Use of Simulation Modeling and Analysis to Design New Production Process and Facility

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Abstract: In order for manufacturing companies to gain competitive advantage, stay competitive, or even survive, they need to develop new products and processes. However, most successful ventures require as much attention on process design as product design. This case study describes how a local company used discrete-event simulation modeling and analysis to help them design the first phase of production for their new manufacturing facility in Mississippi. The local company needed to determine the equipment and personnel required for a lean manufacturing implementation of a new high-technology product line, composite fan blade platforms for jet engines, using newly designed production processes. This project was conducted as the plant was being constructed and as the products and processes were finishing prototype production. One key aspect of the study is the demonstration of the importance of including variability in planning and the significant impact it has on fulfilling production requirements. The model was developed by faculty, students, and staff from the Bagley College of Engineering at Mississippi State University (MSU) in conjunction with the local company's engineers.

Keywords: discrete-event simulation, lean manufacturing, process design

Introduction

In this case study, we describe how simulation modeling was used to help a local company design the product flow for its new facility in Mississippi. At the time we began the modeling effort in May 2008 the company was constructing a new facility that would produce composite fan blade platforms for jet engines using new production processes. Obviously this undertaking by the local company posed many challenges, but in this paper we focus on the development of a discrete-event simulation model that was used as a decision-support system to help the production system designers create a facility that effectively and efficiently implements a lean production environment.

This paper is organized as follows. We begin with a brief introduction to simulation modeling and an overview of the product being produced and the production facility. This is followed by a description of the simulation model, example analyses that were conducted using the model, and conclusions and future directions.

Simulation Modeling

A model is an abstraction or simplified representation of a real system that enables exploration of the behavior of that system without having to directly interact with the system itself. As shown in Figure 1, the decision makers – which can be at the enterprise, department, or work-station levels – use information from the real system, consider various alternatives, and conduct experiments with the models, all prior to taking action and implementing decisions in the real system. In the case discussed in this paper, a model was used to investigate alternative layouts, processes, labor assignments, etc. in order to understand their effect on performance and to identify the "best" design, all prior to implementation in the new facility.

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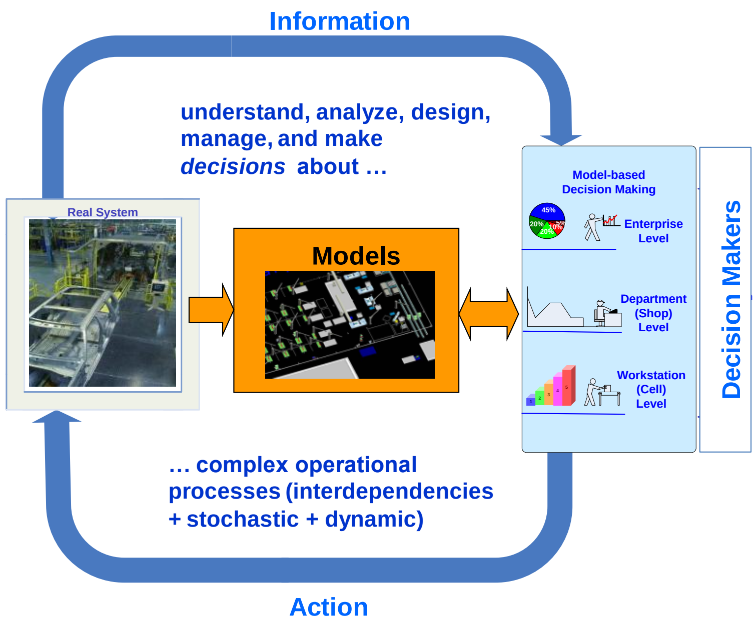

Figure 1. Model-based decision making

Discrete-event simulation (DES) is a type of modeling that addresses systems that are complex, dynamic, and stochastic. System complexity depends not only on the number of elements that need to be considered in a system, but on the degree of dependency among those elements. Obviously, production systems have many elements that are highly interconnected and thus have numerous dependencies. A dynamic system is one where its states change over time, thereby complicating analyses. Stochastic systems contain elements of uncertainty, again complicating analyses. For example, the time it takes a human to complete a task, such as an assembly operation, is stochastic; that is, the time varies each time the task is performed and that variability is expressed as a probability distribution.

Figure 2 provides a high-level representation of a simulation model. As shown in the figure, some of the inputs that are provided to a model are decision variables, those that are under the control of the decision maker, and others, that, while they affect system behavior and performance, are uncontrollable. The model, through its logical and mathematical representations, converts the inputs into outputs. The outputs describe the behavior of the system and provide estimated measures of system performance. Since in a stochastic model some of the inputs are random variables, the outputs from the model must also be random variables. Therefore, statistical analyses are used to analyze the output. As illustrated in Figure 2 through the feedback loop from outputs to inputs, users adjust the value of the decision variables based on the measures provided by the simulation model. In this manner users observe, understand, and assess the impact of decisions on system performance. This iterative process continues until a satisfactory solution is obtained.

Simulation models are typically built using specialized software. In this project we developed the model in *Flexsim* [1], a state-of-the-art simulation package that provides excellent visualization, modeling, and analysis capabilities through its extensive library of modeling objects. *Flexsim*'s open object-oriented architecture facilitates customization of these elements in order to effectively model production systems. Its seamless interface with *MS Access* and *MS Excel* enhances the ability to import the data that are needed to run the model and export results from the model for further analyses. Just as in a real system, communication and coordination among objects is critical. As a result, we extensively use *Flexsim*'s messaging capability to control model operations and emulate system behavior.

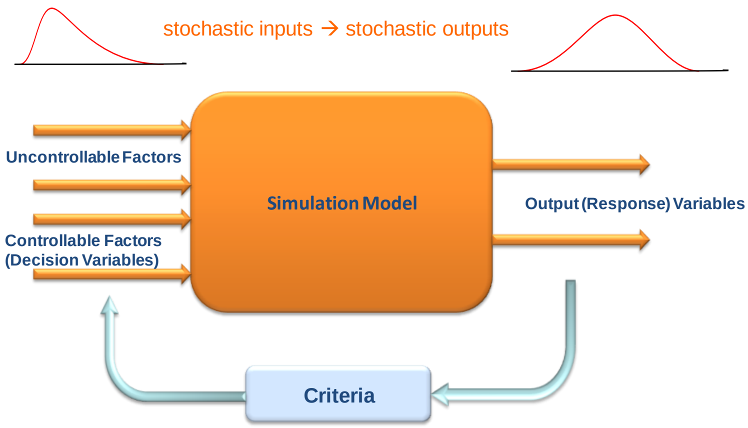

Figure 2. High-level representation of a simulation model.

The simulation model was used as a decision support system (DSS) during the project; i.e., it was embedded in the production system design and decision-making processes. While there are various types of DSSs, the model described in this paper is the core of a model-driven DSS. The model was heavily used to assess alternative production system configurations and designs and to evaluate how well the system responded to possible changes in the environment, such as changes in customer demand. The model described in this paper spans most of the categories in Pidd's characterization of modeling approaches [2] that is shown in Figure 3. As the graph at the top of the figure indicates, DSSs at the lower end of the spectrum tend to be routinely used and involve little human interaction. In our case, the model went beyond routine decision support in that it represented possible system designs and changes; and, in fact, the model oftentimes generated insight for debate. The model was developed for a single use – to help design the new production facility – and there was a high level of human interaction. The model design team worked very closely with production system design team, making frequent changes to the model and providing feedback on the impact of the changes that were being considered. In addition, the design team was trained to use *Flexsim* and therefore was able to make some of the changes and conduct some of the analyses themselves.

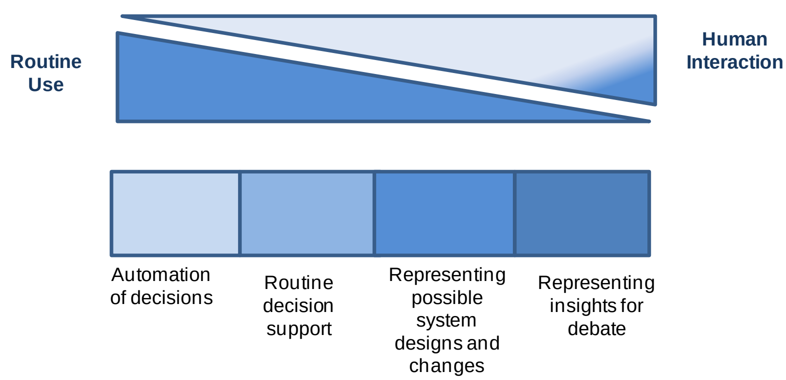

Figure 3. Types of modeling approaches (from Pidd[2]).

Overview of Product and Production Facility

As mentioned above, the local company recently constructed a 300,000 sq. ft. jet engine components factory in Mississippi. The new plant utilizes highly sophisticated composite manufacturing processes. The initial components produced at the plant are carbon-fiber and epoxy-resin composite fan platforms that are installed between the front fan blades of aircraft engines, such as the X90 and Xnx. The X90 is used on the Boeing 777 and the Xnx will be used on the Boeing 787 Dreamliner. An example fan platform is shown in Figure 4; the component is less than two feet in length and weighs less than five pounds.

Figure 4. Example jet-engine fan platform.

Figure 5 provides a simplified illustration of the product flow. All of the different types of composite fan platforms are produced on the single, shared production line. The functional areas that make up the production line are not drawn to scale; they only indicate the main production steps and flow. The production line is designed using lean manufacturing principles. The composite fan platform starts from rolls of pre-impregnated (pre-preg) composite fibers that contain matrix materials that bond when subjected to heat and pressure. In the Ply Cut area, the material is cut into a variety of shapes. The cut shapes are layered in the Layup & Debulk area to form the components of the fan platform; in general, the components are referred to as preform parts. While it depends on the product, there are typically about six preform parts in a composite fan platform. The preform parts are trimmed and loaded into a container, called a coffin. A set of fixtures are used in the coffin to support the parts. The coffin and parts are then processed at a Press. Once the Press cycle is complete the preform parts have been formed into a single unit that is the basic fan platform. The coffin is transported to an Inspection area where the coffin and fixtures are disassembled and the fan platform is removed and examined. As shown in Figure 5, the fan platform then goes through a series of processes before it is complete: Milling, Bonding, Painting, and Final Inspection. The coffin and fixtures are cleaned and made ready for reuse.

Simulation Modeling Approach

The local company's advanced manufacturing facility in Mississippi was dedicated in October 2008. In May 2008 a team of industrial engineers from MSU joined with a team of the local company's production engineers to help design the initial production system for the new facility. Production processes were based on lean manufacturing principles. The MSU team consisted of a professor and a graduate student from the Department of Industrial and Systems Engineering in Starkville, MS and a staff industrial engineer from the Center for Advanced Vehicular Systems Extension in Canton, MS. They used their modeling and simulation expertise to help the local company's team analyze and evaluate alternative system designs. MSU developed a baseline model of the facility and trained the local company's engineers in the basics of simulation modeling and the use of *Flexsim* simulation modeling and analysis software. For several months the two teams worked closely together modeling and assessing alternative equipment configurations, production personnel assignments, and product mix demands.

Screenshots from the simulation model are provided in Figure 6. The main image is of the overall production system, from Ply Cut through Final Inspection, and parallels the product flow diagram in Figure 5. Of course, the model is much more detailed than the cursory description outlined in Figure 5. The two inserts in Figure 6 provide close-up images of the representation of the Layup & Debulk and Coffin processing areas in the model.

Each run or replication of the model covered a one year period; i.e., operation of the plant over 52 weeks, with each week consisting of five 24 hour work days, or 374,400 simulated minutes. Running on an IBM *Intel® Pentium®* 4 CPU 2.40 GHz with 512 MB of RAM with the Microsoft Windows XP operating system, each replication took just under one hour of computing time.

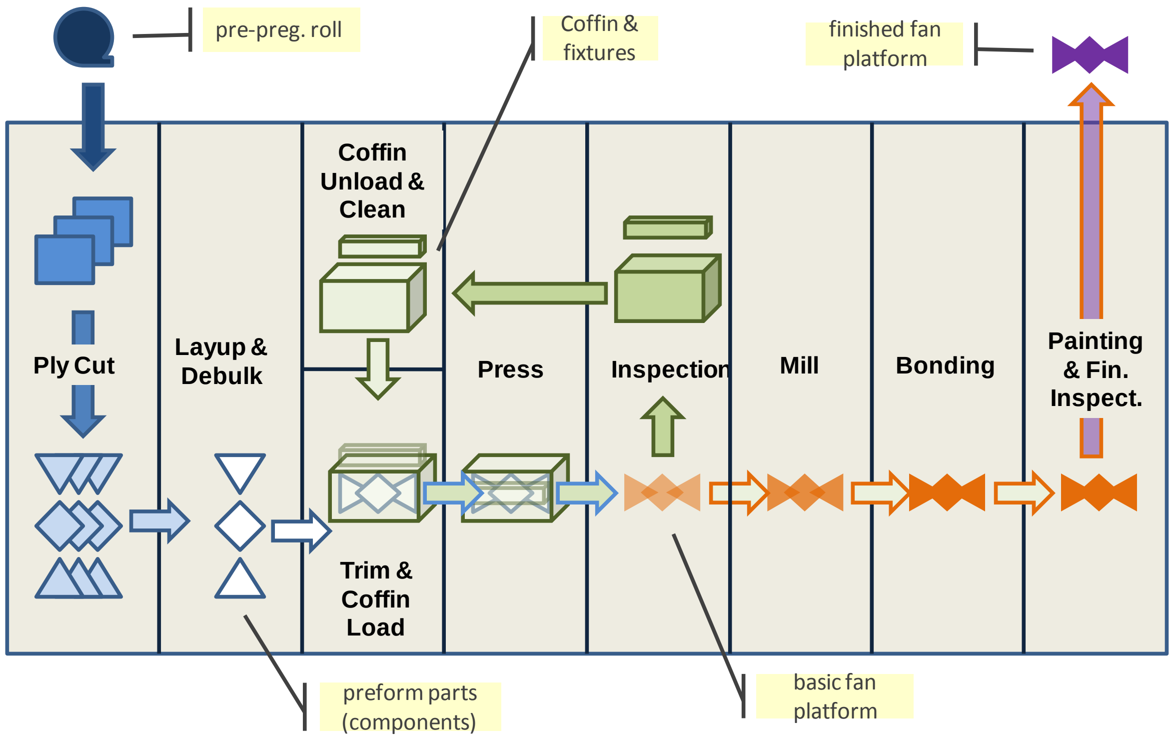

Figure 5. General product flow through functional areas.

Analyses

As indicated earlier, the model was used to investigate a wide variety of issues in the design of the lean production facility; but, there is only space in this paper to discuss a few of the analyses. Nonetheless, these few examples should demonstrate the power of simulation modeling and analysis and the value it brings to the design process.

The Layup & Debulk and Coffin areas were investigated in detail during the project. One of the analyses in the Layup & Debulk area involved the interactions between the operator at each layup/debulk station and other operators that performed some of the debulk tasks and moved sets of the preform parts to the Trim area. In the Trim and Coffin Load area, as shown in Figure 5, all of the preform parts for a fan platform, along with a set of fixtures to support the parts, are assembled into a coffin prior to the Press area. After processing at the Press, the preform parts have been transformed into a basic fan platform. The platform subsequently undergoes additional processing to become the final product. The coffin is routed to a cleaning area where it and its associated fixtures are cleaned and prepared for reuse on another set of preform parts. One concern in this area was having the appropriate coffin available for loading when needed. Another matter for analysis was the design of the monorail system that transports the coffin and fixtures through the cleaning process.

Like most studies of this type, we conducted analyses to identify bottleneck operations. A bottleneck is that part of the system that, due to capacity or performance issues, constrains the output of the entire system. Other than some issues in the Layup & Debulk area, no areas caused significant wait times or buildup of inventory prior to processing.

One key concern in all manufacturing systems is the corrupting impact of variability. Manual tasks inherently contain variability; i.e., the time to complete a task varies from occurrence to occurrence. Such things as individual operator proficiency, fatigue, material properties, rework, and a variety of other disruptions all contribute to variability in production times. This variability tends to propagate through the system and, unless properly accounted for in planning, will cause lower than expected throughput or output from the system. Since many of the processes used in the local company's plant are new processes, there was no history on their variability. Therefore, the model was used to assess the impact of various assumed levels of variability on production performance.

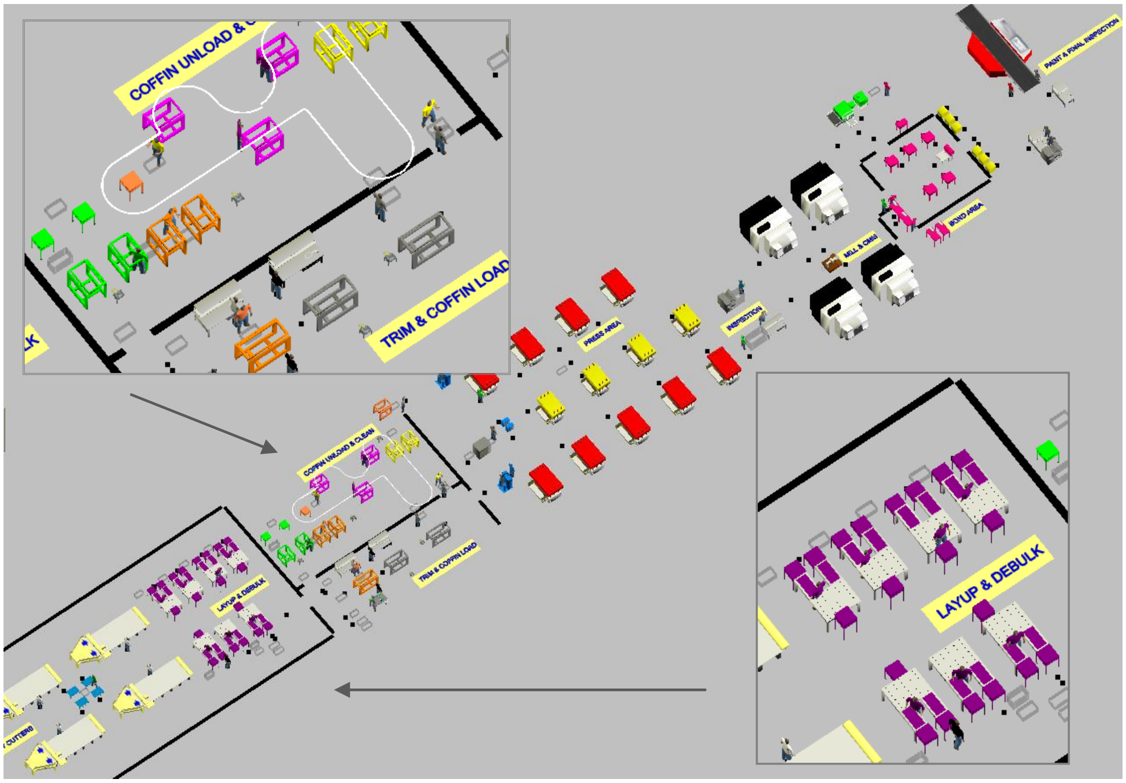

Figure 6. Screenshots from the *Flexsim* model of composite fan platform production line.

The model was run with different levels of variability. A common statistical measure of variability is the standard deviation, σ. A low standard deviation indicates the observations tend to be close to the mean (μ); conversely, a high standard deviation indicates the data are spread over a wide range of values. In order to better compare levels of variability, the standard deviation is often scaled by the mean μ; this is referred to the coefficient of variation, denoted as *k*, where $\mathrm{k} = \sigma/\mu$. The durations of all manual tasks were subjected to various levels of variability, i.e. various levels of *k*, in order to assess the effect on performance. The manual task durations are assumed to be normally distributed with mean μ and a standard deviation that is a fraction of the mean, k*μ, with *k* varying from 0 (deterministic or constant durations) to 0.25. That is, Duration ~ Normal(μ, k*μ) where k = 0, 0.05, 0.10, 0.15, 0.25.

A coefficient of variation of 25%, k = 0.25, is not especially high. In the case of the normal distribution this means that 95% of the observations are expected to be within ± 50% of the mean. If the mean duration is 100 seconds and k = 0.25, then we'd expect 68% of the durations to be between 75 and 125 seconds and 95% of the durations to be between 50 and 150 seconds. In the case of the exponential distribution, the mean and standard deviation are equal and thus k = 1.0.

In order to demonstrate the effect of the shape of the probability distribution, we consider each duration to be uniformly distributed with mean μ and coefficient of variation k= 0.25. The uniform distribution is typically specified in terms of its low value *a* and high value *b*. It can be shown that *a* and *b* can be set to $\mu(1-\sqrt{3}k)$ and $\mu(1+\sqrt{3}k)$, respectively, in order to obtain a uniform distribution with mean μ and standard deviation kμ.

The weekly demand for each type of fan platform varies across any planning horizon. The local company constructed 13 possible weekly demand patterns for their products. In essence, these represent 13 different product mixes that would need to be produced in a week. The simulation model, when provided a product mix, estimates the time, in days, to complete production of all products in the mix; this is referred to as makespan. Table 1 provides examples of the sensitivity of the effect of different product mixes and different levels of variability on makespan. Since all but the first case have stochastic process times for the manual operations included in the model, the resulting performance measures are also stochastic. Therefore, their values are reported as the mean of 10 replications of the model. In order to provide the reader with a sense for the variability of the performance measure from replication to replication, the lowest and highest values for Product Mix 1 for Case 2 (Normal, k=0.05) is 1.37 and 1.40 and, respectively; the lowest and highest values for Product Mix 13 for Case 5 (Normal, k=0.25) is 4.35 and 4.77 and, respectively.

In general, there is not much difference between the cases that have no variability and 5% variability. However, holding the assumed probability distribution constant, the impact clearly increases as more variability is introduced into the system. While it depends on the product mix, makespan generally increases by about 15% between the 5% and 25% cases. This is especially noteworthy since a significant amount of a product's makespan (approximately 36%) is spent in the press and ovens and those durations assume to have no variability. The effect of the uniform distribution is not as great as the normal, for the same level of variability, because it is bounded and large durations are not possible.

Table 1. Estimated impact of product mix and variability on makespan.

Case	1	2	3	4	5	6
Distribution	None (constant)	Normal	Normal	Normal	Normal	Uniform
k	0	0.05	0.10	0.15	0.25	0.25
Product Mix	Days	Days	Days	Days	Days	Days
1	1.39	1.38	1.44	1.45	1.54	1.54
7	2.77	2.78	2.84	3.07	3.26	2.96
13	3.86	3.87	4.14	4.23	4.52	4.25

Since the planning horizon used in the simulation analyses is one year, the model processes a sequence of 52 weekly product mixes. Figure 7 shows that as the variability in manual processing times increases, there is a noticeable increasing trend in the average number of days required to meet the production demand for each case.

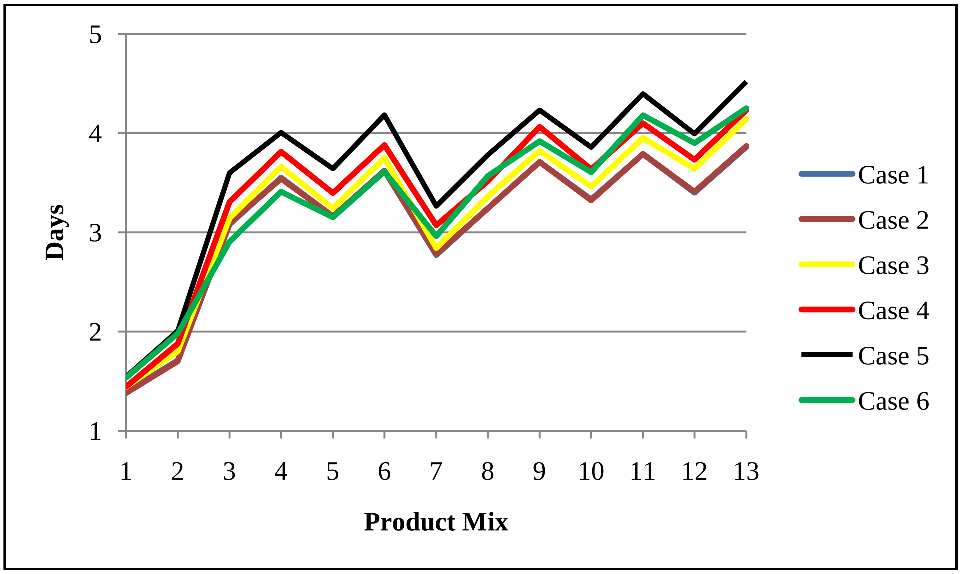

Figure 7. Average days required for each product mix by case.

Another example of the effect of variability is in the calibration area. Two workstations calibrate fan platforms during the production process. The calibrating process can be performed on either workstation, but would go to the first workstation that is available. As the variability increases, the output of the second workstation significantly increases, while the output for first station decreases. Therefore, the single, shared production line becomes more dependent on the second workstation in order to meet production requirements. Table 2 provides the estimated output for each calibrating workstation for each case.

Table 2. Estimated output for each calibrating workstation by case.

Object	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
First Calibrating Workstation (units)	53,836	51,466	47,206	45,000	42,447	47,732
Second Calibrating Workstation (units)	24	2,394	6,654	8,860	11,413	6,128

Conclusions and Future Directions

This case study demonstrates how a discrete-event simulation model can enhance the design of a manufacturing facility. The model was an integral part of the facility design process. It was used as a decision support system to help designers quickly assess the performance of various alternative production configurations and resource allocations. One of the analyses conducted during the project was an examination of the sensitivity of manual processing times to various levels of variability. The analysis clearly showed the significant negative effect on system throughput and cycle time when even a relatively small amount of variability is introduced into the proposed lean manufacturing system. The model proved to be an effective design and planning tool.

The model's return on investment can be increased by imbedding it in a user-friendly decision support system. The model, in its present form, can only be used by those familiar with simulation modeling and *Flexsim*. However, the DSS would enable those unfamiliar with simulation modeling to use the model to support their decision making on routine basis. Before developing the DSS, a set of use cases would need to be developed to define who would use the model and how they would use it. Since the fan platform area is just the first phase of production in the local company's facility, the remainder of the plant needs to be modeled and interfaced with the model discussed in this paper.

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