzeStress1 and (2) a secondary chain (surrounded by a red, dashed box) with RoutePipe2, Locate2 and AnalyzeStress2. For a specific project being studied, it is assumed that pipe supports will flow through the primary chain. The purpose of the secondary chain is to illustrate that resources engaged in the primary chain may perform work for other projects also; that is, they multitask.

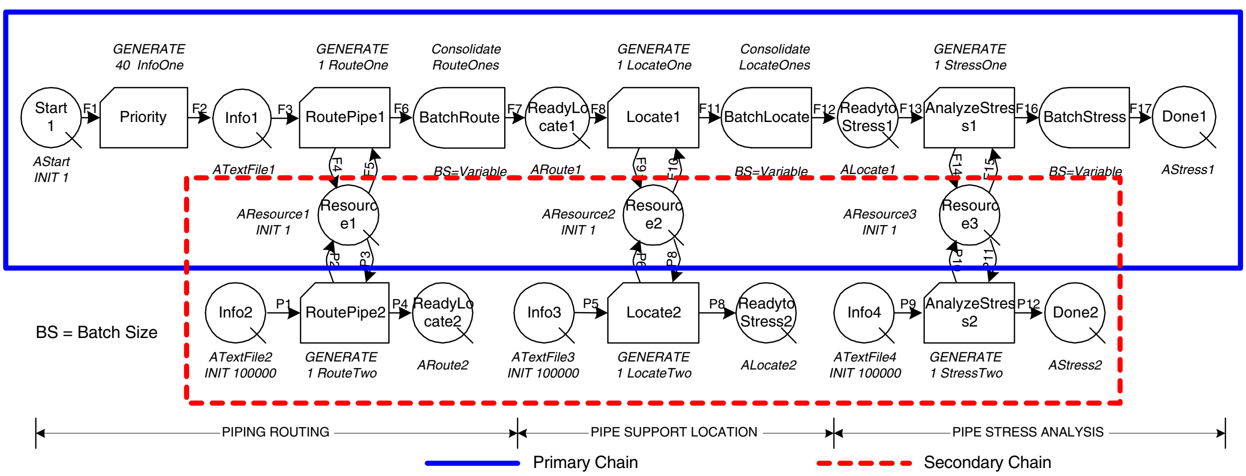

Figure 2: STROBOSCOPE Process Model of Design Tasks for Pipe Supports

2. The inputs and outputs of each task in the secondary chain are independent of those of other tasks: they are decoupled (e.g., the output from RoutePipe2 does not yield direct input into Locate2, whereas output from RoutePipe1 fed into Locate1) to reflect that the amount of work designers have on different projects can vary substantially.
3. The effect of batching is introduced only in the primary chain since the secondary chain has been decoupled. This effect is included in the design phase using three different consolidator nodes (see Table A in Appendix for an explanation of the various nodes used in Figure 2) called BatchRoute, BatchLocate, and BatchStress.
4. The duration of each task may vary over a range of values, which mimics variability in the design of various kinds of pipe supports.

6 IMPLEMENTATION AND SIMULATION OF SUPPLY CHAIN TASKS

Using Figure 2's graphical representation of supply chain tasks, several deterministic and probabilistic simulation scenarios were implemented. The resources that remain constant in these scenarios are:

1. The number of pipe supports to be designed for the project flowing through the primary chain (represented by Info1) is equal to 40 units. This number corresponds in order of magnitude to the number of supports that are engineered to suit the main steam system of a power plant project. It is sufficiently large to yield interesting simulation results, yet sufficiently small for the simulation processing time to remain small.
2. The number of pipe supports that enter the secondary supply chain is equal to 100,000 units. This number is set high to reflect the assumption that the design firm has a lot of work to do. The project schedules that define due dates on any of their design tasks are ignored; otherwise, they would affect the prioritization of work and thus the task priorities of shared resources (as is elaborated on later in the paper).
3. The number of resources Resource1, Resource2, and Resource3 is set equal to 1 unit for all models. These resources will be shared by the primary and the secondary chain in scenario 2. Table 1 summarizes the two scenarios that are detailed next.

7 SCENARIO 1: DETERMINISTIC MODEL WITH BATCHING

The first simulation scenario illustrates the contribution of batching to lead time. Only the primary chain with deterministic task durations is considered in this model. It will serve as a baseline for comparing behavior against other, probabilistic simulation scenarios that combine uncertainty, multitasking, and batching.

Scenario 1 has been simulated considering different batch sizes as listed in Table 2. In all cases, the durations of the tasks RoutePipe1, Locate1, and AnalyzeStress1 are, respectively, 2.25 mh/8 mh = 0.28, 0.5 mh/8 mh = 0.06, and 2.05 mh/8 mh = 0.26 working days per support (Table 3). These values represent the averages of the data shown in Figure 1, converted into the equivalent number of working days per support.

Table 1: Simulation Scenarios

Scenario	Type of Model	Chain	Focus
1	Deterministic	Primary	Batching
2	Probabilistic	Primary + Secondary	Batching + Variability + Multitasking

Table 2: Batch Sizes and Resulting Total Process Simulation Times for Scenarios 1 and 2

Run	**BatchRoute** [number of supports]	**BatchLocate** [number of supports]	**BatchStress** [number of supports]	**Scenario 1** Duration [work day]	**Scenario 2** Duration based on 100 simulation runs [work day]	
					Mean	Standard Deviation
1	1	1	1	11.52	11.69	0.32
2	2	2	2	11.84	11.88	0.29
3	4	4	4	12.48	12.54	0.30
4	8	8	8	13.76	13.72	0.31
5	10	10	10	14.40	14.45	0.30
6	20	20	20	17.60	17.52	0.23
7	40	40	40	24.00	24.01	0.34

Table 3: Task Durations for Scenarios 1 and 2

Task	**Scenario 1 Task Duration** [work days/ support]	**Scenario 2 Task Duration** [work days/support] Normal [mean, standard deviation]
RoutePipe1	0.28	Normal [0.28,0.05]
RoutePipe2	n/a	Normal [0.28,0.05]
Locate1	0.06	Normal [0.06,0.01]
Locate2	n/a	Normal [0.06.0.01]
Analyze-Stress1	0.26	Normal [0.26,0.05]
Analyze-Stress2	n/a	Normal [0.26,0.05]

The results of these simulation runs are plotted in Figure 3. The relation between batch sizes (which, for convenience were chosen to be the same for each of the three tasks in any given run) and lead time here is linear. As is to be expected, the worst situation arises when the batch size is equal to the total number of supports in the system: this situation results in the longest lead time. In this run, a batch size of 40 for each task results in a lead time more than twice the lead time obtained with a batch size of 1.

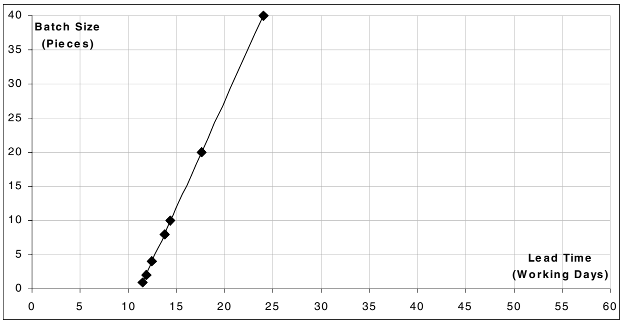

Figure 3: Effect of Batch Size on SC Lead Time

Figure 3 demonstrates that batching is an important consideration in process design because the bigger the batch size, the longer the lead time of the process overall. While this finding is nothing new in the field of production management (e.g., Hopp and Spearman 2000), managers of engineering design projects and managers of construction projects are not necessarily aware of it. If they understood this finding better, they would more consciously shape batch sizes with project schedule and overall supply chain performance in mind.

8 SCENARIO 2: PROBABILISTIC MODEL WITH BATCHING, VARIABILITY, AND MULTI-TASKING

Scenario 2 illustrates the impact of batching combined with variability and multitasking on lead time. Table 3 (shown previously) presents the probabilistic task durations that are used to simulate variability in the system for scenario 2. Normal distributions are used. For example, the normal distribution applied to RoutePipe1 means that 68% of the time that task's duration will fall within the range delimited by the distribution's mean plus-or-minus one standard deviation. Specifically, 68% of the time, RoutePipe1's duration will be greater than 0.23 (0.28-0.05) working days per support but less than 0.33 (0.28+0.05) working days per support.

The secondary chain now has been added to the model in order to mimic the effect of various degrees of multitasking in the system. The degree of multitasking is determined by the percentage of time a shared resource—when given a choice—will work on a task in the primary chain rather than on a task in the secondary chain. This percentage of time is denoted by the term 'task priority.' For example, if a resource as shown in Figure 2 is assigned a task priority of 30%, it reflects that, when that resource becomes available, it will randomly select to work on a task in the primary chain 30% of the time, and on a competing task in the secondary chain the remainder 70% of the time.

Several simulations have been run considering a task priority ranging from 10% to 100%. Table 2, also shown previously, presents the outputs from this model corresponding to the various batch-size combinations as shown in each row, and the extreme case in which the 'shared' resources Resource1, Resource2, and Resource3 have a task priority of 100%, which means that they virtually do not multitask. This output was computed using data from 100 random simulation runs.

In reality, engineers multitask between two or more design processes. Especially when their performance is measured by billable hours, they don't want to be idle while waiting for information or other prerequisites needed to continue a task they have started. Instead, they will proceed with another task they can work on. In practice, multitasking may be controlled by execution priorities and corresponding performance metrics and incentives.

Figure 4 shows that lead times not only increase with an increase in batch size, but also with a decrease in task priority given to the project whose process is captured in the primary chain. For example, the figure shows that a batch size of 30 supports and a task priority of 80% (P = 0.8), results in an average lead time of about 23 working days. A batch size of 30 but a task priority of 50%, results in an average lead time of 54 working days, which is more than double the previous lead time.

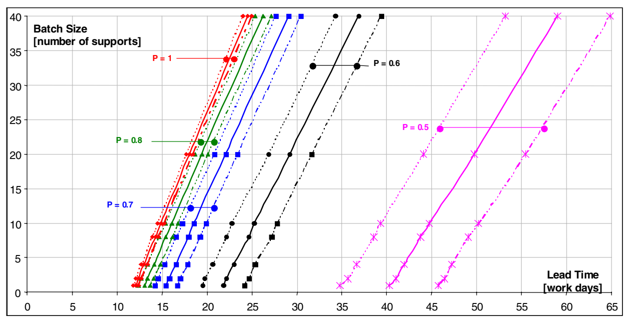

Figure 4: Lead Time (mean ± one standard deviation) vs. Batch Size for Different Task Priorities (P), Using Data from 100 Random Simulation Runs

Figure 5 shows the effects of batching, uncertainty, and multitasking from the perspective of lead time vs. task priority for different batch sizes. Again, lower task priorities yield increasingly longer lead times.

The models as described show how the delivery of capital projects can be viewed as a series of tasks that depend on other tasks for handoffs occurring at discrete times. In order to illustrate how handoffs affect performance, Figures 6 through 8 graph the outputs of three differ-

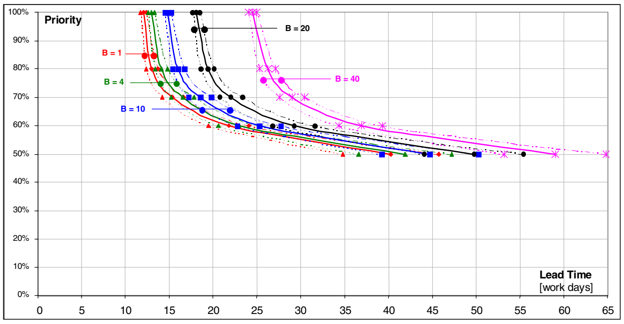

Figure 5: Lead Time (mean ± one standard deviation) vs. Task Priority for Different Batch Sizes (B)

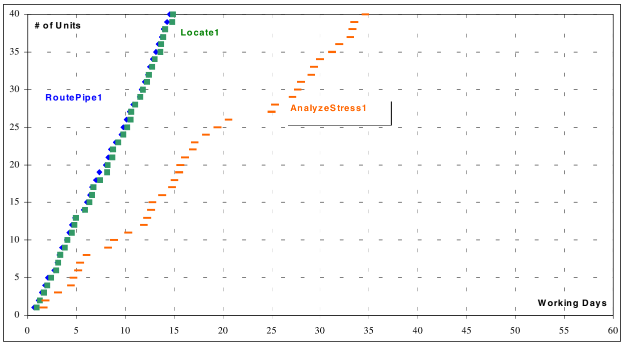

Figure 6: Lead Time vs. Number of Supports for Batches of 1 Support

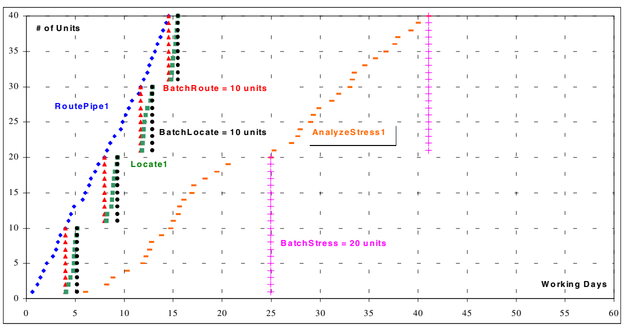

Figure 7: Lead Time vs. Number of Supports for Varying Batch Sizes (10 for RoutePipe, 10 for Locate, and 20 for AnalyzeStress)

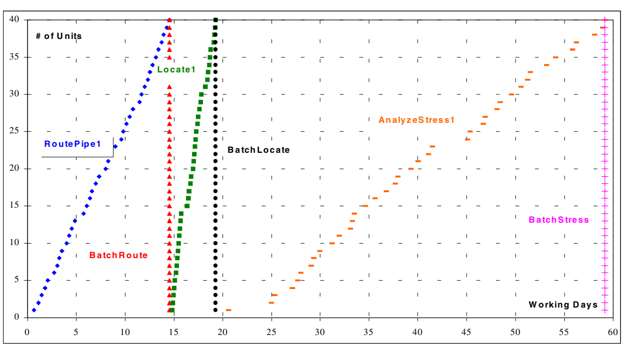

Figure 8: Lead Time vs. Number of Supports for Batches of 40 Supports

ent simulation runs showing the timing of handoffs between tasks in the primary chain, based on different batch sizes and a 50% task priority of the primary over the secondary chain.

In terms of lead time, the ideal situation is created when the batch size for each task is 1, so that the handoffs are frequent, the flow is smooth, and the overall process incurs the least delay. This ideal situation often is impractical, though, because of setup times that make it more rational for the 'optimal' batch (economic lot size) in any one process to be greater than 1 unit.

Figure 6 illustrates simulation output in case all task handoffs should occur in unit batches of 1. It shows a lead time of 35 work days or 7 weeks. Figure 6 also makes it clear that the system is unbalanced: tasks progress each at a different pace. The actual pace is indicated by the slope of each line. The fastest possible pace is indicated by the duration of the task as given in Table 3. For instance, Locate is the fastest task of all, yet, because RoutePipe is slower but hands off an output to it, Locate can only go as fast as RoutePipe in this configuration. So, while 7 weeks is the shortest lead time obtainable with the current configuration, that lead time could be reduced by balancing the system using means such as multiskilling (multiskilled resources can perform any one of several tasks), allocating multiple resources to perform a single task, or re-engineering the tasks altogether. Rother and Harris (2001) provide guidance for creating continuous flow. In this particular case, if an engineer were trained to both locate supports and analyze pipe stress, the system would be closer to a desired balance. That engineer would take 0.5 mh + 1.8-2.3 mh or 2.3-2.8 mh per support, which would approximate the 2-2.5 mh per support needed by another engineer to route pipe.

Figures 7 and 8 illustrate the effect of batching in units larger than 1. Figure 7 considers three different batch sizes: respectively 10, 10, and 20 supports for the activities RoutePipe1, Locate1, and AnalyzeStress1 (these numbers were chosen arbitrarily). Each vertical line in the figure represents an output batch being handed off as input to the next task. For instance, Locate1 outputs units that accumulate into a batch of 10 units relatively fast. Then, there is a delay until RoutePipe1 releases more output before Locate1 can proceed using as input the next batch handed to it. During this delay, Locate1 multitasks with Locate2 in the secondary chain or simply remains on stand by. Figure 7 shows that these larger batch sizes result in a larger lead time, now reaching 42 work days or more than 8 weeks.

Figure 8 considers the largest possible batch size for this model, in this case 40 supports, resulting in a lead time of 59 work days or nearly 12 weeks, which is significantly greater than the 35-day or 7-week lead time obtained with unit handoffs.

9 CONCLUSIONS

Eight weeks of lead time as compared to a few hours of value added time are easily rationalized when one considers production system design factors such as batching, variability, and multitasking. Admittedly, these factors are not necessarily at play in this supply chain, and other factors not mentioned here may be at play instead or in addition. Any or all can be detrimental to supply chain performance but they are often overlooked. Indeed, our experience indicates that practitioners in the architecture-engineering-construction industry, those involved in the delivery of capital projects, are not well versed in production system design.

Design-, construction-, and project managers in general would learn from studying principles and practices of not only project management but also production management. They stand to gain from understanding batching, variability, and multitasking better and streamline their processes accordingly in order to improve overall performance. Awareness of these factors is a first step towards proactive management that will result in lead time reduction, which in turn can contribute to schedule compression.

The models presented in this paper have shown how simulation can be used as a tool to represent a construction supply chain (granted, the case studied here is an almost trivial excerpt). The models could then be altered to document alternative production system characteristics and to generate simulation output to assess performance. In similar vein, Tommelein (1998) modelled the off-site supply chain and the on-site construction tasks related to the design, fabrication, and installation of pipe spools. Other supply chains could be modelled likewise.

Those wishing more specifics on opportunities for improving supply chain performance in the delivery of pipe supports may wish to consult Arbulu (2002) and Arbulu and Tommelein (2002a, b). While this paper has used a part of the design phase in the supply chain for pipe supports as the basis for modeling, simulation, and data analysis, this application is only incidental to the study as presented. The study's findings are generally applicable.

ACKNOWLEDGMENTS

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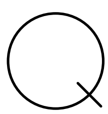
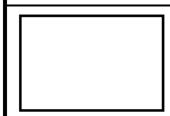
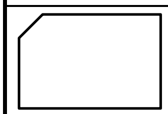
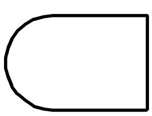
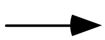
APPENDIX

Table A summarizes the functionality of the STROBO SCOPE symbols that are used in the model presented in Figure 2.

Table A: Selected STROBOSCOPE Symbols

SYMBOL	NAME	EXPLANATION
	**Queue**	Is a holding place (buffer) for 0, 1, or several resources waiting to become involved in the succeeding combination activity. Queues may contain generic or characterized resources. The latter are distinct from one another and they can be traced as individuals through various network nodes during simulation. The logic describing the ordering of resources upon entry into a queue of characterized resources is termed a DISCIPLINE.
	**Normal (activity)**	Describes a certain type of work to be done, or a delay, of a known (probabilistic) duration from start to finish. May require a single resource or no resource at all.
	**Combi (-nation activity)**	Like a normal, describes a certain type of work to be done, or a delay, of a known (probabilistic) duration from start to finish. Unlike a normal, requires several resources in combination for its performance and draws what is needed from the queue(s) that precede it.
	**Consolidator**	Acts as a counter up to n (n is an integer value specified with the node): after n resources have been released into the consolidator, all n resources at once will be released from it.
	**Link**	Shows flow logic. Should be labeled to meaningfully describe the resources that flow through it. If the link emanates from a queue, a DRAWORDER may be specified to sequence resources being drawn from the queue.

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