Simulation Applied to Improve Transmission Hub Machining Processes

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Abstract

We describe the application of discrete-process simulation to identify and quantitatively evaluate process improvement opportunities within a manufacturing system. Simulation has proved itself a valuable, powerful tool for manufacturing process improvement due to its ability to analyze the many subsystems (e.g., material handling, scheduling, in-process storage, and value-adding machining operations) concurrently. Additionally, the use of simulation provides valuable support to the use of analytical methods which search for global, not local, optimum process configuration and operating policy.

Keywords

Process improvement, in-line process storage, discrete-event process simulation.

Introduction

In this paper, we describe a case study of simulation in the context of improving a transmission hub machining process. Our description comprises a discussion of demonstrating the capabilities and limitations of simulation to plant engineers and managers, defining the objectives of the study in terms of process improvement opportunities, gathering needed operational data, developing, verifying, and validating the model, experimenting with the model, analyzing its results, and working with plant managers and engineers to implement the recommendations spawned by the model. Resolution or amelioration of commonly observed practical problems in simulation studies, such as efficiently capturing and understanding process detail, choosing appropriate software tools, maintaining project momentum via concurrent activities, establishing model credibility, and conducting sensitivity analyses to compensate for missing or uncertain data, are included. We then indicate likely directions for further work.

The focus of this search for process-improvement opportunities was one department within a large automotive plant. This department receives unmachined hubs from a supplier and performs a variety of machining operations on them, thereby preparing them for inclusion in the assembly of an automatic transmission. In order to properly meet plant-wide system constraints, it was imperative that the hub machining process produce output at the rate required by the downstream assembly department. The department engineers and managers were keenly interested in identifying bottlenecks and measuring their severity quantitatively, assessing the location and size of in-process strategic buffers, and determining the most appropriate number of pallets required to avoid starvation of downstream operations. Several areas along the line contained large multilevel circular gravity buffers ("silos"), where hubs would accumulate until required by downstream processes. These chutes, guiding objects in a downward helical path, combine simplicity with conservation of floor space [15]. One of several areas of focus was improving the choices for location, quantity, and size of these silos. Another segment of the line targeted for detailed investigation included a line of serialized test stands known to be problematic based on historical empirical data.

Defining Study Objectives, Scope, and Rôle of Simulation

Engineers and managers responsible for ongoing improvement of transmission assembly processes wished to increase throughput cost-effectively, identify bottlenecks and quantify their effects on system performance, reduce manufacturing cycle time, and reevaluate the locations and capacities of in-line process storage. In discussions with these engineers and managers, manufacturing process analysts touted simulation as helpful in achieving processes improvements due to its abilities to consider interacting process subsystems collectively and to accommodate stochastic variability beyond the reach of closed-form analytical methods [2, 7]. Indeed, these capabilities of simulation in the manufacturing domain help account for the fact that manufacturing process improvement is one of the oldest, yet most consistently active, domains of simulation application [4].

Rather than attempt to model and study the entire, very large and complex, transmission assembly process, the process improvement team decided to restrict the scope of the study to one department, the hub machining department, where empirical observation implied significant process improvement opportunity. This restriction of project scope, and hence model size, frequently advocated in the literature [1], promised to provide useful results more rapidly from a model that was markedly easier to construct and validate. Additionally, restriction of project scope provided a higher comfort level among those plant engineers and managers not already familiar with the methods and capabilities of simulation. Their confidence in simulation was also increased by discussion of its use elsewhere in the automotive industry to assist in addressing similar challenges in similar contexts; [9] and [6] are typical examples of such use.

Collection and Analysis of Process and Operational Data

As is typical in simulation analyses, large quantities of data had to be collected, understood, and analyzed; no simulation model is any better than the data used to build it [13]. The analysts first achieved overall understanding of the process by examining work flow diagrams and touring the plant floor to observe the process. To better understand the complexity of the system, the simulation team used a laptop computer equipped with a mini video camera to capture the details of the hub machining processes. This video proved to be invaluable during the design stage of the simulation process. The diagram below shows the conceptual workflow among the basic operations.

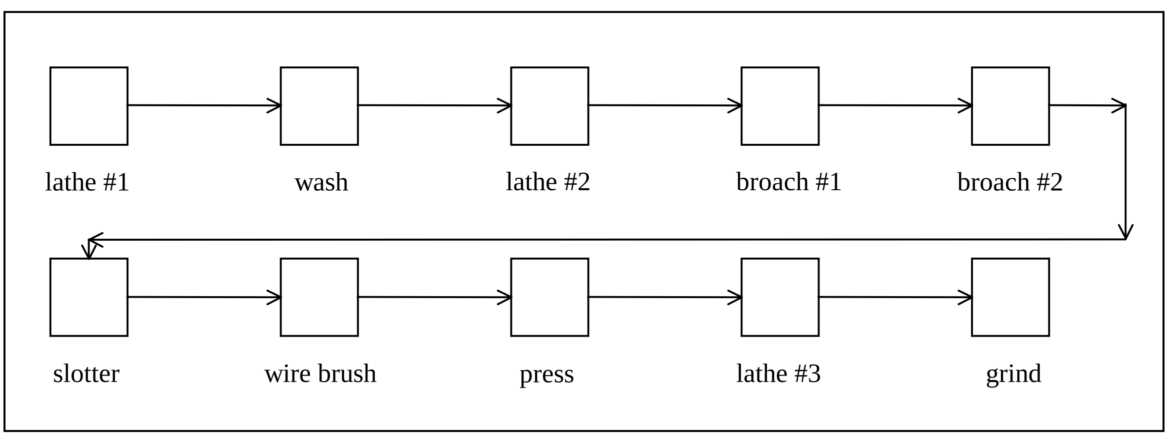

Figure 1: Operational Workflow in Transmission Hub Machining

Several of these operations included serialized test stands for in-line, interim product testing. Several large silos were located among these operations to accommodate in-line storage; as mentioned above, the production engineers and their managers were particularly interested in the possibility of choosing better locations and capacities for these silos. While traveling downstream among the operations, the hubs used pallets; palletization not only increases the likelihood of achieving future cycle time improvements at various operations but also allows flexibility of planning to accommodate anticipated but as yet quantitatively imprecise increases in demand [12]. However, simulation studies of other palletized systems [20, 21] provided warning of the perhaps counterintuitive "Too many pallets may be even worse [for efficiency and throughput] than too few." These pallets in turn traveled on conveyors.

After the simulation analysts understood the overall process layout and workflow, they began to collect and analyze system performance data. These data included the cycle times of both manual and automatic operations, the scheduled shift and break times for all pertinent workers, the time between failures and time-to-repair of all equipment having planned (preventive maintenance) and/or unplanned (random malfunction) downtime [19], tool life and changeover times, the travel time between successive pairs of operations, the capacities of the existing silos, and the proportion of parts rerouted upstream from test stands for corrective rework. For example, the cycle times of manual operations were obtained from existing plant time and motion studies of the standard type described in [11]. As is frequently the case in simulation studies, not all data required for accuracy of the simulation model was readily available from historical records; hence, additional time was required to interview plant engineers [18].

After data collection, the analysts examined stochastic data (such as sets of numbers representing times between failures or times to repair various machines) to decide which closed-form statistical density function, if any, represented a good fit to the data. These examinations were undertaken with the software tool ExpertFit™, which uses statistical tests such as the chi-square, Kolmogorov-Smirnov, and Anderson-Darling tests to assess the validity of describing empirical data sets as standard density functions [10]. For example, the durations of machine downtime were often approximately Weibull or log-normal; those of uptime (time to next failure), Weibull or gamma. In the few cases where this examination indicated inability of canonical density functions to describe the observations accurately, those observations were used to define an empirical density for direct random sampling.

Building, Verifying, and Validating the Model

The simulation analysts next built a prototype model of the production process, a step requiring only two weeks. As a result of discussions with the plant production engineers, the software tool ProModel™ was chosen for both the preliminary model and the more detailed model which would ultimately be derived from the initial model. This tool permits concurrent construction of a simulation model and its animation, supports the discrete process-simulation viewpoint through convenient logical constructs, and provides a free run-time version which allowed engineers at the plant to experiment by running a completed model with various values for numeric parameters such as cycle times or storage capacities [3]. Additionally, the free "run-time" license provided by ProModel™ allows client engineers (in this context, the production and process engineers at the plant) to perform ongoing what-if scenarios by changing numeric quantities within the model and to better understand when further model development and revision, such as adding equipment and making layout changes, might prove beneficial in making profitable decisions.

Several techniques proved useful to the model builders in verifying the model, i.e., confirming that it operated as they intended. Detailed traces of model execution pointed to all corrections necessary to ensure that each entity followed the proper workflow path among the operations. Structured walkthroughs, in which each team member, having built a portion of the model, explained its intended operation to fellow team members, served to expose oversights for prompt correction [16]. Executing the model with all sources of randomness removed (i.e., replacing all probability densities by the mean or the mode) provided assurance that no conspicuous numeric errors, such as inadvertent mixing of durations expressed in minutes with durations expressed in seconds, were present in the model.

The simulation analysts and plant engineers then worked together to validate the model, i.e., confirm that it accurately represented the existing production system relative to the questions and improvement opportunities underlying the project. The animation and consequent easy visualization were of great assistance to easy and sure achievement of common understanding between the plant engineers and the simulation analysts, hence providing assurance of model validity and spawning higher confidence in its subsequent predictions [14]. Final validation runs of the base model produced output which matched observed system performance in all metrics of interest (such as average and maximum content of each silo, average waiting time at noticeable queues within the system, machine utilizations, and hourly throughput available to downstream operations) with relative errors of 3½% or lower.

Experimentation and its Results

Experimentation began with runs of the base model which had just been validated. The plant-floor production system was, from the simulation modelers' viewpoint, a steady-state system (not a terminating system such as a bank or restaurant), inasmuch as work each new shift or day began with the system loaded with work in progress from the previous shift or day [8]. Furthermore, all system performance metrics of interest to the engineers pertained to steady-state behavior. Therefore, the analysts chose a system warm-up period of twenty-four hours; at the end of this simulated time, the ProModel™ software was instructed to clear all statistics and resume accumulating them from the current system state, rather than from the original "model empty and idle" state. The initialization period of twenty-four hours was deemed sufficiently long due to:

- plant engineers' comments that the effects of rare shutdowns (e.g., power outages caused by severe storms and necessitating clearing the system) became "invisible" after that time
- visual interpretation of the model prediction of system metrics versus time; these graphs, viewed as time series, indicated disappearance of initialization trends within twenty-four hours
- use of an initialization bias test [17] which indicated its absence.

To obtain confidence intervals of system performance metrics sufficiently narrow to support managerial decisions, five replications of all runs were made.

The first experiment undertaken was the addition of buffer capacity just downstream from the first broaching operation; the base model had no silo there. Since downtime of this operation was high, operations downstream from it were frequently starved, although operations just upstream from it were rarely blocked. However, the increase in throughput obtainable via such an addition was disappointingly small relative to the high capital investment implied by installation of a new silo there. Plant engineers noted that increasing the capacity of an existing silo would typically be considerably less expensive in capital expenditure, engineers' and workers' time, and degree and duration of disruption, than installation of an entirely new silo.

Therefore, experimentation was redirected to the examination of reallocation of capacities among the existing nine silos. Typical base-case conditions among these silos are shown in the following table.

Table 1. Silo Utilization, Base Case

Silo number	Fraction of time empty	Fraction of time partly full	Fraction of time full
1	0.00	0.55	0.45
2	0.00	0.05	0.95
3	0.00	0.01	0.99
4	0.07	0.93	0.00
5	0.00	0.01	0.99
6	0.08	0.92	0.00
7	0.97	0.03	0.00
8	0.76	0.24	0.00
9	0.72	0.28	0.00

The simulation analysts and plant engineers then examined a wide variety of proposals for allocating the existing total capacity differently among the silos. An example of the improvement thus obtainable is shown in the following table.

Table 2. Silo Utilization After Reapportionment of Capacity

Silo number	Fraction of time empty	Fraction of time partly full	Fraction of time full
1	0.05	0.70	0.25
2	0.07	0.20	0.73
3	0.01	0.15	0.84
4	0.04	0.90	0.06
5	0.02	0.06	0.92
6	0.08	0.82	0.10
7	0.80	0.20	0.00
8	0.70	0.28	0.02
9	0.65	0.31	0.04

The reallocations shown in the above table entailed increasing the total silo capacity by only 8%, and showed ability not only to increase throughput by 3% (a small but statistically significant [$\alpha = 0.10$] and welcome increase), but also to decrease its standard deviation by 12%. As can be inferred by comparing Table 2 with Table 1, the lesser frequency of "silo full" was associated with fewer and briefer upstream blockages. Similarly, the lesser frequency of "silo empty" was associated with fewer and briefer downstream starvations. Hence the plant and production engineers concluded that the most promising route to rapid, relatively low-cost productivity improvements was via reallocation of in-line storage.

Indications for Further Work

Further experimentation with the model is planned relative to increasing or decreasing the number of pallets in circulation, assessing the effects of undertaking capital expenditure to decrease the cycle times of certain operations and/or add machines operating in parallel, and evaluating possible reallocation of manpower among the operations. Additionally, changes in product mix are expected, and production engineers anticipate using the model to obtain early warning of any system adjustments that may be needed to accommodate such changes. This transfer of "ownership" of a simulation model from the specialists who originally constructed it to its frequent users has been described and advocated in numerous case studies (e.g., [5]) as not only greatly increasing the usefulness of simulation, but also enhancing its visibility.

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Appendix

ExpertFit is a registered trademark of Averill M. Law & Associates.
ProModel is a registered trademark of PROMODEL Corporation.

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