Performance modeling of interacting human-machine distributed processes:

Building a Simulation Model to Characterize Interacting Workflows and to Explore New Workflow Alternatives

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Abstract

Sortie Generation Rate (SGR) is an important metric for air dominance. Lockheed Martin must demonstrate that the Air System can fly the sorties during an allotted time and deliver the capability to the war fighter. Aircraft turnaround time- the time between when the aircraft touches down, refuels, rearms, and completes inspections in order to release the aircraft, to aircraft wheels up - plays an important role in achieving the SGR requirement.

The turnaround process is highly complex and includes multiple interacting human in the loop workflows at multiple workstations at an airbase, and varies from base to base. This paper describes an empirical method of identifying and measuring the primary process tasks, flows and interactions that contribute to the turnaround time, and a modeling and simulation approach to evaluating proposed changes to the process. The goal of the described study was to improve process improvement decision making by using empirical data and modeling and simulation capabilities that consider the entire turnaround process as a system.

1. Introduction

For this paper, the selection and design of the suite of data collection tools developed to populate the models and the models themselves are described in Section 2. Section 3 describes how the tools were used to perform structured experiments to evaluate the impact of changes to the processes. Conclusions are presented in the final section.

A stochastic, agent-based model was developed to capture the dynamic and interacting processes that comprise the turnaround process. This model:

- Records, validates the characteristics of the current workflows
- Explores “what-ifs” and alternatives to the workflow
- Forecasts the impact of future builds and capabilities

The customer and Lockheed Martin Aero received the emerging results containing tasks driving the turnaround time between April and August 2014.

The study was undertaken to determine the major contributors to the turnaround time, and identify process changes that could be implemented to help meet the required SGR. At that time, there was no empirical method of identifying, measuring and mitigating the factors contributing to the turnaround time due to the complexity of the turnaround process that includes multiple interacting human in the loop workflows at multiple workstations.

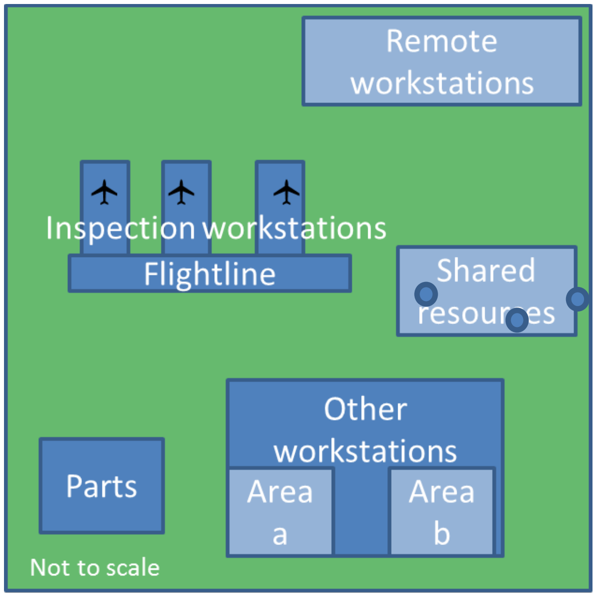

Figure 1 Overhead View of Example Distributed Work Area

The three main elements of the turnaround time process that were considered included the aircraft inspections on the flightline, the signoff that all of the inspections and refueling have been completed, and the review and disposition of any maintenance codes that were downloaded from the aircraft. This study did not address weapons reloading. As shown in Figure 1, these three processes may not be co-located and resources, such as fuel trucks, may be shared. Additional inspections may take place at workstations that are a significant distance away from the flightline. If these three elements are successfully completed, a "Ready for Flight" signoff releases the aircraft for the next mission.

A team consisting of collaborating engineers from multiple Lockheed Martin business areas and the customer was assembled to baseline the process model. Studying and observing the aircraft turnaround process revealed that a stochastic model capable of representing behavior and relationships in both time and space would be beneficial to representing this process. The AnyLogic ® modeling and simulation (M&S) environment fulfilled these requirements. Additionally, the team found the variety of views of the model and its outcomes could be easily generated in AnyLogic ® and were useful for presenting the model to all levels of developers, customers and senior leadership.

Data was collected and processed for the study using data collection tools developed by LM Advanced Technology Laboratories (ATL). The processed data was populated into an agent-based simulation model that represented the current operational turnaround process at two operational bases. Multiple structured experiments were performed to both validate the models and forecast how changes to the processes might affect the turnaround time.

Lockheed Martin funded the effort through a corporate IRAD led by Aeronautics and ATL. Both Aeronautics and Mission Systems and Training (MST) provided turnaround process expertise to support the technical team. ATL led the development and implementation of the data collection tools and the simulation models. The customer was an integral part of the entire process providing turnaround process expertise as well as input regarding the experiments to be performed. The IRAD was a successful collaboration between multiple Lockheed Martin business areas and the customer

2. Design the data collection and modeling and simulation tools

Figure 2 shows the steps used to develop the tools that were used to collect the data and build the aircraft turnaround simulation model. Each of the steps is described below.

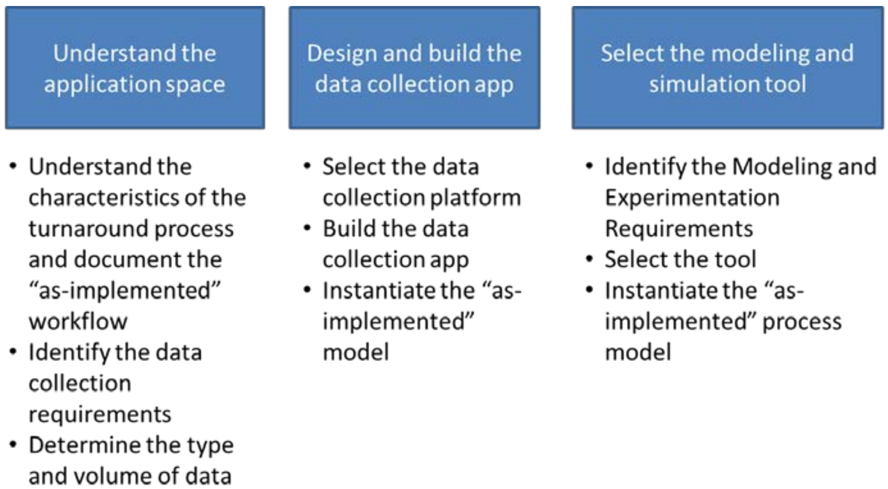

Figure 2 Development process for the turnaround study tool suite

Understand the Application space

Understand the characteristics of turn around process and document the "as-implemented" workflow

The first step in the methodology, as shown in Figure 2, was to understand the turnaround process as it was implemented at each location. Lockheed Martin Subject Matter Experts (SMEs) provided several ATL team members with a two-day immersion tutorial that covered various aspects of the turnaround process, as well as a review of the customer's "as-designed" turnaround process model. Once these processes were understood, a suite of tools was designed to enable recording, validation and understanding of the "as-designed" process. Each base has policies that result in distinctly different "as-implemented" processes. Differences were found in all aspects of tasks, task ordering and resource usage. Interviews with Lockheed Martin and customer SMEs and Lockheed Martin maintainers captured these differences, resulting in different "as-implemented" models for each base.

The data collection tools were modified several times over the course of the project, as the team became familiar with how people were using the tools as well as how the tools needed to store the data to more easily interface with the data cleansing and aggregation tools.

Identify the data collection requirements

The main requirements for the data collection tools were:

- The user had to be able to collect multiple start and stop times against multiple tasks simultaneously without losing track of which tasks were being timed. This turned out to be a difficult requirement to meet, as people would forget to stop the timer when a task ended, especially longer tasks, or situations when multiple tasks were active simultaneously.
- The tool had to be portable and allowed on the flightline as well as in classified-areas. No electronic collection means were allowed in the classified areas, so those data had to be collected and recorded using a stopwatch and a pen and paper (the "dual pen and paper approach").
- The tool had to be able to create a data set that could be ingested into the model. This requirement was also levied on the dual pen and paper collection approach that addressed the classified-area collection requirement.
- It had to be possible to collect ad-hoc information on observed tasks, such as an optional or new inspection that may not have been captured in the "as-designed" approach . For instance, waiting times for certain support equipment were added in the early workflows, as the "as-designed" process focused primarily on tasks and did not include time for some of the logistics of completing the tasks, such as moving support equipment, getting tools, etc.
- The prototype tool had to be ready in two weeks from the time the development was started, including purchasing the hardware and developing and installing the software.
- The data was collected by a variety of people, so no specialized training could be required. The training had to be able to take place in a hotel conference room in about two hours.

Determine the type and volume of data required

Figure 3 shows business process analysis aspects of the turnaround process that were examined to determine the type and volume of data required.   For each step in the workflow, actors, resources, dependencies and other process definition data were identified. The data collected in real time were the start and stop times of each task. There were approximately 35 tasks that were collected on for about 50 flights with between 1 and 4 observers for each workstation location. The actual volume of information collected was not substantial, but this was the first comprehensive data collection effort for these types of programs, and the first time such data would be available for turnaround experimentation.

In addition to the start and stop times, it was important to provide an audio recording capability to capture activities that were important observations during the process, or were outside of the -process as it was defined and entered as a workflow into the collection tool for a particular collection event. For example, observers might record the reason that a task was taking longer than expected, or record that they had accidentally pushed the wrong start button. Such information was valuable when trying to interpret the data, and especially when trying to adjudicate outliers.

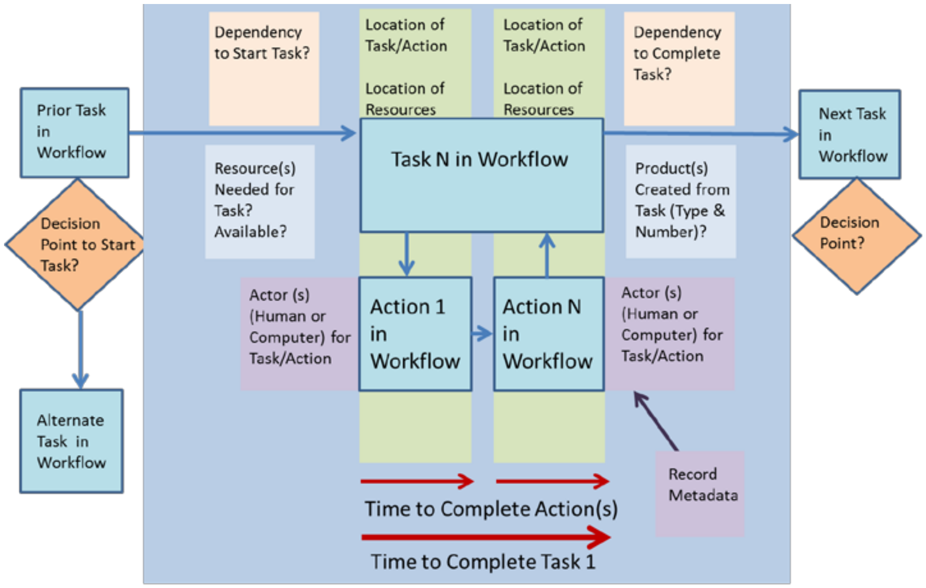

Figure 3 Business Process Analysis for Determining Data Needs

Design and build the data collection App

Select the data collection platform

The team leveraged and enhanced an existing ATL Android app for workflow authoring and data collection that would provide the input data for a simulation model, with a backup pen and paper template that contained the required fields for collecting data in classified areas where the Android was not allowed. Leveraging this existing capability enabled the team to meet the two-week development time for the app.

Build the data collection app

The enhancements made to the ATL workflow authoring tool enabled users to enter required identifying information for the data collection, such as their name, the tail number being collected on, their collection location, etc. Start and stop timers were added to the tool, as were the audio recording buttons. Over the course of the project, numerous updates were made for usability purposes, both in the data entry tool itself, as well as in the backend data storage and subsequent data cleansing, evaluation and reduction. Figure 4 shows a conceptual drawing of the application that was built.

Instantiate the “as-implemented” model

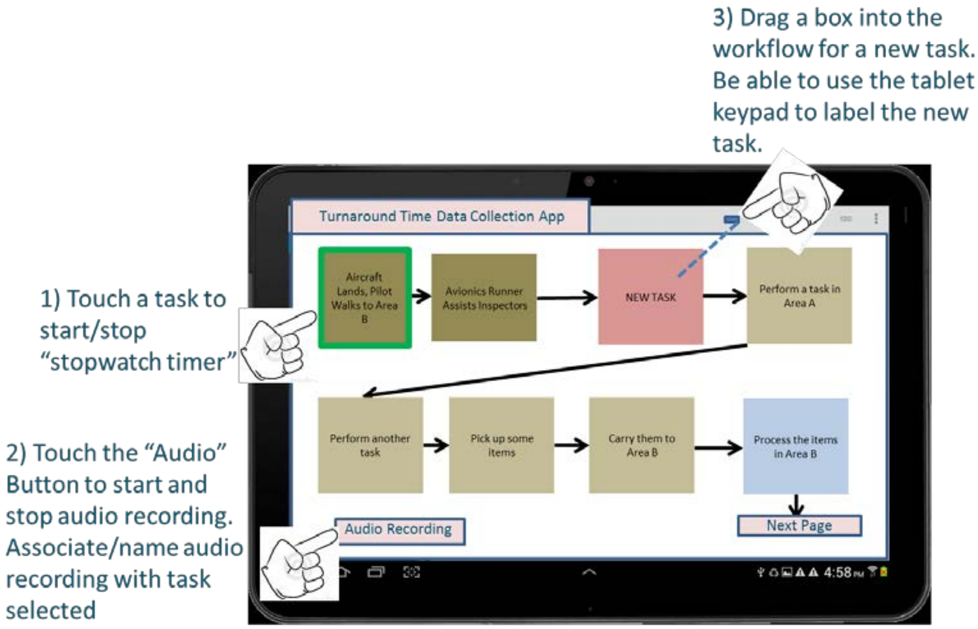

Figure 4 A Conceptual Drawing of the Data Collection App on and Android

Each location (both physical workstations at a single base, and different bases) had a different workflow, and different actors, resources and spatial layouts. In addition, the activities at the different workstations significantly varied and were largely independent. These factors allowed the larger process flow to be broken up by workstation, which was helpful in reducing errant and missed start and stop button-pushes. Each tablet had all of the sub- processes loaded on it, so any tablet could be used at any workstation. At any one time, only the process flow relevant to the particular workstation was showing. Multiple aircraft could be timed simultaneously at one workstation when necessary. Interconnection of the tasks on the user interface in the data collection app was provided to help orient the user, but did not impose any collection restrictions. Through the interface, the user could add tasks on the fly if new tasks were identified during a collection period. The user could also record comments against specific tasks. The data collection application was designed to be highly flexible and adaptable. New process models can be easily loaded when necessary, whether needed to support a different location or to update an existing process based on observations from a previous collection activity. The application can be used to collect data on virtually any manual, machine, or man/machine process that can be observed.

Select the modeling, simulation and experimentation platform

Identify the Modeling and Experimentation Requirements

With each data collection, the “as-executed” process emerged from the start/stop times of each task in relationship to each other. Over a period of time, it became clear that not only were the task durations non-deterministic, but the task ordering was also non-deterministic. Several modeling requirements emerged from the data collection activities:

- The model needed to be stochastic, due to the wide variance noted in the initial data collection for both task duration and ordering. The model needed to have the capability to quickly assemble and run Monte Carlo experiments for comparison purposes.
- Building and modifying the model needed to be easy and fast. That included adding and removing tasks, as well as modifying the flow.
- Data collection and processing tools needed to easily interface with the model, and new data would need to be quickly processed and loaded into the model to support "what-if" experimentation
- The model needed to have a presentation layer that could represent the data and processes at multiple levels of abstraction / detail to support both process "deep dives" with developers and the customer, and presentations to senior leadership.
- The results had to be substantiated / verified supporting decisions based on the empirical evidence produced by the model.
- The ability to examine impacts of alternative workstation layouts was highly desirable

Select the tool

These requirements set a high bar for the needed modeling and simulation environment, and the concomitant data collection and processing capability. Given these requirements the preferred solution would be to use an agent-based modeling and simulation (M&S) environment that included experimentation and presentation capabilities. The AnyLogic ® M&S environment met these conditions with the added benefit of recent team experience with the tool.

Once the required capabilities of the M&S environment had been identified, and AnyLogic ® selected as the M&S tool, the actors, resources, tasks, etc. that were identified during the business process modeling step (Figure 3) were implemented. For example, the model included individual aircraft, as well as individual maintainers and support personnel involved in turning the aircraft. The modeled tasks were those that were identifiable by data collectors who were not maintainers; had an observable duration (nominally more than 3 minutes); or were deemed to be important from previous analyses, regardless of how long they took. Figure 5 shows how the business process modeling informed the development of the simulation model.

Instantiate the "as-implemented" process model

The "as-implemented" process flow was developed in AnyLogic ® along with multiple visualizations. The AnyLogic ® process flow (Figure 5) and the geospatial views (Figure 1) were primarily used by the developers and for validation with the customer. The Monte Carlo view (Figure 7) was used primarily during experimentation, as it easily highlighted the impact of changes to the process flow. Baseline models of the "as-implemented" processes were built to elicit feedback on what changes the customers were interested in exploring. The models were refined over time to include features such as spreadsheet input and output for loading the distributions into the tasks and storing the results, respectively. The models ran in a deterministic mode for debugging purposes, as well as single and multi-run Monte Carlo modes. The Monte Carlo runs could be cross-referenced back to the spreadsheet output to see the delays of each of the tasks for every run.

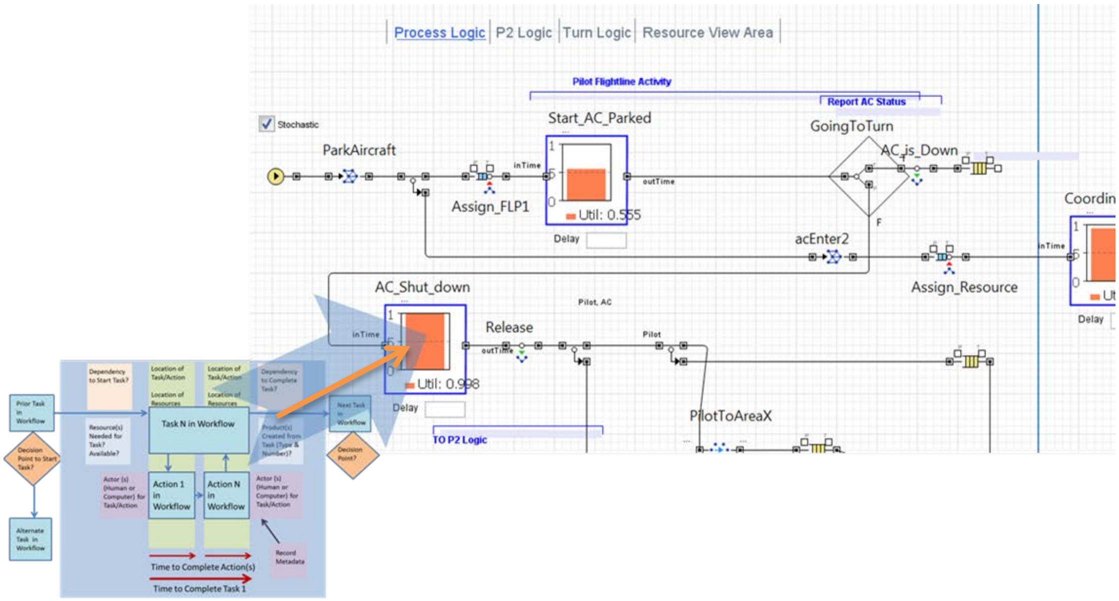

Figure 5 Business Process Model informs the construction of the Simulation Process Model

3. Running an Experiment

The purpose of the experiments, called excursions, was to quantify the impact of process changes whether through deletion of process steps, a proposed reduction in the amount of time needed to execute a process step, or redefinition of portions of the process to make them more efficient.

Figure 6 shows the process used in performing a series of excursions starting with an “as-implemented” process.

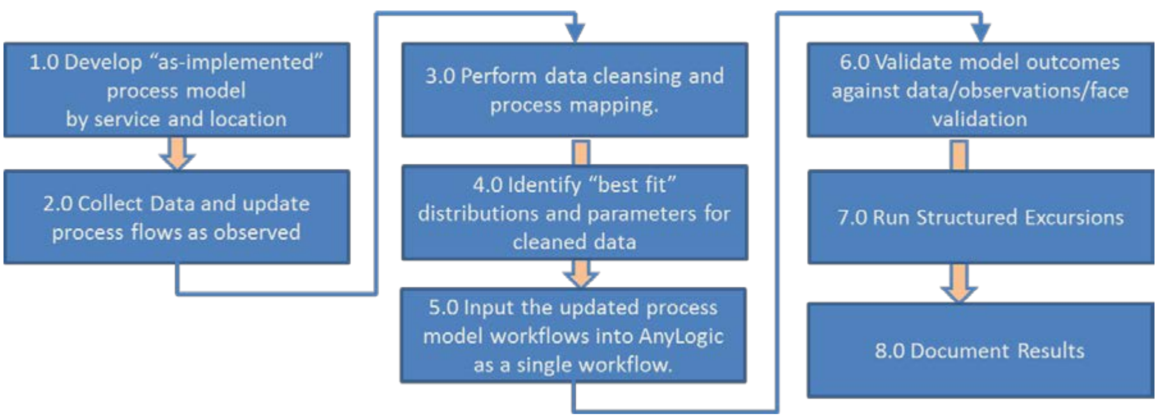

Figure 6 Process flow for performing excursions

The “as-designed” process was captured from the maintenance process instruction. SMEs assisted in creating the “as-implemented” process based on the interpretation of the process in the context of local policies for each location. The individual tasks for the “as-implemented” process flow and how they were connected were loaded into the tablet application before data collection began.

The data were collected at multiple workstations at two bases. The best data was attained by observers with in-depth knowledge of the process being captured. In areas where tablets were not permitted or in instances where a team member was not able to use the tablet application, a pen and paper template was available that had fields for the same data that was collected on the tablet.

Processing the data from the collection application into the modeling and simulation tool consisted of a complex data cleansing pipeline. The data was offloaded from the tablets and grouped by aircraft, workstation and location. Exploratory views using Gantt charts were developed from the processed data start and stop times to expose the process flows. Since most tasks were observed by multiple people, the Gantt charts were also used by the data analysts to adjudicate outliers, some of which were true outliers, and some of which were simply the result of someone not pressing the stop button. Pen and paper collections were translated into a comma separated value (csv) format and then translated again into the tablet data format and processed through the common pipeline. The activities required for this pipeline have been documented in a user guide and are supported by a small user interface.

The set of durations for each task were fit to one of approximately 10 distributions such as normal, triangular, exponential, Weibull, etc., that were available in the modeling and simulation tool. The type and parameters of the distributions for each task were then provided as a spreadsheet input file for the simulation model.

Input the process model workflows into AnyLogic ® as a single workflow per location

As noted, the Gantt charts were instrumental in extracting any changes to the process flow. Such changes were captured in the simulation model through modification of the paths through the model, updates to the probability of selecting one path over another, or changing a task parameter such that the task could occur anywhere from 0% to 100% of the time. All of the task timing and selection changes were effected through the modeling input file. Actual workflow path changes had to be implemented in the model itself. Reducing need for direct alterations to the model was important, as it made experimentation with the model more readily available to anybody with access to the runtime version of the model and the input spreadsheet, including the SMEs and the customer.

Review and baseline the model

Once the process flow had been updated in the simulation model and the distributions selected, the model was run for 1,000 Monte Carlo iterations. The goal for the initial model was to generate a baseline for the activities for each location, after which excursions could be run. The baseline models emerged as the models were iteratively run and the outcomes were compared to what was experienced on location. Additional data cleaning occurred during this step, as we found inconsistencies that were not caught in the initial cleaning. Figure 7 shows a histogram as an example outcome from a Monte Carlo runs.

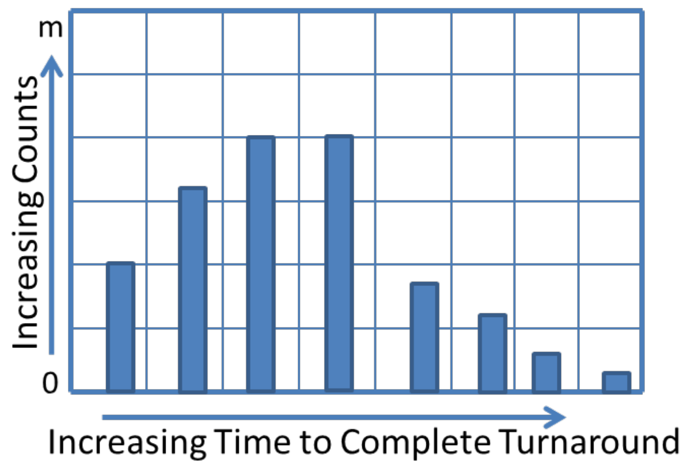

Figure 7 Example Monte Carlo Turnaround Duration Output

Structured Excursions

During the course of the study, the team held two model excursion summits with the customer. The customer provided the desired excursions prior to the summits and the most recently collected data and process established the baseline. In these collaborative forums, the team and the customer reviewed the list of excursions one at a time and implemented the changes to the simulation parameters which would empirically show the effect of the proposed changes in the baseline process. As with all complex process flows, there was no single solution, and fixing one critical path quickly revealed the next critical path. This analysis opened many doors to conversations that would have been difficult to motivate without these tools. The emerging results were presented during Lockheed Martin leadership meetings with the customer.

4. Conclusions

This study demonstrated how a holistic approach to modeling the entire turnaround process as a system of interacting parts provided helpful and sometimes surprising outcomes. By looking at the entire processing path instead of a single component of the process, the true drivers of turnaround time could be identified. Concrete suggestions with empirical evidence showed which modifications to the process would make the most difference, and the potential range of that difference. The data collection / modeling and simulation approach proved valuable because:

- It quantified the variability in the task durations and guided further investigation as to the causes.
- Interdependencies between tasks were revealed that were not obvious when looking at the individual parts of the process
- In-depth critical path analysis became possible. When a critical path was analyzed and changes to the process were proposed the next critical path emerged. This type of cause and effect analysis, using non-deterministic data would be difficult to perform without this type of simulation
- A new channel was opened for discussion and collaboration amongst all of the participants

Acknowledgements:

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