Simulation Aids Long-Term Capacity Planning at a Sunglasses Manufacturing Plant

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***Abstract*— Discrete-event process simulation has long been able to analyze knotty problems arising in manufacturing, warehousing, health care, transportation (rail, air, bus, etc.), and service industries such as banks, restaurants, and hotels. These knotty problems include challenges such as reducing inventory, increasing production (throughput), deploying workers efficiently, and reducing both lengths of queues and time spent in those queues. Indeed, from a historical perspective, the first, and still some of the most conspicuous, successes of simulation have been achieved in its applications to manufacturing. The application of simulation described in this paper arose in the context of manufacturing safes from their raw-material shells. Simulation, in contrast to other methods such as closed-form optimization, is highly capable of accommodating high process variability and almost automatically providing "best-case" and "worst-case" (as well as averages) for important performance metrics such as lengths of queues and waiting times in queues. Additionally, the animation which routinely accompanies simulation helps non-technical managers understand the results. In this context, the most painfully pressing problem was excess inventory, coupled with too slow and too meager output. The simulation study guided engineers and managers as they endeavored to both reduce the inventory and increase the rate of output – only very rarely can these two objectives be achieved concurrently.**

Keywords-discrete-event process simulation, manufacturing, capacity planning, throughput, queuing analysis, inventory control.

I. INTRODUCTION

In the roughly half-century since discrete-event process simulation made the transition from research curiosity to vital business-analytics tool, the earliest and also some of its most impressive successes have occurred in its applications to manufacturing processes (Law and McComas [1]). For example, (Zülch and Zülch [2]) applied simulation to the design of hybrid U-shaped assembly systems, an NP-hard problem of assigning operations to stations within an assembly line. Simulation effectively established priority rules for scheduling of a flow with simultaneously loaded stations, as documented by Hermann ([3]). A hybrid approach of a genetic algorithm and simulation produced excellent results in a job-sequencing problem within a semi-automated production process, as described by Mosca, Queirolo, and Tonelli [4].

The present application of simulation is to a semi-automated manufacturing line producing safes (strong reinforced metal boxes, resistant to burglary, for the secure storage of relatively small valuables (e.g., jewelry, passports, stock certificates, etc.). Severe economic challenges besetting this process included excessive raw material inventory (expensive in both space and time), insufficient production output achieved too slowly, and inefficient deployment of workers resulting in both conspicuous idle time and sporadic lack of a worker needed to perform a task of high urgency, such as repair of a malfunctioning machine. Discrete-event process simulation, unlike many other analytical techniques such as closed-form optimization, has several significant advantages which made it highly suitable for attacking these challenges:

1. Ability to routinely accommodate high process variability via appropriate use of specified suitable probability distributions
2. Ability to provide extreme values, in addition to expected values, for key performance metrics such as waiting time in queue, length of queue, time-in-system, and output per working day
3. Ability to provide, routinely and with nearly zero incremental effort, an animation which greatly helped non-technical management personnel understand and accept the results provided by the analysis.

It has often been well and truly said that "simulation is like a movie, not like a still photograph."

The rest of this paper is structured as follows: Section II presents an overview of the manufacturing process and Section III a description of data collection. Section IV describes the construction, verification, and validation of the model. Section V presents its results. In Section VI we present conclusions and indicate likely directions of future work.

II. OVERVIEW OF THE MANUFACTURING PROCESS

The manufacturing process which constructs safes from raw materials is a semi-automated assembly line comprising a total of eighteen workstations, nine of which are automated and nine of which are manual. The manual workstations are each operated by two workers. All eighteen workstations have idiosyncratic cycle times and downtime performances (time to failure and time to repair). The line has limited space for incoming raw materials immediately upstream from the first workstation and a buffer of capacity three, for finished product, just downstream from the last workstation. Workflow is entirely linear along all eighteen workstations, with zero buffer capacity in the seventeen transits between the workstations. Furthermore, material movement is done by an indexed conveyor, as described by Gunal, Sadakane, and Williams [5]; that is to say, no part movement can be undertaken until:

1. All eighteen workstations have completed their processing cycle, *and*
2. All workstations are ready to accept a new part (i.e., are not "down.")

Each workstation sends a "job over" signal when it has satisfactorily completed its cycle and hence is willing to "let" the conveyor index. Only when that signal has been received from all workstations can the conveyor index (move each work-in-process item forward one workstation).

Raw material arrives from a warehouse via a truck able to carry twenty shells. These shells are measured against tolerances and reworked if necessary before proceeding to the first workstation (reworked shells have priority over newly arriving shells). As they proceed to the first workstation via forklift, these shells are grouped with other components (lugs, stiffeners, and joint strips). Due to in-process space constraints, the forklift transfers shells only when the number of shells already waiting at the first workstation falls below six. This same forklift transfers finished safes from the last workstation to an in-plant storage location. The tasks to be done manually at the nine manual workstations are sufficiently dissimilar that workers (who are not cross-trained) are constrained to work only at their designated workstation.

Factory managers were keenly aware of process deficiencies and highly eager to eliminate or mitigate them, but also wished to proceed circumspectly due to the following downsides:

1. Experimental revisions to the process would entail lost production time.
2. If a proposed improvement involved rearranging machines, and then failed to live up to its promise, returning the machines to their original locations would be costly in both time and money.
3. Upper-level financial managers naturally wanted to see strong evidence of expected improvements before investing corporate funds.
4. In the absence of analytical tools, any heuristic cost-benefit analyses of proposed changes would be frustratingly vague.

As it so often has in the past, discrete-event process simulation, by virtue of allowing the actual system to continue operation while proposed improvements to it are studied via analysis of a model, provided an attractive circumvention of this seeming impasse.

III. INPUT DATA AND ITS ANALYSIS

The automatic workstations have essentially constant cycle times. The manual ones do not; for each of them, actual cycle times were collected via deliberately unobtrusive observation (beware the Hawthorne effect, as cautioned by Kroemen and Grandjean [6]). These data were then fitted to theoretical closed-form distributions using distribution-fitting software. The techniques of using such software have been documented by Chung [7], and the specific software used, Stat::Fit® is described by Leemis [8]. For each of the nine manual workstations, the algorithms in this software (Anderson-Darling, Kolmogorov-Smirnov, and chi-squared) recommended use of a uniform distribution. Likewise, times between failures and times to repair were fitted to all eighteen workstations using exponential and PERT distributions respectively. The PERT distribution, like the triangular distribution, has minimum, mode, and maximum parameters, but also two advantages over the triangular: it is differentiable throughout the interior of its range, and it has less probability mass in its tails – the converse of the latter being a criticism frequently directed against indiscriminate use of the triangular distribution.

Other needed data were readily available. The carrying capacity of the supply truck, and its travel time between the warehouse and the assembly line, were readily observable; the same was true for the forklift travel times and capacity. Experience indicated 10% of the shells must be sent to rework before entering the processing line. Furthermore, the shift schedules, including break times, followed by the assembly-line workers and the three mechanics of the maintenance department (required to repair failed workstations) were known.

IV. MODEL CONSTRUCTION, VERIFICATION, AND VALIDATION

Simio® simulation software, thoroughly documented by Thiesing and Pegden ([9]) and Kelton, Smith, and Sturrock ([10]) was used to build the simulation model of the manufacturing plant. This simulation software tool, both powerful and easy to learn and use, provides canonical constructs for entities, material-handling vehicles, conveyors, workstations, and workers. In the model, in accordance with current practice, shells arrive from the upstream plant via truck to storage, from whence they are moved to the first workstation by forklift. The shells then move sequentially among the eighteen workstations via the indexed conveyor. Then the truck returns the finished safes to the originating plant. The model also includes downtimes and repair operations (undertaken by specialized workers) at the workstations, plus workstation changeover times required when a new type of shell is about to enter the production line. Currently, such a changeover is restricted to occur only at the start of a new work shift, with the changeover being done during the scheduled time between successive work shifts. Simio® allows the modeler to represent process logic such as this in a "drag-&-drop" flowchart, shown in Figure 1 (Appendix). Additional examples of Simio® modeling constructs which proved very useful in this model were

"Material," to conveniently track raw-materials usage and needs for replenishment, and "Monitor," which can trigger appropriate logic within the model when the value of a state variable (e.g., an inventory level) crosses a certain threshold value in a specialized direction (downward, upward, or both).

Verification was undertaken first; then validation was undertaken. Techniques described by Hugan ([11]) were used; these techniques included structured walkthroughs, step-by-step examination of the animation (which Simio® automatically built as the simulation model was built), and close monitoring of the output metrics: queue lengths and inventory levels in the model versus those observed in practice, percentage of time workstations were idle waiting for other workstations to complete their cycle so the conveyor could index, frequency of trips made by the truck and the forklift, and utilization levels of the mechanics assigned to repair malfunctioning workstations. After adjustments to the model and correction of errors, the final model coordinated to 5% tolerance with system observations and historical data.

V. RESULTS OF THE SIMULATION MODEL

After completion of verification and validation, the model representing the current system was run for 20 replications of 24 hours each. Results agreed with currently observed values of performance metrics within 4%. At this point, the client managers accepted the model as valid and credible, opening the door to evaluation of one or more potential improvements. Both managers and analysts, based on extensive industry experience, were cognizant of the possibility of synergy: "Change A may produce negligible improvement; change B may produce negligible improvement, yet change A+B may produce significant improvement."

To investigate various potentials for improvement, Simio® (and many other simulation software tools similarly) provides an Experiment option permitting concurrent evaluation of many Scenarios. In each Scenario, different values for model parameters (ranging widely among, for example, downtime frequency, downtime duration, buffer sizes, numbers of workers, cycle times, operational policy changes, etc.) may be specified. The multiple Scenarios are then run on a "one-click" basis and specified performance metrics (e.g., average and maximum length of queue and/or time in queue) easily compared via automatically generated graphs and tables. This approach proved both more flexible and quicker to implement than the perhaps more traditional "define a fitness function and run an optimization loop."

Having already noticed (1) the low utilization of the delivery truck (recall it is responsible both for bringing shells from the warehouse to the production line being modeled and also for carrying completed safes back to the warehouse) and (2) chronically high work-in-process [WIP] levels, the first potential improvement modeled was "have the truck run twice as frequently with half the load sizes" – loads were reduced from 20 to 10 in both directions. For this first attempt at improvement, the carrying capacity of the forklift remained at 3. The following "before & after" improvements were observed:

TABLE 1. SUMMARY OF FIRST IMPROVEMENT ATTEMPT

Performance Metric	Before Load Reduction	After Load Reduction
Average incoming shells in queue	5.69±0.14	3.99±0.12
Average outgoing safes in queue	6.93±0.20	3.76±0.06
Type 1 safes produced	58.9±4.08	69.7±2.21
Type 2 safes produced	26.10±4.30	45.8±2.29
Utilization of forklift	64.93±1.13%	57.04±0.50%
Utilization of truck	8.19±0.29%	20.80±0.36%

The confidence level for these intervals is 95%; note that no two of the before-versus-after intervals, considered pairwise, overlap.

The second step toward improvement stemmed from the observation that the three maintenance workers (both in observed practice and in the runs of the model made thus far) had very low utilizations. Therefore, the model was run with the reduced loads of 10 shown above and only one maintenance worker instead of three. In view of the low worker utilizations, this revision of the model was run with replications of length 500 hours, versus 24 hours. Utilizations of the three workers were 2.2%, 2.67%, and 2.58%; when only one worker was allocated to maintenance work, (1) The significant improvements achieved by the reduction in truck load size (more than 20% for both types of safes) were maintained, and (2) The single worker's utilization remained extremely low at 7.86%.

Neither of these enhancements required any capital investment; indeed, the second one actually reduced staffing requirements. As the next and third step forward, the client managers and simulation analysts noted that whereas the current assembly line was completely linear, it could potentially be reconfigured in a "U" shape. This reconfiguration would surely entail expense, but held two enticements whose generic attractiveness has been confirmed by Groover ([12]):

The distance traveled by the forklift between the last workstation and the truck, when carrying completed safes, would be reduced from 30 meters to 7 meters (of relatively minor importance).

Three workstation pairs -- 8 and 12; 6 and 14; and 4 and 15 would be much closer together, making it practical to cross-train those pairs of assembly-line workers (of major importance).

A model animation snapshot of this revised layout of the assembly line appears in the Appendix (Figure 2).

This new scenario presented an interesting modeling challenge readily handled by Simio® logical expressions incorporated into the model logic. Specifically, the challenge can be characterized as follows: Suppose each of two workers, A and B, are busy on a task. Working alone, worker A will need x minutes, and has already worked y minutes (y < x) when worker B finishes his task on another machine and joins worker A. Worker A's remaining time now decreases from (x – y) to (x – y) / 2. Indeed, observation of the actual work undertaken at the manual workstations, plus discussion with the client managers, supported the assumption (underlying this computation) that the participation of a second worker involves negligible overlap or redundancy of work. In this scenario, the following improvements appeared:

1. Worker 4 utilization increased from 31% to 67%, more than double
2. Worker 8 utilization increased from 39% to 73%, nearly double
3. Worker 14 utilization increased from 68% to 77%, slightly more than a 10% improvement
4. Ninety safes of type 1 were produced
5. Fifty safes of type 2 were produced

Notably, all of improvements (1) – (3) brought the utilization in question nearer the traditional 80% which is a good theoretical compromise between low utilization and excessively long queues and wait times therein.

The fourth and final improvement undertaken during this study involved enhancement of the changeover procedure. Whenever a new part type (change from safes of type 1 to safes of type 2 or vice versa) occurred, the workstation must be empty to make required tooling adjustments. Between any two shifts, half an hour is dedicated to these changeovers. The enhancement consisted of having a "deliberately empty workstation" during assembly – that is, "don't load the first (new type) part on the assembly line until the conveyor has indexed once." Thus, each workstation gets a "breathing spell" cycle slightly shorter than eight minutes, and a changeover requires less than five minutes (providing slack). When the modified schedule was incorporated into the model, the number of type 1 safes remained ninety, and the number of type 2 safes produced rose from fifty to sixty.

VI. CONCLUSIONS AND FURTHER WORK

A sequence of three successive improvements to the process under study, the second and third building upon the previous, significantly improved productivity, inventory levels, and worker utilization percentages. Furthermore, the client is now persuaded of the analytical capabilities and powers of discrete-event process simulation, and hence has already begun to explore its use in additional "continuous improvement" endeavors.

Further explorations are planned, including optimizing the inventory for other components of the safes (e.g., lugs, stiffeners, and joint strips). Also, further financial analyses are planned to optimize the costs of operating the assembly line.

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APPENDIX

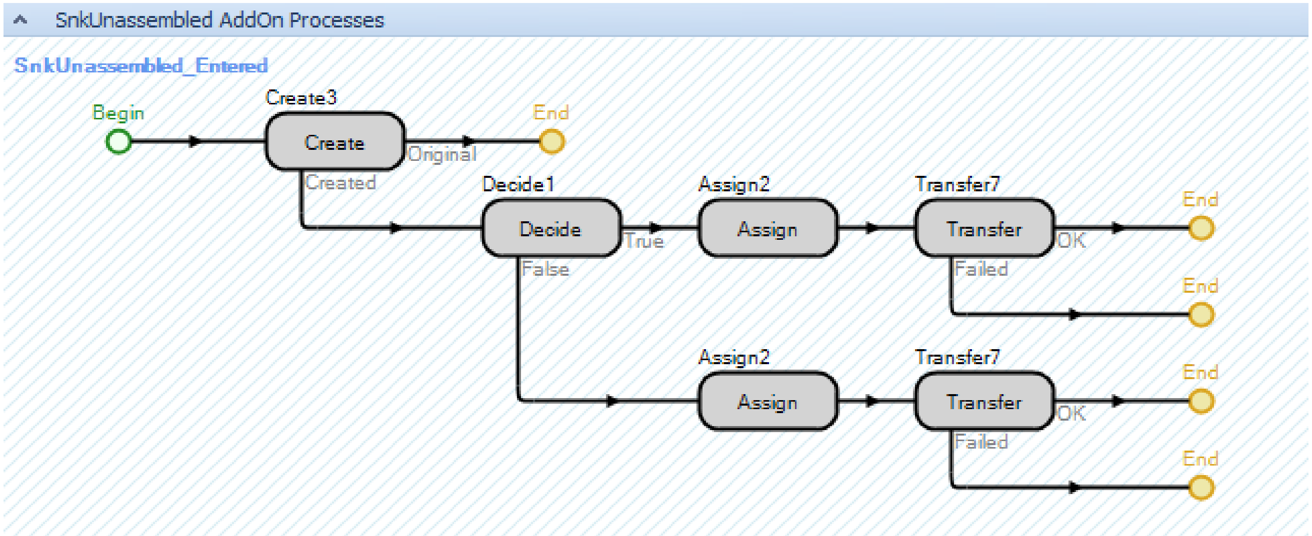

Figure 1. Shift Changeover Logic; Loading New Shell Type at Start of a Shift

Figure 2. Model Animation Showing the Revised “U”-Shape of the Assembly Line