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Letter to the Readers

GET YOUR IDEAS OFF THE GROUND

Those who know me are probably aware of my lifelong passion for hunting. And while those moments of exhilaration in the great outdoors are the times that are most remembered, the preparation far outweighs the few days when the hunt actually takes place. In fact, adequate preparation carries just as much importance to the success of a hunt.

For my white lab Leo, those months of training are essential to learning the key words, sounds, and hand signs that allow him to augment his natural retrieving skills with the ability to flush a bird out from the brush. All of that practice will culminate in a trip to North Dakota for one week of hunting, and his effort pays off almost immediately: I simply use the command “get the bird in the air” and Leo springs to action, flushing out a pheasant and giving me an opportunity to take one single, well-aimed shot. The season is less than 10 minutes old and my bird dog has already proven his worth.

Much like Leo, simulation software can be the perfect companion to meet your own goals. Whether the system is a production system, warehousing system, material handling system, or a people system, simulation can expose problems and even provides the tools necessary to retrieve the solutions. Some managers and engineers spend their whole careers searching for tools to help them make correct decisions when faced with tough challenges. I believe, for many, that search could end today.

The papers in this issue of *FlexSim Quarterly* also deal with “getting the bird in the air,” but they do so both figuratively and literally: one deals with the simulation of passenger check-in and baggage screening in an airport, and the other focuses on the production of jet engine components. These case studies demonstrate some of the analytical capabilities found in a great simulation package and show just how effective simulation can be in the hands of capable, motivated engineers.

All the best,

Bill Nordgren
CHIEF EXECUTIVE OFFICER
FlexSim Software Products, Inc.
Simulation Analysis of Passenger Check-In and Baggage Screening Area at Chicago-Rockford International Airport

Prajwal Khadgi

Spring 2009

Abstract

Air transportation today is probably the most effective and convenient mode of traveling, considering the short travel time and the increasing affordability for people. The airport is always a place of movement, with people traveling back and forth as well as a large number of flights flying in and out of the region. The various operations inside the airport terminal are not always easy. At peak times, airport operations can become very busy and cumbersome. By using simulation, the airport system can be modeled into a computer program, and the effects of various parameters—such as number of passengers on a flight—can be studied. Thus steps can be taken for effective operation during such conditions. In this paper, the passenger check in area and the baggage screening area have been simulated using an object based simulation modeling tool, FlexSim. After completing the model, various scenarios were evaluated to provide an optimum working scenario for efficient operation.

Introduction

Defining the various functions, operational units and constraints of a working system, providing a certain set of input variables and operational conditions, and observing the resulting changes in the output variables in a virtual computer based model in order to understand the effects of changing conditions in a system may be considered as Discrete Event Simulation (DES). Simulation is a very efficient tool for optimization and development of systems. When the variables of the system are deterministic and simple linear methods can be applied to solve for the optimal solution, simulation may not be a good option to represent the system. However, when the variables of the system are probabilistic and there exists a lot of stochasticity, using simulation is the perfect representation of the system. The working system being studied in this paper is an airport management system. In an airport the basic variables that need to be considered are passenger arrival rate, check in times, number of passengers on a flight, baggage screening times, security checking times, waiting times, etc. All of the mentioned variables are probabilistic and thus it is necessary to consider these stochasticities while trying to solve for an optimal solution for effective operation.

With the increasing number of people traveling both domestic and international, efficient operation of an airport system to minimize customer inconvenience, without having to compromise security standards, becomes an important issue. Simulation tools have proven to be very effective in this sector for providing forecast models of various scenarios, which help in making operational decisions in airport management. The various sectors that can benefit from simulation analysis are Passenger Check-In, Security Checkpoint, Baggage Screening, Baggage Claim at Arrival, Air Traffic Control and Taxiway Management, and Facility Design for Development. Simulation can also be used to model other specific areas within the airport such as parking, shuttle system, and passengers waiting at specific concourse. Among the above mentioned points, the ones that directly

1Originally published in NIU Engineering Review. Used with permission.
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deal with customers are Passenger Check-In, Security Checkpoint, and Baggage Claim. Since it is very important to consider customer satisfaction in a service sector, using simulation at these places to help study and reduce customer waiting times or process times seems plausible.

**Rockford International Airport**

Located 68 miles northwest of Chicago, Rockford International Airport is a medium size airport that provides non-stop flights to nine destinations—such as Las Vegas, New York City, Orlando, Phoenix, Cancun, etc—and is operated by four air service providers. Even though it only operates flights to selected destinations, the airport still has up to 31 departures per week, depending on the season. Since 2007, the number of passengers traveling through Rockford has increased to around 215,000 per year [1].

Rockford International Airport (RFD) has a two level terminal, with passenger check-in, baggage claim and an airport café on the lower level, and security, departure gates and a restaurant on the upper level. When the passengers arrive at the airport, they first stand in a queue and wait for one of the check-in agents to be available. Passengers usually arrive in groups of one to four, but sometimes there may be families with seven or more members. For every flight there are usually three check-in agents attending the passengers. The agents check in the passengers and weigh their baggage. After weighing, the baggage is put on a conveyor belt, which transfers the baggage to a baggage screening area. Each baggage is screened through an automatic screening machine and the screened baggage is tagged and sent to the aircraft. If there are suspicious items, the baggage is taken out and re-checked by hand. Some items cannot be screened through the automatic machine and have to be hand checked. Transportation Security Administration (TSA) is responsible for all security procedures including the baggage screening. After the check-in is complete, the passengers are sent to the upper level, where they go through a security check and wait in the lounge to board the airplane.

Rockford Airport is a medium capacity airport facility that usually operates one flight at a time. For this reason, there isn’t a lot of rush at the terminal during normal operation. However, at peak hours and holiday seasons the flow of passenger increases and the airport facility can become very crowded and busy. These high capacity hours can be easily foreseen according to the number of flights arriving and departing at a certain time, and thus necessary arrangements can be made to handle such situations. The number of check-in agents can be increased up to a certain number, but the baggage screening process cannot be quickened. The total number of TSA personnel in the baggage section can also be increased as necessary depending on the urgency of the situation. The total number of passengers taking a flight may also vary and the number of flights may increase during high capacity operations.

In this paper, the effect of various parameters in airport operations were studied for the average waiting time for passengers, processing times and idle times for the agents, and maximum queue content of baggage. For this purpose the lower level of the airport—consisting of the check-in area and the baggage screening area—were simulated in an object based simulation tool, FlexSim. The building of the model will be discussed in brief in the following sections. Various scenarios were set up to study the effects of multiple flights, number of passengers on flight, number of check-in agents and the baggage screening mode. These scenarios and case studies will also be discussed further in the paper.

**Data Collection and Analysis**

The necessary data required for the study had to be taken in the beginning. In order to do this, Rockford Airport was visited during operational hours prior to flight departures for observation of the passenger arrival pattern, check-in procedures and baggage screening procedures. A stopwatch was used to record the times between passenger arrivals, taking into account the number of passengers arriving together as a group. The time taken for the check-in process was also observed and the number of baggage checked in was recorded. In the baggage screening area, it was observed that, although an automatic screening machine was used, the conveyor belt was not connected to the machine. As a result, the agent had to manually load the machine and manually load out the bags from the machine. The time taken to
load the baggage into the machine, load baggage out of the machine, screen the baggage, and manually check the baggage were all recorded. In order to have enough information to accurately represent the system, data was taken over multiple days.

After collecting the necessary data, the data distributions had to be evaluated to feed into the simulation model. Expertfit and Input Analyzer were used to come up with the appropriate data distributions. For the inter-arrival times of the passengers, the data was first randomly split into three parts. Two-thirds of the data was fit into Input Analyzer, and a gamma distribution $\text{GAMM}(3, 38.7, 1.3)$ was observed (Fig. 1). Next, the remaining one-third of the data was used to validate this distribution by fitting the previous parameters into the data and observing the corresponding p-value of the chi squared test. Since the p-value was 0.329, which is much greater than 0.05, the gamma distribution was selected. Also, the entire data was entered into Expertfit, which returned a distribution of $\text{Gamma}(2.907407, 38.700486, 1.303549)$. This further validates the distribution for the inter-arrival times of the passengers.

Similar methods were applied to formulate the distribution for passenger check-in times, which resulted in an exponential distribution $\text{Expo}(44, 86, 1)$. In the baggage screening area, the distributions for scan time, load in time and load out time were evaluated using Expertfit. The distribution for scan time was found to be $\text{Loglogistic}(34.698113, 8.120486, 2.348135)$; for load in time the distribution was $\text{Weibull}(3.933333, 3.199017, 0.744261)$; and for load out time the distribution was $\text{Gamma}(0.000000, 0.906343, 13.653779)$. The process of recheck by hand is only done 10% of the time, so sufficient data was not available to fit a distribution. Using the small amount of data collected, a uniform distribution of $\text{Uniform}(235, 313)$ was chosen. These distributions were later used in the various objects of the simulation model.

![Figure 1: Two-thirds of the data for inter-arrival times, fit to the Gamma distribution.](image)

## Developing the Model Using FlexSim

The simulation model consists of two major sections: passenger check-in and the baggage screening, connected by a conveyor belt that transfers baggage from the check-in area to the baggage screening area. A source object was used to create the passengers arriving into the airport. The source was fed with the distribution for inter-arrival time, as calculated in the previous section. To represent the different number of people coming in groups, different “itemtypes” were given to the flowitems on creation. According to data collected, the numbers of people in a group were 1, 2, 3, 4 and 5 for 43%, 36%, 13%, 5% and 3% of the time, respectively. This causes FlexSim to assign different itemtypes according to a percentage. For example, a flowitem having an itemtype of 3 would represent a group of 3 passengers. A global table “counter” was also defined to count the number of passengers arriving. A code was given in the source object that increased the value of the counter table by the number of itemtypes of the flowitem. By keeping track of this counter table, the total number of passengers that have arrived can be observed and the source object can be stopped when the maximum allowed number of passengers is reached. This maximum number of passengers can also be stored and retrieved from another global table.

After the passengers were created, they had to be sent into a queue to wait for available check-in agents. The source object was connected to an accumulating conveyor object “entrance lane,” which represents the queue of passengers. The output port of *entrance lane* was then connected to the processor objects representing the check-in counters. The

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flow rule for the flowitems from entrance lane to the check-in counters was set as first random port available. For building purposes four check-in counters were created, which later may be closed or opened depending on requirements. For each counter an operator was used, so there were four check-in agents at the start of the model. To simulate the baggage weighing and drop off process, the message and create flowitems on message functions were utilized. A code was written on exit of each passenger to evaluate how much baggage to check in. According to collected data, the number of baggage checked in for every check-in process was 0, 1, 2, 3 or 5 for 27%, 52%, 15%, 4% and 2% of the time, respectively. The parameter 0, 1, 2, 3 or 5 would then be evaluated according to the given percentages and the message would be sent to the center port object, which in this case was a queue object representing the weighing scale. The queue object, on receiving this message, would then create a number of flowitems equal to the parameter from the message. Figure 2 shows the passenger check-in counters and the agents putting baggage on the conveyor.

Figure 2: Part of the simulation model showing the check-in counters and agents.

A conveyor was used behind the check-in counters and the queue objects—which create baggage—were connected to the conveyor. The check-in agents were made to transfer the baggage onto the conveyor according to highest priority. After the passengers complete the check-in process, they are made to exit the model via a sink object, simulated to go to another section of the airport not considered in the model. The baggage then goes into the baggage screening section through the conveyor. In the baggage screening area, two different types of screening methods are modeled. A single automatic screening machine was modeled by using a processor with the loglogistic distribution. Three manual screening machines with the uniform distribution were also placed. The conveyor was connected to the automatic machine but utilized an operator to load in the baggage and another operator to load out the baggage. Ten percent of the baggage coming from the check-in area were sent to the manual machine for manual checking, which utilized another operator. The automatic screening machine was given a capacity of three, so it could scan three bags at a time. Out of the screened baggage, 10% was considered for recheck and sent back to one of the manual machines for manual checking. After the checking was complete the baggage was sent through another conveyor to a sink object to take it out of the system, simulating the baggage going into the aircraft. There were three agents at the baggage screening section. Figure 3 shows the baggage screening area as well as a slight overview of the entire simulation model.

Figure 3: Baggage screening area.

For the purpose of evaluating different scenarios, various global tables and user events were used in the simulation model to facilitate for the change of variables. The maximum numbers of passengers on a flight were recorded on a global table "Maximum
number of passengers.” Since three source objects were incorporated to simulate scenarios with multiple flight operation, the varying numbers of passengers on these flights were recorded in the global table. These values can be changed later for different cases. The selection of the check-in agents was done by using a global table “Selecting check-in agents.” This table had four rows for the four agents with values of either 1 or 0. The value 1 corresponds to an agent being active and operative, whereas a value of 0 means that the agent is inactive. These values can be manually changed to select the agents and the selecting process is done by incorporating a user event at the beginning of the simulation.

At time 0 FlexSim evaluates the given event. If any of the global table values for check-in agents are found to be 0, then the input port of the corresponding check-in counter is closed. This prevents flowitems from going to that processor and simulates the agent being inactive. Also, to open the source object for multiple flights, a user event is used such that the output port of the source objects are opened or closed as desired. At time 0, source for flight1 is opened and the others closed. Then, according to the departure time of the second and third flights, user events are used at the particular times to open the source for flight2 and flight3.

Multiple Scenarios and Analysis

In order to do a simulation analysis of the system, various cases and scenarios were evaluated. This paper provides three case studies, each with different scenarios.

Case I

The first case was evaluated for various responses by changing the method of the baggage screening procedure. It was observed that, since the conveyor was not attached to the automatic machine, an operator had to manually load and unload the machine. Also, it was known that the baggage screening process was completely manual before the purchase of the automatic screening machine. Three scenarios were observed: the current procedure, completely automatic (without manual load in/out) and completely manual screening. In almost all the cases, the variable parameters were the number of passengers on the flight and the number of check-in agents to use. Various output parameters such as average waiting time for passengers, maximum content of baggage queue, and the utilization of check-in counter were observed. For Case I, the number of passengers used was 215 and number of check-in agents was 3.

Case II

The second case evaluated the responses of the system by changing the number of passengers on the flight and also the number of check-in agents. This evaluation was done for the current baggage screening process and for a single flight only. Nine different scenarios were set up in the Experimenter tool in FlexSim. In the Experimenter, the number of experiment variables was set and the path for the variable was given from the tree nodes. Various scenarios were added and the variables changed. The simulation was run for 10 replications for each scenario, and the results were obtained at the end of the experiment in an MS Access format. The different scenarios for Case II were selected as shown in Table 1.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>No. of passengers</th>
<th>No. of check-in agents</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>215</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>215</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>215</td>
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<tr>
<td>7</td>
<td>175</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>175</td>
<td>3</td>
</tr>
<tr>
<td>9</td>
<td>175</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 1: Scenarios used in Case II.

Case III

The third case evaluated the effect of multiple flights. For this user events were used to open the source object for the remaining flights. The source for flight1 was opened at time 0, the source for flight2 was opened at time 5400 (after 1.5 hrs) and the source for flight3 was opened at time 10800 (after 3 hrs). Then, six different scenarios were set up by changing the number of passengers on each flight and
the number of check-in agents. The scenarios were set up as shown in Table 2.

### Results and Conclusion

Running various scenarios in this model supports a lot of decision making processes in the airport management system, such as how many agents to keep, scheduling various resources and flight scheduling according to available resources. The results of the various scenarios can be obtained through simulation modeling such as this, and the effects of various changes in variables can be studied without actually having to change the variables in the real system. For each of the cases defined above, the different scenarios were run for 10 replications each and the results were studied. In this section the results of the three cases will be briefly discussed.

For Case I, the effects of different baggage screening methods were studied. The model was run for three different scenarios; the current procedure, completely automatic (without load in/out) and completely manual screening. For each of these scenarios, the results were obtained. It was discovered that for the manual screening method, the maximum baggage content on the baggage conveyor was 20, compared to only 6 for the current method. The average waiting time for baggage on the conveyor greatly reduced from 844.22 sec to 29.97 sec by adding the automatic screening machine to a manual method. It can further be reduced to 17.56 sec by connecting the conveyor to the machine and eliminating the load in/out process. The method of baggage screening does not affect the check-in process, but increases the waiting time of baggage on the conveyor and decreases the throughput rate of the baggage.

For Case II, the number of check-in agents required according to the changing number of passengers on a flight was studied. For a flight with 215 passengers, increasing the check-in agents from 2 to 3 to 4 caused a significant decrease in the average passenger waiting time: from 715.06 seconds to 94.14 seconds to 37.63 seconds. Similar results can also be seen for flights with 100 and 175 passengers. It was observed that the average waiting time for passengers does not significantly change for 100 and 175 passengers, even though it decreased from 715.06 seconds to 418.92 seconds when the number of passengers reduced from 215 to 175. Also, it was seen that the average wait time for the baggage on the conveyor increased when using more check-in agents. This clearly shows that by having more check-in agents the average waiting time for the passengers is reduced, but the baggage on the conveyor are increased due to faster processing.

For Case III, the effect of multiple flights was studied. The model was set to create passengers for three different flights departing 1.5 hours apart. The first source created passengers at time 0, the second source started creating after 1.5 hours and the third source opened after 3 hours. These three different scenarios were evaluated for Case III. We can see that for a constant passenger arrival with 200 passengers on all flights, the average waiting time reduces from 948.15 seconds to 34.58 seconds by using 4 agents instead of 3. This extremely high waiting time may be a result of the high number of passengers arriving at a certain point in time. By reducing

<table>
<thead>
<tr>
<th>Scenario</th>
<th>No. of passengers (Flight1)</th>
<th>No. of passengers (Flight2)</th>
<th>No. of passengers (Flight3)</th>
<th>No. of check-in agents</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>200</td>
<td>200</td>
<td>200</td>
<td>3</td>
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<td>200</td>
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<td>3</td>
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<tr>
<td>6</td>
<td>100</td>
<td>150</td>
<td>150</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 2: Scenarios used in Case III.
the number of passengers to 100 on the second flight, the check-in process is eased even more. The average waiting time was found to be 271.15 seconds for this scenario, which was further reduced to 35.79 seconds by using 4 agents. In the case of low passenger arrival (100, 150 and 150 passengers on the respective flights) the average waiting time was even further reduced to 67.20 seconds with 3 agents and 25.83 seconds with 4 agents. Thus, the waiting time of the passengers depends on the number of passengers arriving for a flight.

By conducting this simple scenario analysis in the simulation model of the airport, conclusions and decisions can be made regarding the behavior of the system in different scenarios. This may prove to be a helpful tool in airport management systems to forecast, optimize and make important decisions in airport facility management. Similar to this model, simulation can be extended to other sectors of the airport as well, to study the effect of one section to another on a completely different level.

References

Use of Simulation Modeling and Analysis to Design New Production Process and Facility\textsuperscript{1}

Lucas A. McDowell\textsuperscript{2}, Allen G. Greenwood\textsuperscript{3} and Travis Hill\textsuperscript{4}

May 2009

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 GE Aviation used discrete-event simulation modeling and analysis to help them design the first phase of production for their new manufacturing facility in Mississippi. The 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 GE Aviation’s engineers.

Introduction

In this case study, we describe how simulation modeling was used to help GE Aviation 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 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

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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.

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

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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 is 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 used FlexSim’s messaging capability to control model operations and emulate system behavior.

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 the 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.

**Overview of Product and Production Facility**

As mentioned above, GE Aviation 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

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[1] FlexSim Software Products, Inc.
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.

![Diagram](image_url)

**Figure 5:** General product flow through functional areas.

**Simulation Modeling Approach**

GE Aviation’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 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 GE Aviation team analyze and evaluate alternative system designs. MSU developed a baseline model of the facility and trained the 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.

**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 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.

The model was run with different levels of variability. A common statistical measure of variability is the standard deviation, \( \sigma \). A low standard deviation indicates the observations tend to be close to the mean (\( \mu \)); 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 \( \mu \); this is referred to as the coefficient of variation, denoted as \( k \), where \( k = \sigma / \mu \). 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 \( \mu \) and a standard deviation that is a fraction of the mean, \( k \cdot \mu \), with \( k \) varying from 0 (deterministic or constant durations) to 0.25. That is, \( \text{Duration} \sim \text{Normal}(\mu, k \cdot \mu) \) 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 \( \pm 50\% \) 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 \( \mu \) 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 \( \mu \) and standard deviation \( k\mu \).

The weekly demand for each type of fan platform varies across any planning horizon. GE Aviation 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 1.4, 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.
Case 1 2 3 4 5 6

<table>
<thead>
<tr>
<th>Distribution</th>
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<th>Normal</th>
<th>Normal</th>
<th>Normal</th>
<th>Uniform</th>
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<table>
<thead>
<tr>
<th>Product Mix</th>
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<th>Days 2</th>
<th>Days 3</th>
<th>Days 4</th>
<th>Days 5</th>
<th>Days 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.39</td>
<td>1.38</td>
<td>1.44</td>
<td>1.45</td>
<td>1.54</td>
<td>1.54</td>
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<tr>
<td>7</td>
<td>2.77</td>
<td>2.78</td>
<td>2.84</td>
<td>3.07</td>
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<tr>
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<td>3.87</td>
<td>4.14</td>
<td>4.23</td>
<td>4.52</td>
<td>4.25</td>
</tr>
</tbody>
</table>

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

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.](image)

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 the 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.

<table>
<thead>
<tr>
<th>Object</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
<th>Case 5</th>
<th>Case 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>First Calibrating Workstation (units)</td>
<td>53,836</td>
<td>51,466</td>
<td>47,206</td>
<td>45,000</td>
<td>42,447</td>
<td>47,732</td>
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<td>Second Calibrating Workstation (units)</td>
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<td>2,394</td>
<td>6,654</td>
<td>8,860</td>
<td>11,413</td>
<td>6,128</td>
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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 facility, the remainder of the plant needs to be modeled and interfaced with the model discussed in this paper.

References

