

USING SIMULATION EARLY IN THE DESIGN OF A FUEL INJECTOR PRODUCTION LINE

Mustafa H. Tongarlak
Bruce Ankenman
Barry L. Nelson

Dept. of Industrial Engr. & Mgmt. Sciences
Northwestern University
Evanston, IL, U.S.A.

Laurent Borne
Kyle Wolfe

Delphi Corporation
Rochester, NY, U.S.A.

ABSTRACT

Delphi Corporation decided to use simulation from concept development to installation of a new multimillion dollar fuel injector production line. In this paper we describe how simulation was employed in the concept development phase to assess whether production targets required for financial viability were feasible and to identify the critical features of the line on which to focus design-improvement efforts.

1 INTRODUCTION

Delphi Corporation is a major supplier of fuel injectors to auto manufacturers around the world. The company is considering a proposal for a new line that will produce the next generation of fuel injectors. There are ambitious requirements on the line's throughput that are essential for the project to be financially viable, and real constraints on the space available for the line and the cost to build it and staff it.

As envisioned, this new production line will consist of multiple process segments, three of which will be placed in a clean room. Figure 1 displays a rough representation of the new line. The three segments inside the clean room were the main focus of our study since they are the most complex, highly automated and costly.

Each process segment may contain as many as thirty machines and robots performing various tasks along accumulating conveyors that convey partially completed fuel injectors from machine to machine in pallets. The conveyors will also act as buffers since they accumulate pallets in front of a machine if it is either down or unable to keep up with the flow of pallets from upstream machines. Transfer of assembled fuel injectors between process segments will be done via trays that are stacked in carts and moved manually by operators. Because contamination is a major concern inside the clean room, parts will be washed before entering the clean room and operators are assigned tasks that do not require them to move between rooms.

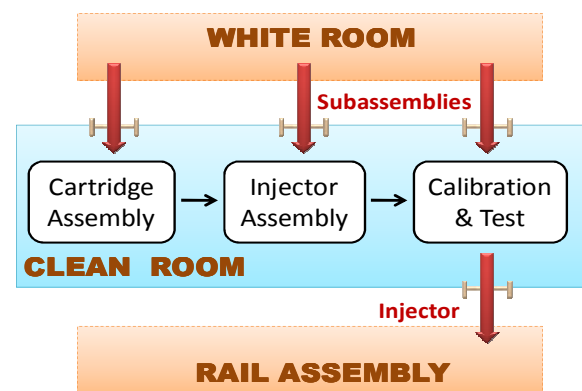


Figure 1: Proposed fuel injector production line.

A simulation model and study was commissioned at a very early stage of designing the new line. The goal for the simulation was to serve as a test bed for candidate production-line designs, both from initial concept to fine tuning and even to examining process-improvement ideas after the line is in place. To simulate a line design it must be fully specified including which machines to use and in what order, conveyor lengths, machine process rates and variability, operator responsibilities and priorities, and failure and repair distributions for each machine, as well as scrap and rework rates on a machine-by-machine basis. Such complete and detailed information is typically not available at the concept stage of the line design, but this is precisely when simulation can be most valuable in helping Delphi to assess whether the project is financially viable and where in the evolving line design the most effort should be spent. Using simulation at such an early stage requires making frequent and significant changes to the simulation base model which can be both time-consuming and difficult to manage. However, the recommendations from the study are often inexpensive or free to implement since the equipment has not yet been built. Once the equipment is built, using simulation to analyze the process is less time-consuming

because establishing the base model is not a moving target. The drawback to this approach, however, is that much of the cost is already sunk and the recommendations from the study may be more difficult to cost-justify. This was our challenge.

Notice that it makes no sense early on to try to optimize the design over the literally hundreds of changeable features because too little is known and too much is in flux. Instead, simulation was exploited to answer high-level questions about the line configuration, with the understanding that the model would later evolve into a representation capable of evaluating very specific questions. That is, the simulation was first to guide the development of new designs by distinguishing critical features and factors from less-critical ones, and later to be updated as new designs emerged. In this way the simulation would provide a perpetual road map for next steps in the design process. This paper is a product of the first phase (about 6 months) of this iterative design process where answering high-level questions about line configuration, conveyor layout, and operator assignments was of primary concern. In this way we will illustrate how simulation can have a profound impact at the concept stage of a complex project.

2 SYSTEM DESCRIPTION AND DATA SOURCES

Clearly machines (including robots) and conveyors need to be included in the simulation model. Most machines will keep running until a failure occurs as long as they are not starved or blocked. Since conveyors will be handling the subassemblies within process segments, operators are needed only for transferring assembled fuel injectors between process segments, filling raw material buffers, repairing machines and periodically performing other tasks such as quality checks, rejected fuel injector handling and preventative maintenance. Even though the system is semi-automated and operators are only lightly involved with actual operations, their supporting role in the system is critical because machine failures will occur, and input buffers will be consumed, leading to lost production if operators are unable to keep up. Therefore, in addition to machines and conveyors, operators, injector trays and material carts were included in the model.

Delphi represented line designs as AutoCAD drawings (that eventually became backgrounds for the simulation animation). More importantly, Delphi also maintained a single Excel spreadsheet with many worksheets called the Manufacturing System Design (MSD) that always contained the current state of knowledge about the line design. This included process information of all types, from raw material buffer sizes and operator task assignments to anticipated machine reliabilities, processing times and processing-time variabilities. Since this information ranged from firm values and commitments to educated guesses, and would evolve

and expand throughout the project, a link was established between the MSD and the simulation model so that the simulation would always be run with the most up-to-date data.

However, the MSD was more than just a data source; it was also used to balance the line to produce k fuel injectors every minute (where k was a value set by Delphi and will not be revealed here). In this semi-automated system where a series of processes are connected to each other, “balancing” simply means that if a particular operation is not able to produce the target k parts per minute then enough parallel capacity is added to keep up with the production requirement. Since the line will operate for 24 hours/day, the production capacity of the line would be $1440k$ parts/day if there were no machine downtimes, no scrap, no process variability and material buffers would never go empty. However, to bring more realism, the MSD also incorporated discount factors for percentage of scrap and downtime by machine, leading to a still optimistic throughput target of $1125k$ fuel injectors per day, or approximately 22% less than the theoretical maximum. Achieving this target is necessary for the new fuel injector project to be financially viable.

The reason that $1125k$ fuel injectors per day may be optimistic is that a static analysis such as the MSD provides cannot account for the impact of process variability, starvation due to lack of material or blocking, operator response time to failures, conveyor congestion, etc. More accurate analysis of the proposed system requires the fidelity of a detailed simulation model which takes into consideration the interactions among all parts of the system as well as randomness inherent to the system. The critical question to be answered by the simulation at the concept stage was whether $1125k$ fuel injectors per day was actually feasible and what it might take to get there.

In the following subsections we list some of the key system elements that figured in our analysis and mention any approximations we made.

2.1 Resources

Each machine is prone to failure and the average time it runs until a failure occurs is represented by a Mean Time Before Failure (MTBF). Once it fails, a machine waits for the appropriate operator to come and fix it. The time it takes for an operator to arrive and then repair the machine is downtime when no parts can be produced. The average repair time is denoted by Mean Time To Repair (MTTR). The MTBF and MTTR are values derived from information in the MSD, and the distributions of the time to failure and repair were modeled as exponential.

2.2 Operators

There are three types of tasks that need operators: Machine Attention (MA) Tasks, Periodic (P) Tasks, and Material Handling (MH) Tasks. Each type of task requires a different set of skills. MA tasks have the highest variability while MH tasks are the most regular. Therefore, operators will not be assigned both MA and MH tasks. However, all operators will have some P tasks they need to perform like quality checks, reject handling and maintenance tasks.

P tasks need to be done regularly every 2, 4, 8, 24, or 120 hours. MH tasks—much like P tasks—are performed periodically but are more frequent than P tasks. However, when P tasks do occur, they have priority over MH tasks. On the other hand, MA tasks are done as needed; i.e., if an operator is responsible for fixing a certain machine, then they only attend to this duty once that machine fails. Mostly because of this random nature of MA tasks, allocation of jobs to operators is challenging and poor operator assignments can hamper productivity. For example, suppose that a certain operator is responsible for repairs on both machine A and machine B. If machine A fails, the operator will respond to that machine as soon as possible. However, if machine B fails while machine A is still being repaired, the actual downtime of machine B will include not just its own repair time, but also the remainder of the time it takes the operator to complete the repair of machine A and any travel time between the two machines. In general, operators can be responsible for repairs on many machines so this effect can be multiplied many times causing substantial downtime. Thus, to whatever extent possible, the MA and P tasks should be balanced among the qualified operators so no single operator is responsible for repair on more machines than necessary. To define a base case for operator assignments, each MA and P task was assigned to only one of the operators, the tasks were grouped by proximity and then were approximately balanced taking into account the relative reliability of the machines. All MH tasks were assigned to an operator who handled no MA or P tasks. An extensive point-to-point walk matrix was developed to accurately account for operator travel times.

Figure 2 is a flowchart representation of the logic used in the simulation model for operator activity. Each operator is given responsibility for performing certain tasks; as soon as an operator completes a task they seek another one unless they have completed their shift or it is time for lunch or a break. Lunches and breaks have priority over tasks. Among the three types of tasks, the highest priority is given to MA tasks, since if a machine is down then filling buffers or handling rejects instead of fixing the machine is considered a bad use of operator time. Also, if two tasks of the same type become due or call for attention, then there is a fixed priority order. For example, if operator 4 is responsible for repairing resources 5 – 3 – 4 – 6 in that order, then 5

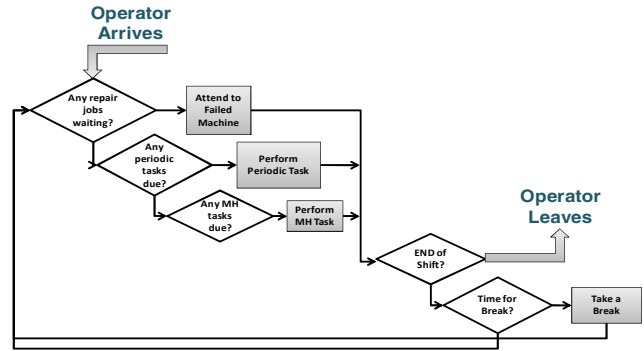


Figure 2: Flowchart of operator tasks.

is repaired first if both 5 and 3 are failed. One way that priorities arise is that the failure of a unique machine is given priority over repair of one of a number of parallel machines.

2.3 Process Variation

Each machine has an average processing time given in its specifications. Because some level of variation exists in processing rates, it is not possible to produce k fuel injectors every minute even when no scrap is produced and no machine is down. Since process variation is a factor affecting production, it needs to be embedded in the model.

With help from the Delphi production team, we classified the process variation of each machine into one of the following three categories based on their knowledge of the process: High, Medium and Low Variation. We assigned a coefficient of variation (CV) for each of these categories. CV is defined as the ratio of the standard deviation to the mean. Since the mean process time was specified, we could then calculate the process standard deviations through these CV values. Using this mean and standard deviation, we specified a normal distribution to generate random processing times for each part processed by that machine.

3 SIMULATION MODEL

The simulation model was developed in version 12.00 of the Arena simulation software (Kelton, et al. 2006). This software by Rockwell Automation was a good choice for the project for the following reasons:

- Arena is well-suited to modeling conveyors. In Delphi's production lines, conveyors are the major mode of material transfer.
- Arena provides a user-friendly interface that makes understanding and modifying the model easier for people other than the modeler. In addition, it gives the ability to create templates through which

similar code can be created for the parts of the model that are likely to be repeated with different parameters. For instance, we designed a template that handles the tasks performed when a part arrives to a machine to be processed, such as picking the part from the conveyor, checking for raw material inventory, processing the part and placing the part back to the conveyor. Once the template is created, a modeler only needs to define machine-specific parameters like conveyor name, machine number, buffer type, etc. and customized code will be generated automatically.

- The model can be linked to a data source (e.g., the MSD, an Excel spreadsheet) to allow for making most minor updates (e.g., changing MTBF for some machines) directly in Excel rather than in Arena. This also preserves data integrity since all Delphi analysis use a common data source.
- Arena provides animation capability that can be used for model validation and demonstration purposes.
- Arena collects and reports most of the necessary statistics by default and lets the modeler add other statistics.

4 SIMULATION EXPERIMENTS AND RESULTS

The main performance measure in our simulation study was long-run average daily fuel injector throughput; i.e., the long-run average number of fuel injectors that can be produced in a 24 hour period. Therefore, we treated this as a steady-state simulation (Banks et al. 2005) requiring a so-called “warm-up period” to get from the initial state (system empty, all input buffers full, all machines operational) to long-run operating conditions. For the base case (described below) approximately one day’s production was adequate, so we made each replication 11 days long with the output data from the first day discarded and 10 days (two weeks) retained. We then made enough replications to estimate long-run average throughput to within 5% relative error, and this required 20 replications. To give some idea of the experimental effort to run one scenario, it takes approximately 8 hours to obtain 20 replications of 11 days on a relatively fast PC. This is a function of both the size and complexity of the system, and the very large number of fuel injector subassemblies in process at any one time. Since all other scenarios are modifications of the base case, we used the same experimental effort (20 replications of 11 days) on each of the scenarios tested. Although throughput was the driving performance measure, measures of operator utilization, machine downtimes, congestion on conveyor segments, and raw material buffer states were also examined.

Results from all experiments were compared to two benchmarks: the base case, which is a simulation of Delphi’s

line design as specified in the MSD; and the target of 1125k fuel injectors per day. If there had been no gap between these two, then the proof-of-concept phase of the line design would be done. Instead, there was a very substantial gap, so the objective became finding the key factors that produce the gap so that they can become the focus of future design efforts. This must be done without specific design alternatives with which to compare, which led to the experimental approach described below. The critical factors were unexpected, but completely understandable after the fact.

4.1 First-Phase Scenarios

To design our preliminary experiments, called “first-phase scenarios,” we listed all of the factors—at an aggregate level—that may contribute to the loss of production. Obviously, if no such factors existed, then we would be consistently producing 1125k fuel injectors per day. The following are some of the factors we listed as potentially critical: Process variability, scrap rates, failure and repair rates, operator assignments, conveyor lengths, and number of pallets on each conveyor.

The first three scenarios that we studied were selected to quantify the effects of process variability, scrap rates, and repair times. Since each machine has a specified scrap rate, variability and repair time, there are literally hundreds of combinations that could be tested. At 8 hours per test, it would be impossible to test the impact of these individual changes. However, since we are primarily interested in broad questions about the effects that have the biggest impact on throughput, we grouped the potential changes into functional categories. For example, instead of investigating each machine’s process variability individually, we investigated the effect by eliminating *all* the process variability; this allows us to quantify the maximum impact that process variability has on the throughput. We constructed similar scenarios to examine the effects of scrap rates and repair time. Thus, the first-phase scenarios included:

- Scenario 1: Base case, the model representation of the factory as reflected in the MSD file and the AutoCAD drawing of the layout.
- Scenario 2: All process variation is removed from the base case.
- Scenario 3: Process variation and all scrap are eliminated from the base case.
- Scenario 4: Repair times are set to zero; that is, as soon as an operator attends to a failed machine, it starts running again and the operator can leave for next assignment.

Scenario 2, which eliminates the process variation, was especially critical because the variation input to the model was based on expert opinion and estimated CV’s. Therefore,

if eliminating all the variation does not achieve a significant production gain, then putting effort into creating better estimates of CV for the processing time of each machine is not essential at the conceptual design stage. If, on the other hand, it makes a significant difference, then we should not make radical design changes before this variation is carefully characterized.

Scenario 3 eliminates both scrap and process variation. This scenario was intended to inform us of the sensitivity of throughput to scrap rates and to determine if it is critical to improve the estimates of the machine scrap rates before proceeding. The purpose of eliminating both process variation and scrap rate together is to use this scenario as a “best case scenario” for this design candidate.

Scenario 4 takes a different approach than 2 and 3. In this experiment, repair times were set to zero while scrap and process variation were retained. The goal was to see the potential of the production line when repairs are done infinitely fast and machines are down only for the amount of time it takes for the designated operator to attend the machine (i.e., response time, which consists of time to complete a periodic task in progress and walking travel time). When repair times were set to zero, operators become more available and as a result response times to failures also decrease. We recognize that this level of service is impossible to achieve but this scenario showed us the benefits of improving machine attention activities.

4.2 First-Phase Results and Analysis

For the base case scenario, the average daily production value estimate was only 800k fuel injectors per day or 71% of the target throughput for the new line. This left a gap of nearly 30% between planned and realized production. The results of scenarios 2–4 shed light on what caused this gap and what design changes would give the largest improvement.

In scenario 2 when process variation was taken out from all of the machines, daily production relative to the goal went up to 75%. In scenario 3, in which both process variability and scrap were eliminated, this percentage became 76%. Both of these drastic and unattainable changes to the system produced only slight reductions in the production gap. Therefore, we concluded that more detailed analysis of machine process variation and scrap rates should be left to later stages of our study after other more influential changes were made to the system.

In scenario 4, in which repair times are reduced to zero, the goal of 1125k fuel injectors per minute was achieved. In fact the average daily production for this scenario was 102% of the target. This significant jump from base case was a good indication that machine downtime is one of the primary causes of the low production in the base case. However, before we jumped to a conclusion too quickly, we

returned to the base case scenario and looked at statistics that were collected to discover other reasons for lost production. There were four types of analysis we were interested in making: Operator availability, pallet congestion, inventory levels, and failure analysis.

Operator utilizations in the base case showed all operators were heavily utilized. Some operators were so very heavily utilized that they often did not complete their periodic tasks, such as quality checks, during their shift and so these tasks were pushed to the following shift. For certain tasks, the operators in subsequent shifts were also too busy to complete these tasks and thus it was clear that these types of jobs would build up and never be completed. An even more significant consequence of having heavily utilized operators is that many machine failures did not get immediate attention from operators and thus operator response time to machine failure began to overwhelm repair time as the primary cause of machine downtime. This raised the machine downtimes for most machines far above the expected downtime and caused dramatic production losses.

Another system measure is congestion on conveyors. A very straightforward way of knowing which conveyor segments experience higher congestion is to look at which segments are heavily utilized for a long time. Before running any of the scenarios, we created 4 utilization states: Fully, Highly, Moderately and Lightly Utilized. Throughout the 10 days of each replication, we monitored the amount of time that each conveyor segment spent in each utilization state. Conveyor segments that spent a high percentage of time in Fully or Highly Utilized states were marked and compared to the machine downtimes in the vicinity of these conveyors. Our conclusion for the base case was that there is a very strong relationship between operators not being able to quickly respond to machine failures and heavy utilization of the conveyor segments just upstream of those machines.

Raw material buffer inventory is also of interest. The question is whether there are machines that go idle due to lack of material. In all of our scenarios, there was one operator dedicated to raw material handling and that operator had no machine repair responsibilities. Thus, this function was not affected by the excessive machine downtime. Our conclusion from analyzing inventory buffers was that the material handling assignments for the base case worked out very well and needed only minor adjustments.

Finally, some detailed failure analysis was done since over utilized operators and highly congested conveyor segments may be the symptoms of another problem: Frequently failed machines. As with the conveyors, statistics on percentage of time each machine is Idle, Busy or Failed were collected. Then, for each machine in the system, we compared resulting downtime percentages to the expected downtime from the MSD model. For the majority of machines in the base case, the downtime percentages were 2–3 times higher than expected (see Figure 3 for a comparison

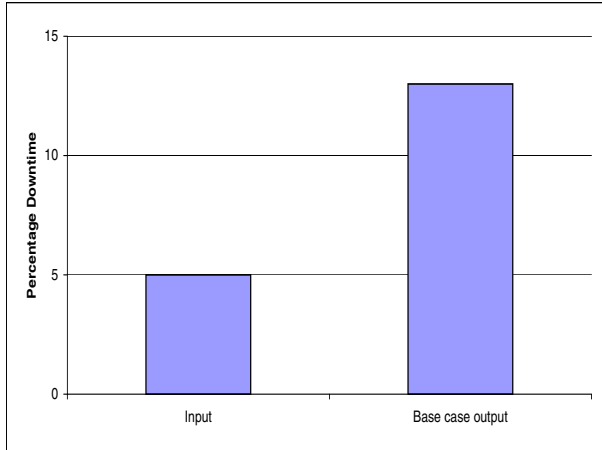


Figure 3: Comparison of input and output downtime percentages for a sample machine in the base case.

of downtime for a typical machine). Thus, we concluded that excessive machine downtime was the primary cause of the 30% gap between the target and the base case scenario.

There are three direct contributors to the average machine downtime: $MTBF$, $MTTR$ and mean operator response time ($MORT$). Percent Downtime (PD) can be calculated as

$$PD = 100(MORT + MTTR)/(MTBF + MORT + MTTR). \quad (1)$$

Percent machine downtime for the MSD model was estimated by observing current machines that are similar to the ones planned for the new production line. Because it directly affects the production, percent downtime for each machine is often recorded. $MTBF$ for the MSD model is also easily collected since machines often have runtime monitors on them. However, separating out the operator response time from the repair time is not typically done, and would in fact be very difficult without a lengthy time study on each machine. This means that we can easily estimate the sum of $MORT$ and $MTTR$, but we cannot estimate either of them individually. When setting up the base case scenario, this problem came into play since each machine must have a distribution specified for both time before failure (TBF) and time to repair (TTR). As a simplification, we assumed that if operator assignments were well designed then $MORT$ would be substantially less than $MTTR$ and thus negligible. Therefore, solving (1) for $MTTR$ we get

$$\widehat{MTTR} \approx \widehat{PD} \times \widehat{MTBF} / (100 - \widehat{PD}), \quad (2)$$

where \widehat{PD} and \widehat{MTBF} are the estimates of percent machine downtime and $MTBF$ from the MSD. Given the results of scenario 4, the assumption that $MORT$ is negligible was

incorrect for the base case and the approximation for $MTTR$ in (2) is poor.

The first response to this information is that all reasonable effort should be made to determine a good estimate of $MTTR$ for each machine so that the base case can be correctly simulated. However, this would require substantial time to carry out data collection at a current production facility with similar machines, if they could be found. Another option, more in the spirit of the use of simulation early in the design process, is to redesign the base case to reduce the operator load and thus reduce the impact of $MORT$. Additional scenarios were used to help to understand the problem of operator loading on the base case and potentially suggest new design directions.

4.3 Second-Phase Scenarios

In light of the results of first-phase scenarios, the second-phase experiments focused on operator availability for machine failures. The operator assignments for the base case scenario involved some critical assumptions, some of which may have a substantial impact on daily production numbers. For instance, in the base case design, each task (a quality check, a machine repair or a material handling job) was assigned to a specific operator and no other operator on that shift could respond to that task. As a result, when a particular operator was heavily utilized, failed machines would often wait for long periods of time before the assigned operator would arrive to start repairs. Similarly, when an operator was gone for their lunch or break, any failed machine assigned to that operator would have to wait until the lunch or break was completed before any repair began. In this highly connected production system, any deviation of a machine from its production target is enough to slow down finished fuel injector throughput.

Another assumption in the base case was that operators leave for lunch or break on schedule as soon as the task at hand is completed. In some cases, this could leave one or more machines failed through an entire lunch or break period. In addition, all of the operators go to lunch or break at the same time, further complicating the downtime problem. Clearly the throughput gap might be reduced by redesigning the lunch and break times of operators, possibly cross-training some operators to provide back-up for others, or by setting the priorities differently regarding lunches and breaks or specific machines.

To quantify the potential of operator redesign, Scenario 5 used the base case, but eliminated lunches and breaks from operator schedules. This experiment was designed to determine an upper bound on the production gain that could be achieved by optimizing the rules on operator lunches and breaks, while the base case implemented a worst-case scenario where lunch and breaks not only have priority, but also all occur at the same time. Of course working

operators without any breaks is not realistic, nor is having them all take lunch at the same time. However, the point of these experiments is not to make a final suggestion for implementation, but instead to guide the design efforts. Furthermore, there are practical ways to implement coverage of lunches and breaks, such as adding support operators to relieve operators when they leave for breaks so all the tasks are continually done.

The selection of scenario 6 was intended to determine how much the approximation of $MTTR$ in (2) affected the daily production rate in the base case. Recall that $MTTR$ for each machine is a direct input to the simulation model. More specifically, each time machine j failed, a random repair time was drawn from an exponential distribution with a mean \widehat{MTTR}_j , which was calculated from (2) using estimates of the downtime and $MTBF$ for that machine or comparable machines from current production lines. Operator response time, on the other hand, is a random output from the simulation model which depends on the random machine failures as well as the operator utilization levels. The approximation in (2) used for the base case assumes that all of the downtime is repair time and we found this to be inaccurate. Scenario 4 went to the other extreme and assumed that all the downtime was operator response time, which we also know is not true since repairs do take time. Scenario 6 attempts to split the difference between these two scenarios and assumes that the repair will account for about half of the downtime and operator response time will be the other half. Thus, for scenario 6, the $MTTR$ for each machine was cut in half. Therefore, the following two scenarios were run as second-phase scenarios:

- Scenario 5: Full relief of lunch and breaks. This scenario has lunches and breaks fully staffed with no reduced efficiency.
- Scenario 6: Mean time to repair ($MTTR$) is cut in half. This scenario anticipates that about half of the machine downtime is operator response time.

In both of these scenarios, the base case assumptions are kept the same except for the changes mentioned. Thus, scrap and process variability rates are included at the same levels as in the base case.

4.4 Second-Phase Results

In scenario 5, where lunch and breaks are fully covered by relief operators, the expected daily production value relative to the production target was 85%. Despite substantial improvement, this shows that even if the base case were redesigned to provide operators that fully cover the lunches and breaks, there would still be a gap between the achieved production and the target of 1125k fuel injectors per day. However, this scenario is still using the assumption that

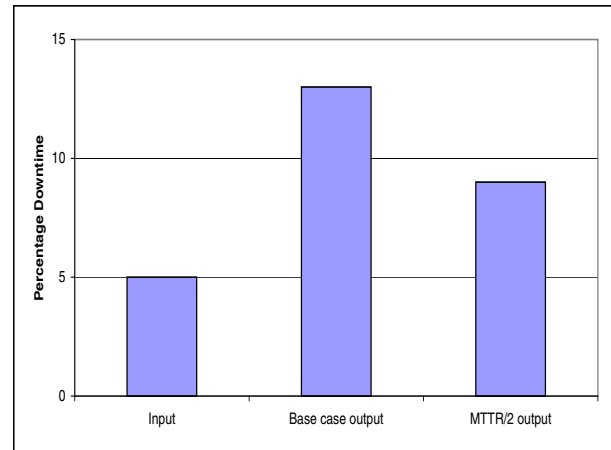


Figure 4: Downtime percentages in base case and in the $MTTR/2$ scenario compared to input value.

the operator response time is negligible and investigation of the downtime for this scenario still does not match the expected downtime from current production lines (see Figure 4). However, in scenario 6, in which lunches and breaks are included, but mean time to repair is cut in half, the throughput is 92% of the target. This indicates that if the $MTTR$ rates were indeed half of the originally proposed $MTTR$ rates, then both downtime and production rates would nearly meet expectations.

Caution must be taken in interpreting scenario 6. The operator response time in the simulation model is based on the level of operator staffing and their assignments. Recall that the downtime estimates from current production machines are also based on some level of operator staffing and some system of task assignment that was not recorded (and are not necessarily relevant to the new production line). Thus, the conclusion of this second phase is that it is vitally important to determine an accurate estimate of the $MTTR$ for each machine that is independent of the operator response time. Only with good estimates of $MTTR$ can accurate estimates of the daily throughput be trusted. Once accurate estimates of the $MTTR$ for each machine are collected, new design candidates can be accurately tested. In particular, scenario 5 indicated that substantial increases in daily throughput can be gained by working out an operator schedule that provides task coverage for operators when they take lunch or breaks.

The results from all six scenarios are summarized in Table 1.

5 CONCLUSIONS

Many real-world projects provide moving targets as the business climate, physical and financial constraints and product concept evolve. This might suggest that simulation, which

Table 1: Comparison of daily production values.

Scenario	Daily Production (relative to target)
1: Base case	71%
2: No Process Variability	75%
3: No PV & No Scrap	76%
4: No Repair Time	102%
5: Full Relief Lunch & Break	85%
6: MTTR/2	92%

is a detail-oriented methodology, is not suitable for system design until quite late in the development of the manufacturing system. However, the ongoing use of simulation by Delphi to design and evaluate their next-generation fuel injector production line illustrates the value of simulation, even very early in the design process. The key is using simulation to answer questions at the right level, including questions about project viability and where to place the most effort in system design. A simulation is capable of addressing these needs well before detailed specifications are available. And if the simulation is constructed in a way that makes it reasonable to update and refine, then it can continue to contribute throughout the project lifecycle.

REFERENCES

- Banks, J., J. S. Carson, B. L. Nelson and D. Nicol. 2005. *Discrete-event system simulation*. 4th ed. Upper Saddle River, NJ: Prentice Hall.
- Kelton, W. D., R. P. Sadowski and D. T. Sturrock. 2006. *Simulation with Arena*. 4th ed. New York: McGraw-Hill.

AUTHOR BIOGRAPHIES

BRUCE ANKENMAN is an Associate Professor in the Department of Industrial Engineering & Management Sciences at Northwestern University. His research interests include the statistical design and analysis of experiments. Although much of his work has been concerned with physical experiments, recent research has focused on computer simulation experiments. Professor Ankenman is currently the director of the Masters of Engineering Management Program and the director of the Manufacturing and Design Engineering Program. He co-directs the freshman engineering and design course (EDC), and is the director of undergraduate programs for the Segal Design Institute. His e-mail and web addresses are <ankenman@northwestern.edu> and <users.iems.northwestern.edu/~bea/>.

LAURENT BORNE is a Project Manager with Delphi Powertrain Systems in Rochester, NY. He holds a Master

of Science degree from the IFP School in Paris, France, an MBA from the Kellogg School of Management and a Master of Engineering Management from the McCormick School of Engineering and Applied Sciences at Northwestern University in Evanston, IL. He can be reached at <Laurent.borne@delphi.com>.

BARRY L. NELSON is the Charles Deering McCormick Professor of Industrial Engineering and Management Sciences at Northwestern University and is Editor in Chief of *Naval Research Logistics*. His research centers on the design and analysis of computer simulation experiments on models of stochastic systems. His e-mail and web addresses are <nelsonb@northwestern.edu> and <www.iems.northwestern.edu/~nelsonb/>.

MUSTAFA H. TONGARLAK is a Ph.D. student in the Department of Industrial and Management Sciences at Northwestern University. His research interests include simulation and metamodeling with applications to manufacturing. His e-mail and web addresses are <m-tongarlak@northwestern.edu> and <users.iems.northwestern.edu/~mustafa>.

KYLE WOLFE is a Senior Industrial Engineer with Delphi Powertrain Systems in Rochester, NY. He holds a Bachelor of Science in Industrial and Operations Engineering degree from the University of Michigan and a Masters of Business Administration degree from the University of Michigan-Flint. He can be reached at <kyle.s.wolfe@delphi.com>.