NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

MODELING THE AIM–9 SIDEWINDER REPAIR LINE THROUGH DISCRETE EVENT SIMULATION

by

Terence A. Caliguire

June 2009

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REPORT DOCUMENTATION PAGE			*Form Approved OMB No. 0704-0188*
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington DC 20503.			
1. AGENCY USE ONLY *(Leave blank)*	**2. REPORT DATE** June 2009	**3. REPORT TYPE AND DATES COVERED** Master's Thesis	
4. TITLE AND SUBTITLE Modeling the AIM–9 Sidewinder Repair Line through Discrete Event Simulation			**5. FUNDING NUMBERS**
6. AUTHOR(S) Terence A. Caliguire			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A			**10. SPONSORING/MONITORING AGENCY REPORT NUMBER**
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.			
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution unlimited			**12b. DISTRIBUTION CODE** A

13. ABSTRACT (maximum 200 words)

Tobyhanna Army Depot (TYAD) is required through Department of Defense (DoD) Lean initiatives and directives to reduce the cycle time of its repair and overhaul lines. The activities involved at DoD repair and overhaul depot facilities are a multi-billion dollar expenditure within the DoD budget. The DoD, in an attempt to reduce expenditures, has focused on Lean manufacturing as an operational strategy oriented toward achieving the shortest possible cycle time by eliminating waste across all depot systems and processes. We establish a discrete event simulation model to study the AIM–9 Sidewinder Missile repair process line, specifically the repair of the Guidance and Control Section (GCS) component of the missile. Currently TYAD does not employ a computer simulation model to support the leaning technique for its repair and overhaul processes. This thesis is the first attempt to model the Sidewinder Repair Line with a computer-aided discrete event simulation. TYAD will implement results from this analysis to help reduce cycle time and garner insights into current policies and procedures employed on the Sidewinder Repair Line. TYAD has identified potential for future use of this analysis by employing the technique of discrete event simulation to augment its DoD-mandated Leaning procedures.

14. SUBJECT TERMS Discrete Event Simulation, Sidewinder Repair Line Model			**15. NUMBER OF PAGES** 91
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	**18. SECURITY CLASSIFICATION OF THIS PAGE** Unclassified	**19. SECURITY CLASSIFICATION OF ABSTRACT** Unclassified	**20. LIMITATION OF ABSTRACT** UU

NSN 7540-01-280-5500 Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18

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MODELING THE AIM–9 SIDEWINDER MISSILE REPAIR LINE THROUGH DISCRETE EVENT SIMULATION

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Submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

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ABSTRACT

Tobyhanna Army Depot (TYAD) is required through Department of Defense (DoD) Lean initiatives and directives to reduce the cycle time of its repair and overhaul lines. The activities involved at DoD repair and overhaul depot facilities are a multi-billion dollar expenditure within the DoD budget. The DoD, in an attempt to reduce expenditures, has focused on Lean manufacturing as an operational strategy oriented toward achieving the shortest possible cycle time by eliminating waste across all depot systems and processes. We establish a discrete event simulation model to study the AIM–9 Sidewinder Missile repair process line, specifically the repair of the Guidance and Control Section (GCS) component of the missile. Currently TYAD does not employ a computer simulation model to support the leaning technique for its repair and overhaul processes. This thesis is the first attempt to model the Sidewinder Repair Line with a computer-aided discrete event simulation. TYAD will implement results from this analysis to help reduce cycle time and garner insights into current policies and procedures employed on the Sidewinder Repair Line. TYAD has identified potential for future use of this analysis by employing the technique of discrete event simulation to augment its DoD-mandated Leaning procedures.

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LIST OF ACRONYMS AND ABBREVIATIONS

AMC	Army Material Command
AMSAA	Army Material Systems Analysis Activity
C4ISR	Command, Control, Communication, Computers, Intel, and Surveillance
DES	Discrete Event Simulation
DoD	Department of Defense
GCS	Guidance and Control Section
NOLH	Nearly Orthogonal Latin Hypercube
NPS	Naval Postgraduate School
SRLM	Sidewinder Repair Line Model
TYAD	Tobyhanna Army Depot
VSA	Value Stream Analysis
WIP	Work in Process

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EXECUTIVE SUMMARY

Tobyhanna Army Depot (TYAD) is required through Department of Defense (DoD) Lean initiatives and directives to reduce the cycle time of its repair and overhaul lines. TYAD employs Lean manufacturing techniques on its Sidewinder Repair Line, but found that Lean techniques failed to diagnose the causes of prolonged cycle times in the repair line. TYAD required more insight into the stochastic nature of its repair line to make needed improvements.

We developed a discrete event simulation to assist their efforts in reducing cycle time and fill the necessary analysis gap. The base model captured the performance of the repair line under the current operating conditions at TYAD. Baseline analysis focused on mean cycle time, throughput, and resource utilization. Model verification and validation included sensitivity analysis of model inputs and model authentication by the experts at TYAD. We then conducted a series of excursions to identify which resources had the greatest impact on mean cycle time, determine the effect of increased Guidance and Control Section (GCS) arrivals, determine the optimal resource allocation plan, and measure the impact of reductions to the workforce.

The mean cycle time for the TYAD Sidewinder repair line under current operating conditions is 2.35 days. The repair line should repair 476 GCSs per year. The repair line operates far below maximum capacity. Workers at ten of the eleven stations have a less than 30 percent utilization rate. Workers in the Clean Room have the highest utilization rate at 54 percent. The process times at the Clean Room have the greatest impact on the mean cycle time and reductions in these times would lead to the greatest decrease in the mean cycle time. Doubling the GCS arrival rate puts the repair line at full operating capacity. Re-allocation of the current workforce to an optimal configuration will reduce mean cycle time by less than 1 percent. TYAD could reduce the workforce at the repair line by 27 percent and only experience a 1.9 percent increase in mean cycle time.

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ACKNOWLEDGMENTS

I would like to thank my thesis advisors LTC Rob Shearer and COL Kirk Benson for their tireless efforts, consistent mentorship, and unwavering dedication to the Army ORSA community.

I would like to thank the men and women of the Tobyhanna Army Depot who work tirelessly to support the Armed Services.

I would like to thank my fellow classmates for their professionalism and team first effort.

And to my wife Holly thanks for all the support and unconditional love. You are my inspiration.

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I. INTRODUCTION

A. OVERVIEW

Tobyhanna Army Depot (TYAD) is required through Department of Defense (DoD) Lean initiatives and directives to reduce the cycle time of its repair and overhaul lines. The activities involved at DoD repair and overhaul depot facilities are a multi-billion dollar expenditure within the DoD budget. The DoD, in an attempt to reduce expenditures, has focused on Lean manufacturing as an operational strategy oriented toward achieving the shortest possible cycle time by eliminating waste across all depot systems and processes. TYAD currently employs Lean manufacturing techniques in most of its processes and procedures that take place at the depot, particularly with its repair and overhaul line processes. However TYAD has discovered that Lean efforts fail to map current repair line policies to performance. TYAD requested support from Naval Postgraduate School (NPS) to understand the relationship between policy and performance.

We establish a discrete event simulation model to study the AIM–9 Sidewinder Missile repair process line, specifically, the repair of the Guidance and Control Section (GCS) component of the missile. The repair line is located at the TYAD in Tobyhanna, Pennsylvania. Currently, TYAD does not employ a computer simulation model to support the Leaning technique for its repair and overhaul processes. This thesis is the first attempt to model the Sidewinder Repair Line with a computer-aided discrete event simulation.

TYAD will implement results from this analysis to help reduce cycle time and garner insights into current policies and procedures employed on the Sidewinder Repair Line. TYAD has identified potential for future use of this analysis by employing the technique of discrete event simulation to augment its DoD-mandated Leaning procedures and help reduce cycle time throughout all applicable repair and overhaul lines.

B. BACKGROUND

1. Tobyhanna Army Depot

TYAD is the largest, full-service electronics maintenance facility in the DoD. TYAD's mission is total sustainment, including design, manufacture, repair and overhaul of hundreds of electronic systems (satellite terminals, radio and radar systems, telephones, electro-optics, night vision and anti-intrusion devices, airborne surveillance equipment, navigational instruments, electronic warfare and guidance and control systems for tactical missiles). TYAD is the DoD's recognized leader in the areas of automated test equipment, systems integration and downsizing of electronics systems. The Army has designated Tobyhanna as its Center of Industrial and Technical Excellence for Command, Control, Communications, Computers, Intelligence, Surveillance, Reconnaissance (C4ISR) and Electronics, Avionics and Missile Guidance and Control systems. The Air Force has designated TYAD as its Technical Source of Repair for command, control, communications and intelligence systems. TYAD currently employs over 5700 workers and is the largest employer in the Northeast Pocono region of Pennsylvania (U.S. Army, 2009).

2. Sidewinder Missile Repair Line

The Sidewinder Missile Repair Line is part of TYAD's Tactical Missile Facility. The repair line facility is a 21,000 square-foot facility, with a Clean Room for servicing and repairing sensitive electronic components. The facility employs over 41 multi-skilled and cross-trained electronics specialists. The United States (U.S.) Air Force, U.S. Navy and several Foreign Nations, who employ the Sidewinder Missile, all send their inoperable missiles to TYAD for repair. Age, excessive training use, environmental damage, weather, excessive exposure to harsh climates, and vibration damage are some of the reasons for depot-level repair.

3. AIM–9 Sidewinder Missile

The AIM–9 Sidewinder Missile is a heat seeking, short range, air-to-air missile employed by fighter aircraft of the U.S. Air Force and Navy, and select allies. The Sidewinder is a simple weapon, designed with the ability for rapid upgrade to the latest technology. There have been various versions of the Sidewinder, which began with its first successful test (AIM–9A) in 1953. The initial production version, designated AIM–9B, entered operational use in 1956. The AIM–9L model was the first Sidewinder with the ability to attack from all angles. The AIM–9M has the all-aspect capability of the AIM–9L model while providing all-around higher performance. The AIM–9M has improved defense against infrared countermeasures, enhanced background discrimination capability, and a reduced-smoke rocket motor. These modifications increase its ability to locate and lock on a target and decrease the missile's chances for detection. The AIM–9M–7 was a modification to the AIM–9M in response to threats expected in the Persian Gulf War zone. The latest Sidewinder missile, the AIM–9X, reached initial operational capability in late 2003 and was approved for full-rate production in May 2004. The AIM–9X provides full day and night employment, resistance to countermeasures, extremely high off-boresite acquisition and launch envelopes, greatly enhanced maneuverability and improved target acquisition ranges. Over 110,000 Sidewinder missiles have been built, with less than one percent fired in combat. The Sidewinder is the most widely used air-to-air missile currently in use in the world. The AIM–9 is one of the oldest and least expensive missiles in the U.S. weapons inventory (U.S. Navy, 2009).

4. Discrete Event Simulation

Discrete Event Simulation (DES) is a common approach used in industry to model repair line facilities. DES, by definition, is an operation, or technique, that studies events that change at separate and countable points in time, within some type of system. A system is an actual, or future, facility or process. Components of a DES include events, event lists, state variables, and parameters. An event is an instantaneous occurrence that may change the state of the system. State variables represent values in the system that change over time (e.g., repair times, inter-arrival times). Parameters are values that do not change throughout the simulation (e.g., number of stations and resources). The TYAD Sidewinder Repair line consists of all the necessary components involved in a DES, including repair stations, machines, workers, stochastic process times, discrete schedules, random arrivals, and departures. Most simulations, due to the size of the studied system, amount of data, number of state variables and parameters, need the assistance of a digital computer to execute (Law & Kelton, 2000).

5. Computer Aided Modeling and Simulation

It is very challenging for any organization to gain insights into the effects of altering a process, without the use of a computer-generated simulation model. If a process is very simple, then a computer simulation may not be needed, but if the process is complex and involves random (stochastic) processes, then a computer-generated simulation is a vital tool to assist in gaining valuable insights about the system. A computer-aided simulation affords the ability to implement changes to the system in the model (on the "screen") and observe the effects of these changes. Many organizations, without a DES to model their systems, physically implement changes on the "floor" of the process location. It may take days to months to discern if the physical changes are achieving the desired effects. This approach can be very expensive and time-consuming if multiple changes to the system are required before the desired objective is met. DES also helps organizations investigate the stochastic nature of the system. Multiple replications of the model yield different realizations, or plausible futures, that the system could experience. Statistical analysis of these futures yields insights into important metrics for the organization (e.g., mean cycle time, maximum queue lengths, and resource utilization).

6. Past Approaches at TYAD

Lean manufacturing is an operational strategy oriented toward achieving the shortest possible cycle time by eliminating waste in the system. Derived from the Toyota Production System, the key thrust to Lean is to increase the value-added work by eliminating waste and reducing incidental work. The Lean strategy often decreases the time between a customer order and shipment, and radically improves profitability, customer satisfaction, throughput time, and employee morale (Rockford Consulting, 2000).

The Process Improvement Division at TYAD applied a DoD-mandated Lean Manufacturing technique to the Sidewinder Line by conducting a Value Stream Analysis (VSA) in April 2007. TYAD's goal for the Sidewinder Repair line was to reduce cycle time by 15 percent by removing non-value added steps (Tobyhanna Army Depot, 2007). Engineers at TYAD began the VSA by charting the course of the missile through the Sidewinder Repair Line and identifying the repair stations and procedures in the line. This course becomes the current state map. TYAD investigated the time the missiles spent at these stations and looked for ways to reduce the overall cycle time for the missiles. TYAD determined these service times from historical data and estimates given by subject matter experts, such as line engineers and workers. TYAD used the VSA to identify "non-value" and "value" added cycle time within all the processes of the repair line. Value added time is associated with aspects of the process that contribute value to the missile (e.g., adding a screw to a board). Non-value time is associated with aspects of the system that do not contribute value to the missile (e.g., waiting in a queue for a resource). TYAD then constructed a future state map to investigate how the repair line would look after reducing any non-value time. The engineers at TYAD experienced several problems when trying to reduce cycle time with the VSA. First, they had limited historical data to help in understanding process times at the various repair stations. Second, the VSA provided no insights into the causes of prolonged cycle time. Third, the VSA provided no information into the utilization of workers in the system, yielding no insight into the capacity the line could manage. Lean manufacturing procedures does not require modeling the system with a DES and the engineers at TYAD did not do so (Hopp & Spearman, 2008). TYAD did implement a standardized process tool layout throughout the repair line, organized work areas to maximize efficiency and organized storage floor room layout to enhance accountability. These reductions in non-value time did reduce cycle time through efficient workstation layout and cleanliness, but TYAD still needed to map repair line policies to performance.

C. HOW WE ARE HELPING

We modeled the Sidewinder Missile repair line in a DES in order to investigate ways that TYAD could reduce cycle time. We took an extensive look at the processes and procedures conducted on the floor of the Sidewinder repair line; interviewed employees, shop supervisors, and process engineers; and walked the ground where the repairs take place. We built a model in Arena, a commercial simulation package that captured the key aspects of the Sidewinder Missile repair line. Our efforts identified a significant under-utilization of workers in the repair facility, which led to several excursions. The remaining chapters of this thesis will discuss the actual system, the model, data collection, output analysis, and excursions conducted.

II. TYAD SIDEWINDER REPAIR LINE

A. INTRODUCTION

The TYAD Sidewinder Missile Repair Line is a 21,000 square-foot facility with a Clean Room. The facility employs 41 multi-skilled and cross-trained electronics specialists. The United States (U.S.) Air Force, U.S. Navy and several Foreign Nations, who employ the Sidewinder missile, all send their inoperable missiles to TYAD for repair. Sidewinder users identify the needed repair through their internal checklists, maintenance procedures, and a 4044 field test machine. The 4044 field test machine identifies electrical faults within the missile. Age, excessive training use, environmental damage, weather, excessive exposure to harsh climates, and vibration damage all necessitate depot-level repair. Users prepare the Guidance and Control Section (GCS) of the missile for movement by removing the GCS from the warhead and propulsion system of the missile. The TYAD Sidewinder Repair Line is only equipped to repair the GCS section of the missile. TYAD receives the GCS with the paperwork identifying the initial results of faults and the findings from the 4044 field test machine. After the GCS arrives at the depot, workers remove the GCS from its packing configuration and store the GCS at a facility near the repair line. Although there are three different customers (U.S. Air Force, U.S. Navy, and Allies), all the repairs and procedures conducted are identical. Figure 1 displays a full picture of the Sidewinder missile, with the GCS section circled. Figure 2 highlights the GCS component of the Sidewinder missile, the component on the repair line. Figure 3 shows a U.S. Navy FA–18 employing a Sidewinder Missile.

Figure 1. AIM–9 Sidewinder Missile with Guidance and Control Section (GCS) circled [After (U.S. Air Force, 2007)].

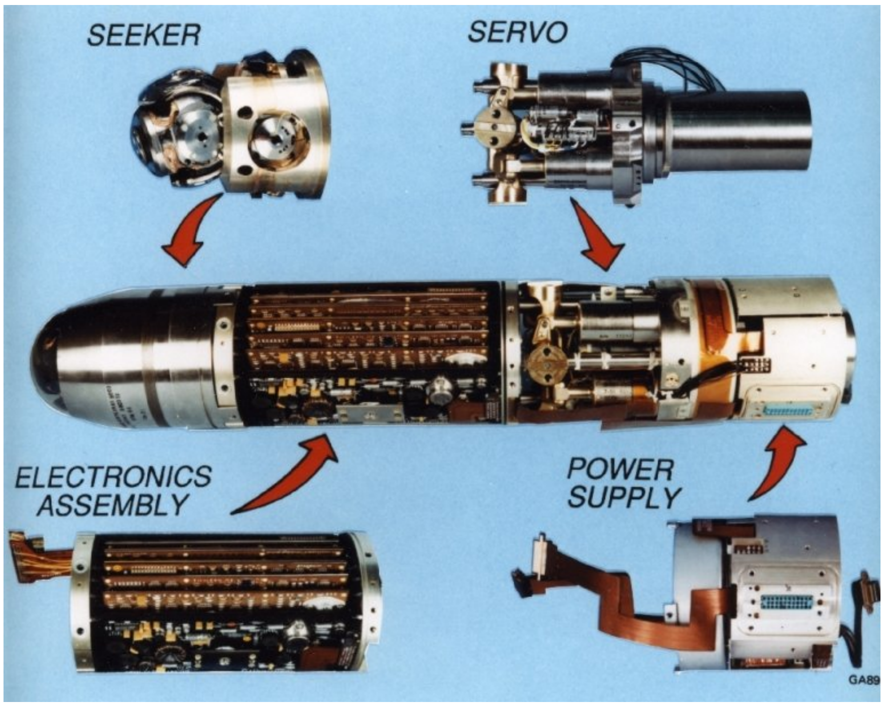

Figure 2. Components of the AIM–9 Sidewinder Missile Guidance and Control Section (GCS) [From (Kopp, 1994)].

Figure 3. U.S. Navy Jet employing a Sidewinder Missile [From (U.S. Navy Digital Imagery, 2005).

B. SIDEWINDER REPAIR LINE FLOOR LAYOUT AND REPAIR FLOW

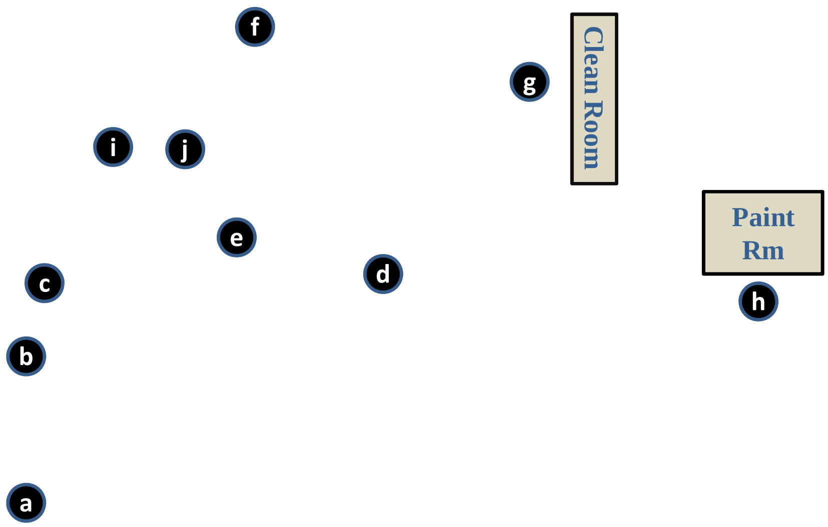

Figure 4. TYAD Sidewinder Repair Line Layout, with black circled letters designating key process stations [After (Tobyhanna Army Depot Industrial Modernization Division, 2008)].

Figure 4 shows the repair line facility. The black circles with white letters denote the locations of process stations. We will refer to processes in this paper by these letters. The GCS arrives to the depot in large can-type containers, where receiving workers remove the packing material at the Can/De-Can area of the floor *(a)*. The workers then place the GCS into the line repair process. There are three phases of testing and repair conducted on the Sidewinder Repair Line: Diagnostic Testing, Pre-Final Repair and Testing, and Final Testing.

Diagnostic Testing has the goal of capturing as much failure information as possible, without repairs or adjustments. Testing begins at Induction *(b)*, where one assigned worker visually conducts an exterior inspection of the GCS and prepares the GCS for movement along the repair line. The worker verifies all attached documentation and removes any unnecessary parts. Diagnostic Testing continues at two 4044 test machines *(c)*, where two assigned workers are available to attach the GCS to the diagnostic 4044 test apparatus. This is an attempt to duplicate and verify the 4044 field test conducted by the user prior to the GCS's arrival to the depot. This step confirms, or denies, the faults listed on the repair card filled out by the user in the field. Testing continues at the Diagnostic Leak and Flow station *(d)*, where two workers are available to test the GCS, to ensure there are no leaks of fluids and that the "plumbing" of the GCS is operating properly. Diagnostic Testing continues at the Diagnostic Boresite station *(e)*, where three workers are available to test the GCS for electronic failures and the focusing of the guidance system. This is where a Seeker failure can occur. The Seeker is an infrared system that uses mirrors and a rotating reticule to guide the missile during flight. The Seeker is the most sensitive part of the GCS and requires repair inside a clean room. Diagnostic Testing finishes at the Diagnostic Rate Table station *(f)*, where five assigned workers man five tables and install artificial fins on the GCS. They then simulate the flight of the missile to test stability during air movement. If the GCS Seeker failed, the workers remove the Seeker from the GCS and move it into the Clean Room *(g)*, where five assigned workers are available to repair the Seeker. The Sidewinder Clean Room is a specialized facility within the repair facility that contains very low levels of environmental pollutants. Workers re-install the Seeker to its parent GCS after repairs are complete. If the Induction worker determines that the GCS shell required painting and stenciling, the worker removes the shell and places it outside the shop floor for movement to the Paint Room *(h)*. This occurs after Diagnostic Testing is complete. The operations at the Paint Room include component etching, stenciling, and painting. Workers at the Paint Room, outside of the repair line floor, conduct the painting procedures.

Pre-Final Repair and Testing consists of additional testing, with specific adjustments and repairs made to the GCS. This is the major phase of repair for the GCS. Repair and Testing begins with the return of the GCS to the Leak and Flow *(d)*, Boresite *(e)*, and Rate Table *(f)* stations. Workers at these stations perform repairs identified as necessary in Diagnostic Testing. The GCS may return to these three stations multiple times, if needed, and moves to each based upon worker availability. The GCS will not proceed to these three stations unless it has its Seeker. The GCS will receive a pre-fabricated shell if the original shell requires painting and stenciling. This pre-fabricated shell will allow the GCS to continue through the three stations. Workers replace the pre-fabricated shell with the newly painted and stenciled original shell before moving the GCS to Final Testing. Pre-Final Repair and Testing finishes with all repairs complete and the GCS mated with its original shell and functional Seeker.

Final Testing consists of verifying that all required repairs and adjustments were made and that the GCS is functioning correctly. Testing begins with the GCS at the Pre-Final assembly *(i)* station, where one assigned worker checks all modifications to the GCS, visually inspects the GCS, and properly torques interior parts. Final Testing continues at the Vibration Test station *(j)*, where one assigned worker utilizes a vibration test machine to simulate flight vibration conditions for the missile. The machine confirms the stability of the interior parts and repairs. Testing continues as the GCS moves through the Final Leak and Flow *(d)*, Final Boresite *(e)*, and Final Rate Table *(f)* stations where available station *(d, e, f)* workers verify that the repairs conducted were proper and valid. Testing continues at the Final Assembly *(i)*, where one assigned worker returns the GCS to its final form, checks the exterior of the missile, and tightens all exterior parts. Testing continues with one final 4044 test *(c)* to ensure no faults remain.

Final Testing finishes at the Final Inspection station *(i)*, as one assigned worker ensures all paperwork is complete to standard and prepares the GCS for return to the Can/De-Can room *(a)*. This completes the Sidewinder Repair Line operation. Workers then pack and ship the GCS to the original user (Hazlett, 2008).

Figure 5 displays a rack of GCS shells. Figure 6 shows the Rate Table station and Figure 7 illustrates an electronic technician repairing a GCS.

Figure 5. This picture shows the Guidance and Control Section (GCS) Shell Rack [From (Tobyhanna Army Depot, 2007)].

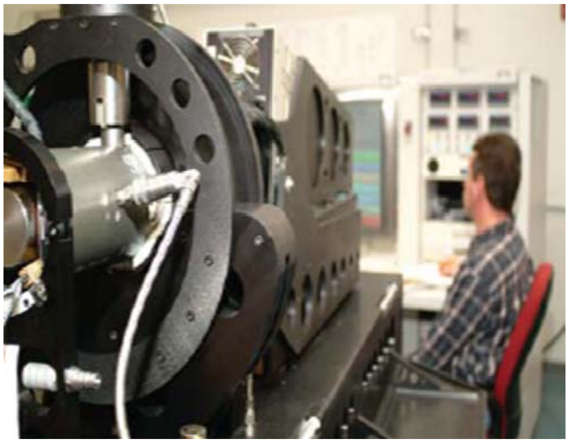

Figure 6. This picture shows a Rate Table Station on the Sidewinder Repair Line Floor [From (Tobyhanna Army Depot, 2007)].

Figure 7. This picture shows an Electronics Technician repairing a Guidance and Control Section (GCS) of the Sidewinder Missile [From (Tobyhanna Army Depot, 2007)].

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III. DEVELOPING THE MODEL

A. ARENA

Arena, developed by Rockwell Automation, is a modeling and simulation software package that enables users to accurately represent a current, or future, process system in a computer simulation model. Arena models many types of processing systems, including supply chain systems, manufacturing, logistics, distribution and warehouse operations, and service systems. The Arena software package allows flexibility in detailing a model to the complexity of the system in question. Microsoft operating systems fully integrate and support Arena (Rockwell Software, 2005).

Flowchart and Data modules are the building blocks for an Arena simulation. Flowchart modules are objects that represent processes in the simulation. Placing flowchart modules on the window screen allows the user to define the processes within the model that represent a current or future system. Data modules are objects that specify the characteristics of various processes.

We chose Arena for this research because of its ability to handle repair service systems. It can identify overall service times, queue build-up, resource utilization, Work in Process (WIP), and potential bottlenecks in the system. It also allows the varying of user chosen factors to see the effects on identified response variables through its OptQuest tool package. Arena's interface with Microsoft Excel provides the ability to read and write data files for statistical analysis.

B. SIDEWINDER REPAIR LINE MODEL (SRLM) MODULES

The SRLM is a series of inter-connected Arena modules that depicts the Sidewinder Repair Line system. These modules are the flowchart and data objects that represent GCS arrival information into the system, path of flow through the system, and exit from the system. Flowchart modules include: (1) Processing modules that model the stations where testing occurs and repairs take place; (2) Decision modules that model decisions as to which paths the GCS will take; (3) Delay modules that model the time delays that the GCS incur during testing and repairs; and (4) Splitting and (5) Batching modules that model the disassembling and reassembling of the GCS. Data modules include: (1) Entity modules that specify entity (GCS) characteristics; (2) Resource modules that model resource (worker) allocation and scheduled downtime; and (3) Queue modules that specify process queue logic. We developed multiple versions of the SRLM, each tailored to a particular analysis studied in this thesis. We present here the base model that represents the Sidewinder Repair Line in its current configuration. *Italicized names* represent the SRLM modules for the remainder of this section. Later in this chapter, we discuss the inputs for all modules, underlying distributions, data collection, and input data analysis.

The SRLM portrays the three phases of the system discussed in Chapter II.

1. Phase One—GCS Arrival and Diagnostic Testing

This is the starting point for the repair line process. A GCS is created as an entity at the *GCS Arrival* Create module and enters the SRLM. Entities are “physical objects” that possess attributes, seize resources, move around the model, can change status, and are affected by other entities. An entity for this model is a single GCS that requires some type of repair. This module is the starting point for the simulation and generates entities based on an inter-arrival time and a number of entities per arrival. Entities then leave the Create module to start processing through the model. The entity then moves to *Time Stamp*, an Assign module. Assign modules designate new values to entity attributes (a value tied to a specific entity) or user defined variables. The *Time Stamp* module assigns the current time to an attribute, capturing when the entity enters the SRLM (Figure 8).

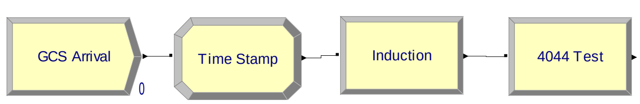

Figure 8. Flowchart Modules from Create module (*GCS Arrival*) through *4044 Test* Process module in Phase One (GCS Arrival and Diagnostic Testing).

The entity begins Diagnostic Testing at the *Induction* Process module. Process modules model action in Arena. These actions include repairs, tests, and reviews of the entity in the SRLM. Process modules specify the time that an entity spends in the module to complete the action. The module also specifies if the entity requires a resource (worker) to complete the action (Rockwell Software, 2005). A resource is a person, equipment, or space that conducts the actions defined in the Process module. We further discuss resources later in this chapter. The entity leaves the *Induction* module and enters the *4044 Test* Process module. The *Induction and 4044 Test* modules represent the first work stations in the Diagnostic Phase.

The entity exits the *4044 Test* module and enters, in succession, the *Diagnostic LF*, *Diagnostic Boresite*, and *Diagnostic Rate Table* Process modules (Figure 9). All GCS entities move through the three modules. This mimics the three diagnostic testing stations (Leak and Flow, Boresite, and Rate Table) that identify needed repairs.

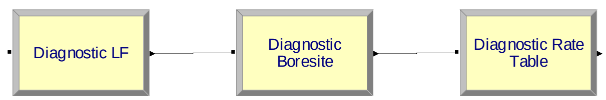

Figure 9. Flowchart Process modules *Diagnostic LF* through *Diagnostic Rate Table* in Phase One (GCS Arrival and Diagnostic Testing).

The last portion of Diagnostic Testing is the determination of (1) whether the entity requires a visit to the Clean Room and (2) whether the shell of the entity requires painting and stenciling (Figure 10). The entity leaves the *Diagnostic Rate Table* Process module and enters the *Clean Room* Decide module. Decide modules allow for decision-making in the model to determine how the entities will move through the system. Conditions dictate the path the entities move along (Rockwell Software, 2005). The entity moves to the *Seeker Repair* Process module if the Seeker requires repair. The *Seeker Repair* is another Process Module, in which the seeker is removed from the entity, repairs are conducted, and the seeker is re-installed inside the Clean Room. The entity, with its repaired Seeker, then moves to the *Painting* Decide module. The GCS entity moves directly to the *Painting* Decide module from the *Clean Room* Decide module if the Seeker requires no repair (Rockwell Software, 2005).

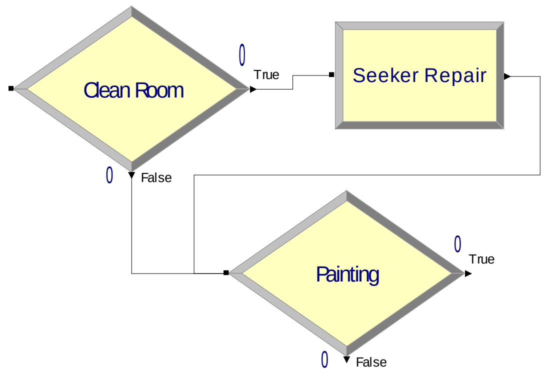

Figure 10. Flowchart Decide modules *Clean Room* and *Painting*, with the *Seeker Repair* Process module. End of Phase One (GCS Arrival and Diagnostic Testing).

2. Phase Two—Pre-Final Repair and Testing

This phase begins downstream from the *Painting* Decision module. If the entity shell was required to visit the *Paint Room*, only the entity shell moves to the *Paint Room*. The remainder of the entity continues on with the primary repair and testing procedures at the *Leak and Flow*, *Boresite*, and *Rate Table* Process modules (Figure 11). We separate the entity from its shell by using the *Separate GCS Shell* Separate module, where Arena makes a copy of the incoming entity. The original entity (representing the shell) moves to the *GCS Shell to Paint Room* Route module. Route modules transfer an entity along a path, with a user-defined delay time, to a Station module. The Route module also facilitates animating the SRLM. Animation is a user construct of the system that helps show movement of the entities through a model (See Appendix A for full animation of SRLM). The duplicate entity (representing the GCS) moves to the *Leak and Flow*, *Boresite*, and *Rate Table* Process modules and then continues downstream until it is matched up with its painted shell at the *Batch 1* Batch module. If the entity shell does not require painting, it moves to the *No Painting* Assign module, where the module assigns the entity shell an attribute value. This attribute will later identify the entity as having its original shell (and will not require batching further downstream). An entity that did not require painting would then flow to the Primary Repair and Testing Process modules (*Leak and Flow*, *Boresite*, and *Rate Table*).

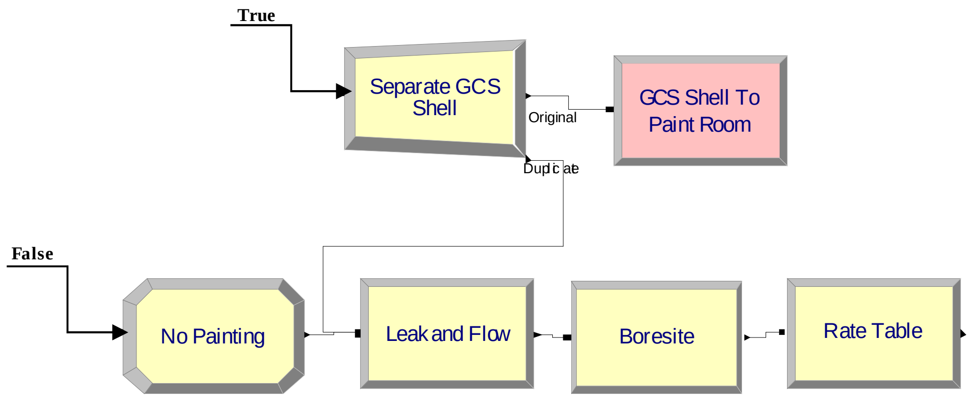

Figure 11. Flowchart modules *Separate GCS Shell* to *GCS Shell To Paint Room* and *No Painting* through *Rate Table*, in Phase Two (Pre-final Repair and Testing).

The original separated entity (shell) leaves the *GCS Shell To Paint Room* Route module and enters the *Arrive Paint Rm* Station module (Figure 12). Station modules refer to physical locations where processes occur and also facilitate animation (Rockwell Software, 2005). The entity leaves the *Arrive Paint Rm* module and moves to the *Paint Room* Process module, where resources begin the painting, stenciling, and etching work. Upon completion of work, the original entity enters the *To Shop Floor* Route module and travels a user-determined time back to the Sidewinder Repair Line Floor. Upon arrival at the *Arrive Shop Floor* Station module, the resources (workers) combine the original entity (shell) with the duplicate entity (GCS) at the *Batch 1* Batch module to form one complete entity. The matched entities may not arrive at the same time, as the process times for the painted entity shell and the duplicate entity may be different. Therefore, the entities (either the shell or the GCS) enter a queue and await their serial-numbered counterpart to complete the batching. Batch modules in Arena are grouping mechanisms based upon a user-defined attribute. We use the serial number attribute to mate the original and duplicate GCS entities. Arena automatically assigns a specific serial number to every entity created. The combined entities move to the *Painted* Assign module and receive another attribute to change the entity's color in the animation.

Entities that did not require painting (because they were not separated) and entities with pre-fabricated shells move from the *Rate Table* Process module to the *Need* *to Batch* Decide module. Further upstream, at the *No Painting* Assign module, Arena assigned an attribute value to the entities that did not require a visit to the *Paint Room*. This attribute value is now used as the condition test for the *Need to Batch* Decide module. If the entity does not have its original shell, it moves to the *Batch 1* Batch module and is married up with its shell and then moves to Final Testing. If the entity has its original shell, it moves directly into Final Testing (Rockwell Software, 2005).

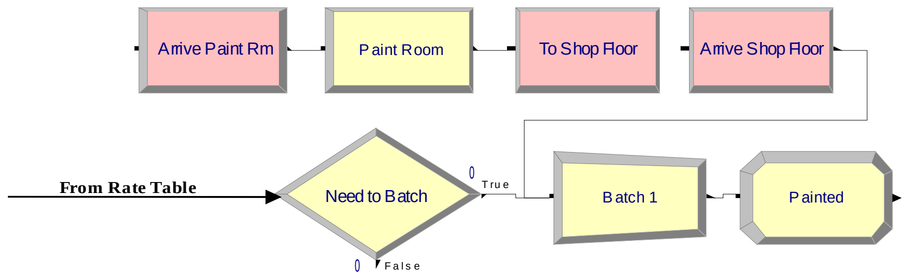

Figure 12. Flowchart modules for *Paint Room* Process module and *Need to Batch* Decide module. The GCS is in its original or newly painted shell and Phase two is complete.

3. Phase Three—Final Testing

The entity enters Final Testing in its original or newly painted shell with all major repairs complete. The entity moves to the *Pre Final Assembly* and *Vibration Test* Process modules (Figure 13), where resources (workers) at these modules prepare the entity for the final round of testing. The entity then enters the *Final Leak and Flow*, *Final Boresite*, and the *Final Rate Table* Process modules. These three modules are identical to the previous *Diagnostic Leak and Flow*, *Diagnostic Boresite*, and *Diagnostic Rate Table* Process modules that the entity entered during Diagnostic Testing. The entity exits the *Diagnostic Rate Table* module and moves to the *Final Assembly*, *Final 4044*, and *Final Inspection* Process modules and completes Final Testing. The entity, having completed the repair line, next moves to the *Time Record* Record and the *Mean Cycle Time* Assign modules. A Record module collects statistical information. We used the Record module here to capture the mean cycle time for all entities. The GCS entity exits the system at the *Exit Repair Line* Dispose module, which signals the end of the simulation (Rockwell Software, 2005).

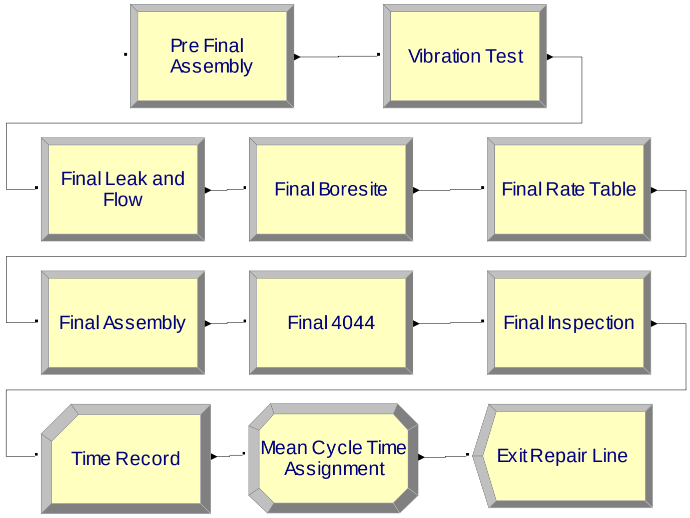

Figure 13. Flowchart modules from *Pre Final Assembly* through *Exit Repair Line*. This flows from the start to the end of Phase Three (Final Testing).

C. SIDEWINDER REPAIR LINE MODEL (SRLM) DATA MODULES

Data modules are spreadsheet-type interfaces embedded within the SLRM that allow the user to define the characteristics of various process elements. The Entity Data module assigns a picture of a Sidewinder Missile during entity creation. This picture allows the user to visually follow the entity through the SLRM.

The Resource Data module allocates resource capacity and schedules resource downtime. Resources are machines, or people, that perform tasks designated in the Process modules. An entity entering a Process module attempts to seize a resource (space, worker, or machine) that is needed to perform the task within the module. If a resource is not immediately available, the entity waits in a queue within the Process module and waits for a resource to become available. The SRLM Resource Matrix (Table 1) represents the current Sidewinder Repair Line resource capacities, the type of schedule the resources follow, and the schedule rule. Four sets of similar process modules (*Diagnostic Leak and Flow*, *Leak and Flow*, *Final Leak and Flow*; *Diagnostic*

Boresite, Boresite, Final Boresite; *Diagnostic Rate Table, Rate Table, Final Rate Table*; and *4044 Test, Final 4044*) compete for like resources (Table 2) with priority of resources based upon arrival time into the queue (first-in, first-out).

Resource	**Maximum Capacity**	**Schedule Name**	**Schedule Rule**
Induction Station	1	Induction Sch	Wait
4044 Machine	2	4044 Sch	Wait
Clean Room Station	5	Clean Room Sch	Wait
L and F Station	2	LF Schedule	Wait
Boresite Station	3	Boresite Sch	Wait
Rate Table Station	5	Rate Table Sch	Wait
Assembly Station	1	Assembly Sch	Wait
Vib Station	1	Vibration Sch	Wait
Final Assembly Station	1	Final Assembly Sch	Wait
Final Inspection Station	1	Final Insp Sch	Wait
Painter	1	Paint Room Sch	Wait

Table 1. Resource list, capacity, schedule name and rule for the base SRLM.

<table>
<tr><th>Process Module</th><th>Resource</th></tr>
<tr><td></td><td></td></tr>
<tr><td>Diagnostic Leak and Flow</td><td rowspan="3">L and F Station</td></tr>
<tr><td>Leak and Flow</td></tr>
<tr><td>Final Leak and Flow</td></tr>
<tr><td>Diagnostic Boresite</td><td rowspan="3">Boresite Station</td></tr>
<tr><td>Boresite</td></tr>
<tr><td>Final Boresite</td></tr>
<tr><td>Diagnostic Rate Table</td><td rowspan="3">Rate Table Station</td></tr>
<tr><td>Rate Table</td></tr>
<tr><td>Final Rate Table</td></tr>
<tr><td>4044 Test</td><td rowspan="2">4044 Machine</td></tr>
<tr><td>Final 4044</td></tr>
</table>

Table 2. Process modules that compete for like resources.

The SRLM Schedule Resource module allows the modeler to vary the resource capacity over time. The Sidewinder Repair Line operates two consecutive eight-hour shifts, five days a week. Each resource follows this schedule, with scheduled downtime for lunch (Figure 14 for the Clean Room schedule). Note that the scheduled downtime for lunch decreases the resource capacity. The SRLM uses the "Wait" schedule rule, which allows the resource to continue working on an entity (GCS) within a process until the task is complete, and then start the scheduled downtime. This mirrors the downtime policy at TYAD. All SRLM resources, except the 4044 Machines, have similar break schedules of one hour downtime per eight-hour shift.

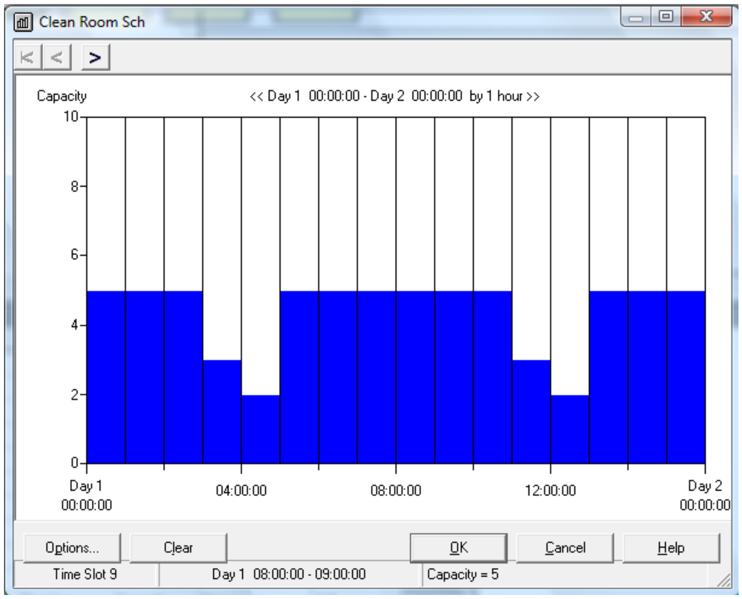

Figure 14. Clean Room resource capacity schedule for 16 hour work day (Arena screen shot).

The Queue Data module establishes the "First In, First Out" logic for queues. The Variable Data module designates and tracks information, through defined variables, necessary to conduct follow-on analysis.

D. DATA COLLECTION FOR INPUT INTO THE SLRM

The Process Improvement Division at TYAD applied a DoD-mandated Lean Manufacturing technique to the Sidewinder Line by conducting a Value Stream Analysis (VSA) in April 2007. TYAD's goal for the Sidewinder Repair line was to reduce cycle time by 15 percent by removing non-value added steps. We used the VSA as a basis and starting point for our data collection effort (Kippycash, 2008).

Students at the Naval Postgraduate School Operations Research Department are required to participate in an "experience tour" and, if feasible, conduct a site visit to assist in the development of their theses. We focused the TYAD site visit on the policies, operations, and procedures conducted at the Sidewinder Repair Line. Walking the repair line and speaking with many of the engineers, supervisors, and workers yielded valuable information in the development of this thesis. A visit to the Process Improvement Division afforded the opportunity to review the VSA it had conducted in April 2007. We quickly identified that there was very little data for the Sidewinder Repair Line. The repair line does, however, contain experienced engineers and supervisors with extensive knowledge of the operation of the line. We solicited their subject-matter expert opinion on the arrival and service times in the system.

We obtained the GCS arrival rate data from the engineers at TYAD. The engineers believe that one to twenty GCSs arrive every week, with ten arriving on average. We converted this weekly rate to a daily rate and, lacking any other information about the rate, decided to model the number of daily arrivals with a triangular(1,2,4) distribution. This distribution reflects our belief that at least one GCS will arrive per day, two will arrive most frequently, and no more than four will arrive per day (Law & Kelton, 2000).

We used the VSA determined upper and lower time estimates for following process stations: Induction, 4044 Test, Diagnostic Leak and Flow, Diagnostic Boresite, Diagnostic Rate Table, Pre-Final Assembly, Vibration Test, Final Leak and Flow, Final Boresite, Final Rate Table, Final Assembly, Final 4044, and Final Inspection. We modeled these process times with uniform distributions. We selected the uniform distribution for two reasons: (1) we knew the minimum and maximum values that the process times could take and (2) we knew nothing about the shape of the underlying distribution (Law & Kelton, 2000).

The VSA determined neither the Seeker Repair process times (Clean Room) nor the Painting/Stenciling (Paint Room) process times. Again, we turned to the experts at TYAD for assistance. We interviewed the Clean Room supervisors and process engineers, soliciting their best estimates for the minimum, most likely (mode), and maximum process times in the Clean Room. They advised us that one day was the minimum, two days was most likely, and five days was the maximum. We then modeled the Clean Room process times, in hours, with a triangular(16,32,80) distribution. TYAD also provided the billing times for the procedures that take place on the GCS Shell at the Industrial Facility. TYAD reported to us that the procedures of refinishing, etching, and painting a GCS Shell take 132 minutes with a "give or take" factor of ten minutes. We modeled these times with a uniform(122,142) distribution.

Next we estimated what percentage of the GCSs will need to go to the Clean Room and what percentage will require painting and stenciling. Lacking historical data, we turned to the engineers at TYAD, who told us that 40 percent of GCSs go to the Clean Room and that 90 percent of GCS shells require painting and stenciling. We cannot overemphasize the reliance on subject matter experts, engineers and repair line supervisors for data input into the SRLM. They provided the parameter estimates for the uniform and triangular distributions when no data existed. We did recognize the dangers inherent in relying exclusively on expert opinion and decided to later conduct sensitivity analysis on the parameter estimates to determine the robustness of the system.

TYAD did have, and provided, historical data for the Leak and Flow, Boresite, and Rate Table process times from Pre-Final Repair and Testing (Esopi, 2009). TYAD utilizes a computer-based data system to track the repair times during the above three processes. TYAD provided two data sets, each with times from the three processes, from 2008 with 88 and 75 serial numbered GCSs repair times, respectively. During Pre-final Repair and Testing, the GCS returns to each station, as required, repairing all deficiencies. Accordingly, we combined the two data sets into one set, summing the process times that each GCS experienced at each station, and then determined the best distribution with which to model these times in the simulation. Due to the possibility of multiple trips to each station, the data showed considerable variability in process times (Table 3).

Process	Mean (minutes)	Standard Deviation	95% Lower Confidence Level	95% Upper Confidence Level	Data Reference
Leak Flow	165.02	109.37	148.05	181.99	L&F Database
Boresite	45.74	25.99	41.31	49.87	Boresite Database
Rate Table	272.34	187.92	240.47	304.21	Rate Table Database

Table 3. Summary Statistics for Leak Flow, Boresite, and Rate Table data sets

We created histograms from the process times of the three stations to better understand the probabilistic nature of the underlying distribution (Figures 15, 16, and 17 are screen shots from S-plus).

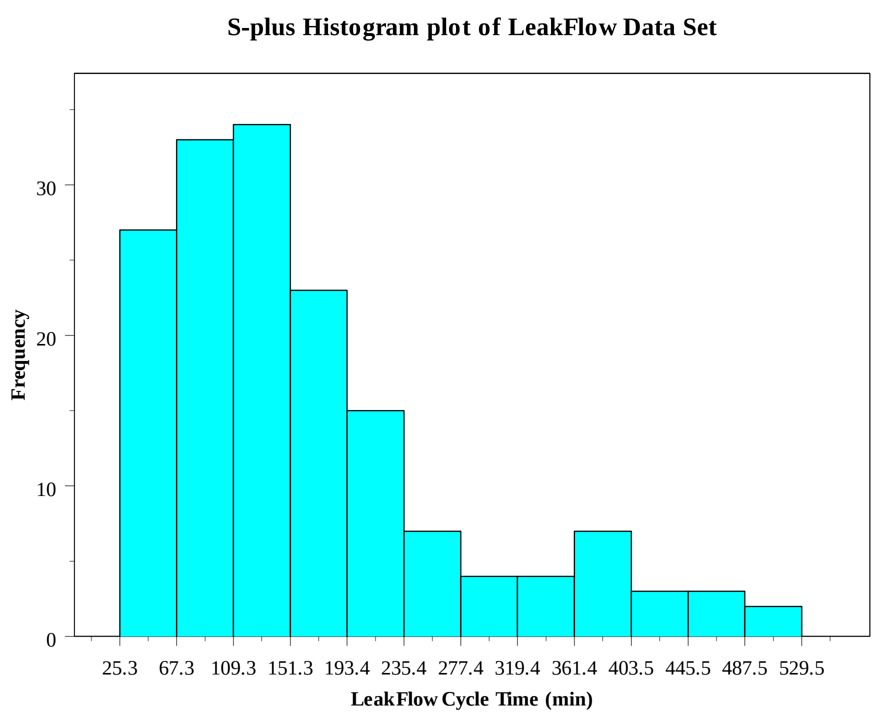

Figure 15. Histogram for Leak and Flow Cycle Time Data Set.

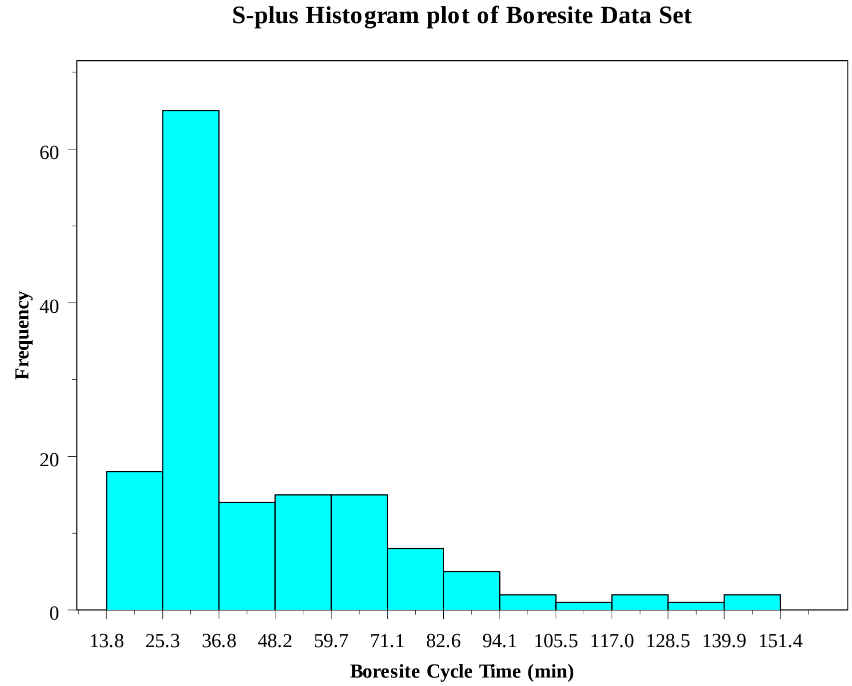

Figure 16. Histogram for Boresite Cycle Time Data set.

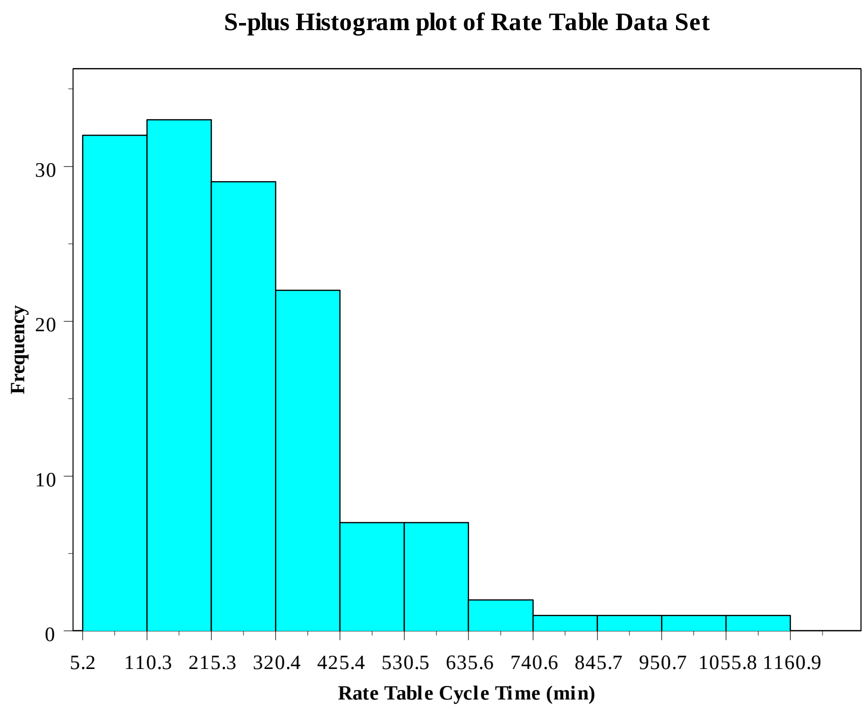

Figure 17. Histogram for Rate Table Cycle Time Data Set.

We hypothesized whether specific continuous distributions could plausibly account for the service times from the Leak Flow, Boresite, and Rate Table processes. We used the Input Analyzer from the Arena Simulation Tool Kit to conduct the input probability distribution selection (Rockwell Software, 2005). The Input Analyzer is a tool that helps determine the quality of fit of probability distribution functions to input data. It fits all the distributions that are part of the Input Analyzer to the input data, estimates the required parameters for each, and ranks them according to the values of their respective square errors. The Input Analyzer also conducts a goodness-of-fit test for each distribution. A goodness-of-fit test assesses how plausible it is to assume that the observed data came from a specified distribution, specifically testing the following null hypothesis (Law & Kelton, 2000).

$$H_0 : x_i \text{ are iid } f(x \mid \theta)$$

The Input Analyzer conducts a Chi-square (χ^2) goodness-of-fit test. The χ^2 goodness-of-fit test compares the differences between the observed values and the expected values of the hypothesized distribution. The Input Analyzer computes the value of the χ^2 test statistic and the corresponding p-value. The p-value is key in deciding whether to reject, or accept, the null hypothesis and describes the plausibility of the null hypothesis, that is, how likely is it that the specified distribution generated the observed data. A level of significance (α) is selected before conducting the test and is used as a cut point for decisions on the null in the following manner (Devore, 2008).

$$p - value \le \alpha \rightarrow reject\ H_0\ at\ level\ \alpha$$

$$p\text{-}value > \alpha \rightarrow do\ not\ reject\ H_0\ at\ level\ \alpha$$

We set the α level for the χ^2 goodness-of-fit test at 0.10, to reject only hypothesized distributions that were highly implausible candidates for the underlying, unknown distribution. Input Analyzer provided the best fit plot (Figure 18), a recommended distribution, and results from the χ^2 goodness-of-fit test (Table 4) for the Leak and Flow process time data set.

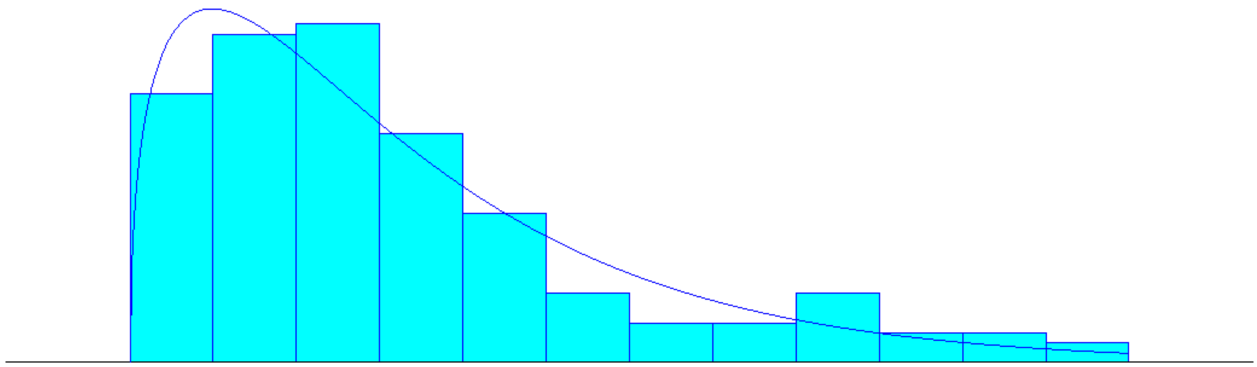

Figure 18. This graph shows a screen shot of Arena's Input Analyzer Histogram of the Leak and Flow Data Set. The Y-axis is frequency and the X-axis is Leak and Flow Cycle Time. The superimposed blue line is the best fit plot of the Gamma distribution listed in Table 4 below.

Distribution:	Gamma
Expression:	25 + GAMM(98.8, 1.42)
Square Error:	0.004
Chi Square Test	
Number of intervals	7
Degrees of freedom	4
Test Statistic	5.22
Corresponding p-value	0.27

Table 4. Gamma distribution expression for Leak and Flow data set.

The hypothesized gamma distribution had a p-value of 0.27, much greater than our significance level of 0.10. We considered this a plausible distribution for the Leak and Flow process time in the SRLM. Input Analyzer provided the best fit plot (Figure 19), a recommended distribution, and results from the χ^2 goodness-of-fit test (Table 5) for the Boresite process time data set.

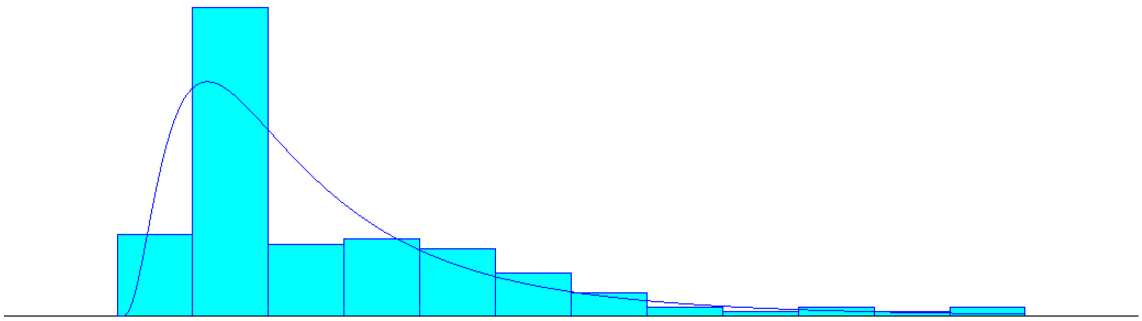

Figure 19. This graph shows a screen shot of Arena's Input Analyzer Histogram of the Boresite Data Set. The Y-axis is frequency and the X-axis is Leak and Flow Cycle Time. The superimposed blue line is the best fit plot of the Lognormal distribution listed in Table 5 below.

Distribution:	Lognormal
Expression:	13 + LOGN(32.9, 29.3)
Square Error:	0.030
Chi Square Test	
Number of intervals	6
Degrees of freedom	3
Test Statistic	20.9
Corresponding p-value	< 0.005

Table 5. Lognormal distribution expression for Boresite data set.

The lognormal distribution had a p-value less than 0.005, much less than our significance level of 0.10. We did not consider this a plausible distribution for the Boresite process time in the SRLM. Given the lack of a plausible known distribution, but the presence of a large historical data set, we decided to model the underlying distribution with a continuous empirical distribution. The drawback of this approach is that the SRLM Boresite process time will never exceed the largest observed data value and never fall below the smallest observed value. This will limit the ability of the simulation to choose extreme values for Boresite process times (Law & Kelton, 2000). Input Analyzer provided the empirical distribution function and summary statistics from the data set (Table 6).

Distribution	Empirical
Expression	CONT (0.000, 13.000,0.115, 24.583,0.547, 36.167,0.649, 47.750,0.757, 59.333,0.851, 70.917,0.912, 82.500,0.946, 94.083,0.959, 105.667,0.966, 117.250,0.980, 128.833,0.986, 140.417, 1.0, 152.000)
Number of Data Points	148
Min Data Value	13.8
Max Data Value	151
Sample Mean	45.6
Sample Std Dev	26.4

Table 6. Empirical distribution expression for Boresite data set.

Input Analyzer provided the best fit plot (Figure 20), a recommended distribution, and results from the χ^2 goodness-of-fit test (Table 7) for the Rate Table process time data set.

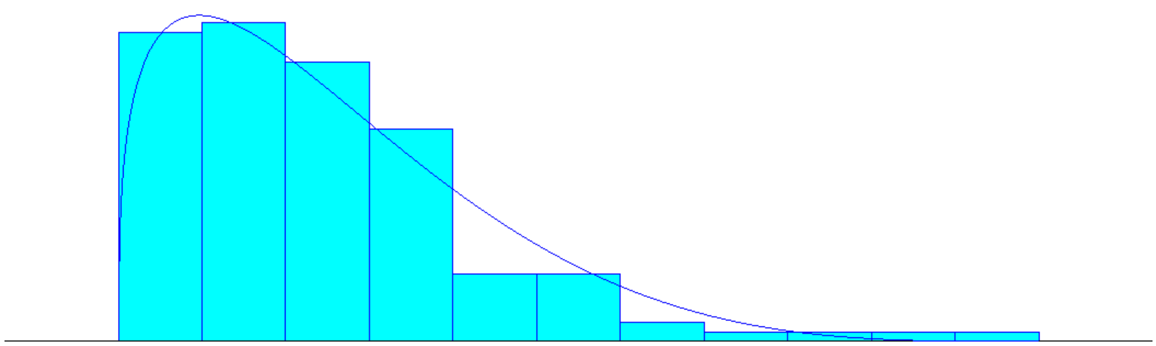

Figure 20. This graph shows a screen shot of Arena's Input Analyzer Histogram of the Rate Table Data Set. The Y-axis is frequency and the X-axis is Rate Table Cycle Time. The superimposed blue line is the best fit plot of the Beta distribution listed in Table 7 below.

Distribution:	Beta
Expression:	5 + 1.16e+003 * BETA(1.32, 4.4)
Square Error:	0.003499
Chi Square Test	
Number of intervals	6
Degrees of freedom	3
Test Statistic	4.46
Corresponding p-value	0.225

Table 7. Beta distribution expression for Rate Table data set.

The hypothesized beta distribution had a p-value of 0.225, much greater than our significance level of 0.10. We considered this a plausible distribution for the Rate Table process time in the SRLM.

We summarize the processes and their distributions in the table below (Table 8).

Process	Arena Module	Distribution	Expression	Notes
GCS Arrival	GCS Arrival	Triangular	TRI(1,2,4)	Arrivals per day (5 day week)
Induction	Induction	Uniform	U[70,80]	Minutes
4044 Test	4044 Test	Uniform	U[20,30]	Minutes
Diagnostic Leak Flow	Diagnostic LF	Uniform	U[40,50]	Minutes
Diagnostic Boresite	Diagnostic Boresite	Uniform	U[40,50]	Minutes
Diagnostic Rate Table	Diagnostic Rate Table	Uniform	U[80,100]	Minutes
Clean Room Decision	Clean Room	T/F	40% True	True = Seeker Requires Repair
In Clean Rm Seeker Repair	Seeker Repair	Triangular	TRI(16,32,80)	Hours (16 hour Work Day)
GCS Painting Decision	Painting	T/F	90% True	True = GCS Shell Requires Painting
Painting of GCS Shell	Paint Room	Uniform	U[122,142]	Minutes
Leak Flow Repair and Testing	Leak and Flow	Gamma	25 + GAMM(98.8, 1.42)	Minutes
Boresite Repair and Testing	Boresite	Empirical	CONT(0.000, 13.000,0.115, 24.583,0.547, 36.167,0.649, 47.750,0.757, 59.333,0.851, 70.917,0.912, 82.500,0.946, 94.083,0.959, 105.667,0.966, 117.250,0.980, 128.833,0.986, 140.417, 1.0, 152.000)	Minutes
Rate Table Repair and Testing	Rate Table	Beta	5 + 1.16e+003 * BETA(1.32, 4.4)	Minutes
Pre-Final Assembly	PreFinal Assembly	Uniform	U[20,30]	Minutes
Vibration Test	Vibration Test	Uniform	U[40,50]	Minutes
Final Leak Flow	Final Leak and Flow	Uniform	U[40,50]	Minutes
Final Boresite	Final Boresite	Uniform	U[40,50]	Minutes
Final Rate Table	Final Rate Table	Uniform	U[80,100]	Minutes
Final Assembly	Final Assembly	Uniform	U[20,30]	Minutes
Final 4044	Final 4044	Uniform	U[20,30]	Minutes
Final Inspection	Final Inspection	Uniform	U[15,25]	Minutes

Table 8. ARENA Distribution summary for all flowchart modules in SRLM.

E. SLRM ASSUMPTIONS

- All GCS entity movements between modules are instantaneous, expect for the movement of a GCS shell to the Paint Room.
- All repair equipment and parts are readily available to the workers.
- 260 working days represent one full calendar year.
- None of the machines fail or require downtime due to maintenance.

F. COMPLETE SRLM FLOWCHART

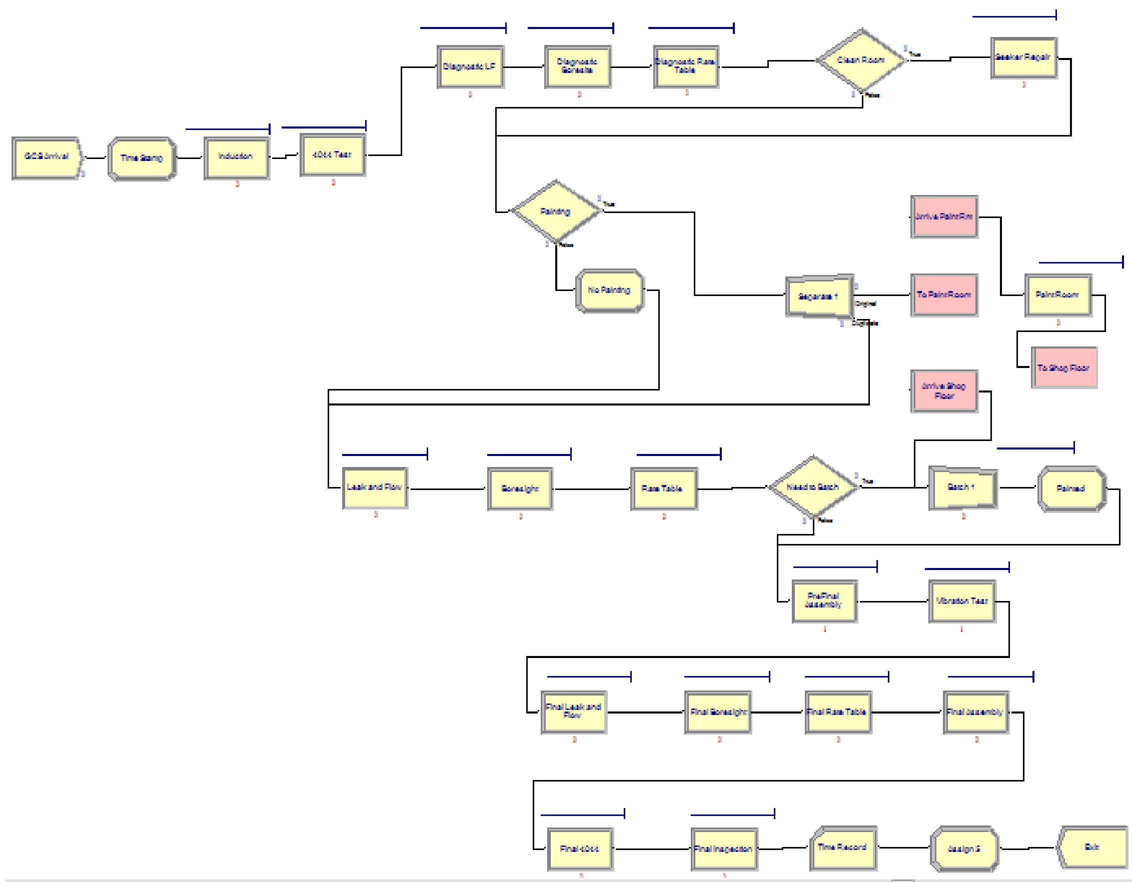

Figure 21. Arena screen shot of complete SRLM flowchart.

IV. ANALYSIS, VALIDATION, AND RESULTS

A. APPROACH

We utilized the base model discussed in Chapter III to investigate how the processes at the repair line interact and to establish baseline metrics. These baseline metrics included: GCS mean cycle time, resource utilization rates, GCS throughput, Work in Process (WIP), queue lengths, and queue times. Mean cycle time is the average time that a GCS spends in the system, starting with the creation of the entity and ending with the disposal of the entity. Resource utilization is the percentage of time that a resource (worker or machine) is busy and not idle. Throughput is the number of entities that exit the system. WIP is the number of entities currently in the system. Queue length is the number of entities waiting for a resource at a process. Queue time is the time that an entity spent waiting for a resource at a queue.

Standard validation for a DES model compares model output with historical data. TYAD did not have sufficient data to conduct such a validation. We conducted multiple face validations by providing the base model and results to the repair line's engineers and supervisors. They agreed the model closely represented the repair line.

We also conducted a sensitivity analysis to determine how sensitive the baseline metrics were to the subject matter expert based process time distributions. This sensitivity analysis included identification of which distribution parameters were most significant.

We developed and executed an experimental design to determine the optimal resource allocation plan and identify which resources had the greatest impact on minimizing mean cycle time.

Our analysis of the base model identified that the system operates far below maximum capacity. This insight led us to investigate what impact reductions in the workforce would have on mean cycle time and the other metrics. It also led us to investigate what arrival rate would drive the system to utilize all of its capacity.

B. BASE ANALYSIS

We used the base SRLM to establish the baseline analysis of the repair line under normal operating conditions. We ran the simulation for 100 years to investigate the steady state behavior of the system and executed 100 replications to better understand the stochastic nature of the system. The system rapidly achieves stationarity for mean cycle time, so we investigated the need to incorporate a warm-up period in the replications. Mean cycle time appears to achieve stationarity (the graph "flattens out") somewhere after one month into a run (Law & Kelton, 2000). We choose three different warm-up periods (0 days, 25 days, and 50 days), ran the simulation, and determined that there was no statistical difference between the mean cycle times. The length of the simulation (26,000 days) sufficiently outweighs the need for a warm-up period. We then ran the simulation, without a warm-up period, and obtained the baseline metrics (Table 9).

	Cycle Time (days)	Cycle Time (hours)	Throughput (# of GCS per year)	Work in Process (# of GCS)
Mean	2.353	37.653	476.71	4.315
Standard Deviation	0.008	0.132	1.09	0.018
95% Confidence Level	0.002	0.026	0.21	0.004
95% Lower Confidence	2.352	37.627	476.49	4.311
95% Upper Confidence	2.355	37.679	476.92	4.318

$$WIP = (Throughput\ per\ day) * (Cycle\ Time)$$

Table 9. Base statistics (mean cycle time, throughput per year, and WIP) of "normal operating" Sidewinder Repair Line

The mean cycle time for the system is roughly 2.4 days for a GCS to complete the repair line. The mean annual number of GCSs repaired is 476.7. The mean number of GCSs in the system (inventory of GCSs from the start to the end of the repair process) is 4.3 (Hopp & Spearman, 2008). We also calculated 95 percent confidence intervals for these metrics. All three confidence intervals are short in length, suggesting that we have accurately identified the mean values for the metrics.

Resources are the people or machines that perform the identified task at each process station. We calculated the utilization rates of the resources at each process for the base model (Figure 22).

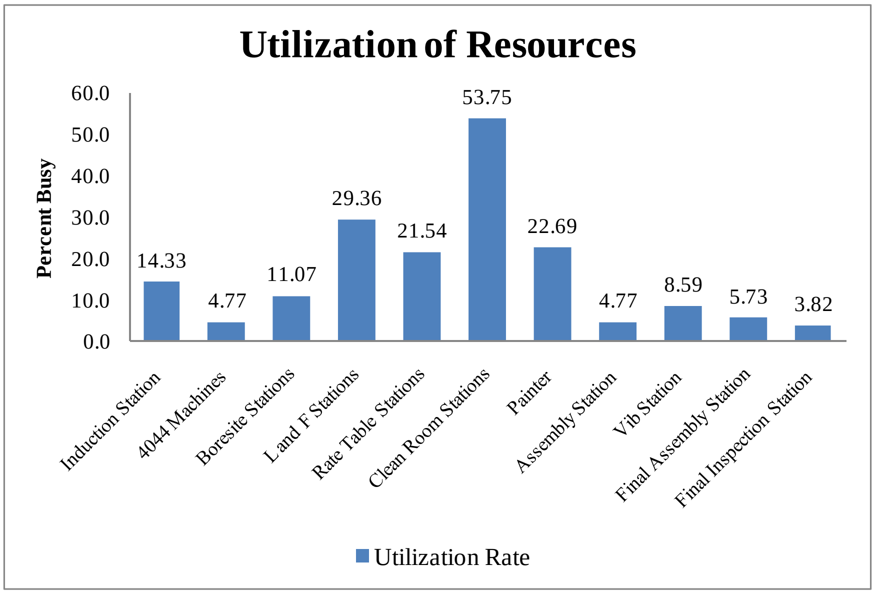

Figure 22. Utilization rates of “normal operating” Sidewinder Repair Line resources.

The Clean Room resources had the highest utilization rate at 54 percent and the Final Inspection resource had the lowest rate at 4 percent. Ten out of eleven resource sets had a utilization rate of less than 30 percent, and five of the resource sets (4044 machines, Assembly station, Vib station, Final Assembly station, and Final Inspection station) had utilization rates below 10 percent. These low utilization rates imply that the resources are under-utilized. These rates provide insight into where the repair line managers could re-allocate workers to reduce cycle time. They also suggest potential areas for cross-training workers on different tasks.

We also calculated the maximum queue length and queue times for each process in the system. A queue is a location where something, or someone, waits until it can move (Hopp & Spearman, 2008). The queuing discipline for the SLRM is first come, first-serve for all process queues. We present the five queues with the longest average queue waiting times below (Table 10).

Queue	Mean Wait Time (days)	Mean Wait Time (hours)
Clean Room	0.164	2.629
Batching	0.147	2.347
Induction	0.043	0.682
Paint Room	0.031	0.498
Leak and Flow	0.010	0.155

Table 10. Top five Process station mean queue waiting times under "normal operating" Sidewinder Repair line.

The Clean Room queue had the longest average wait time (2.6 hours), largely driven by the process times in the Clean Room (mode-32 hours) in the SRLM. Not surprisingly, the Clean Room resources had the highest utilization rates. These metrics suggest that re-allocating resources with lower utilization rates to the Clean Room might reduce mean cycle time.

C. VALIDATION

Standard validation for a DES model compares model output with historical data. TYAD did not have sufficient data to conduct such a validation, so we conducted multiple face validations with experts at TYAD. During the development of the base model we periodically shared the base model structure to ensure accurate portrayal of the repair line. TYAD identified errors in the model flow on several occasions, which we corrected. We added animation to the model that we recorded and shared with TYAD. They agreed the model closely represented the repair line. A more thorough validation based on historical data would further authenticate the model (Hazlett, 2008).

D. INCREASE PROCESS TIME DISTRIBUTIONS

The baseline analysis depends upon the validity of the service times provided by the subject-matter experts. We conducted a sensitivity analysis of the service time distribution parameters to determine the robustness of the baseline results. We developed an experimental design in which we incrementally increased process times. The design would then yield insights into when process times would influence mean cycle time and identify the most significant process times. We constructed the design by shifting the distributions' upper limits to the right, increasing the maximum value that each distribution could return as a percentage of the minimum value. Specific construction methods depended upon the process time distribution. The lower bounds for the uniform distributions were shifted right to the base mean value. The upper bounds for the uniform distributions were set percentages above the base mean value (Table 11).

Induction Process	
Percent above Mean	New Distribution
10	UNIF[75.0,82.5]
20	UNIF[75.0,90.0]
30	UNIF[75.0,97.5]
40	UNIF[75.0,105.0]
50	UNIF[75.0,112.5]

Table 11. Induction Process distributions per percent above mean.

The lower bounds, modes, and upper bounds for the triangular distributions were constructed as set percentages above their corresponding base value (Table 12).

Clean Room Process			
Percent above Low Parameter	Triangular Min Spread	Triangular Mode Spread	Triangular Max Spread
10	16.0 - 17.6	32.0 - 35.2	80.0 - 88.0
20	16.0 - 19.2	32.0 - 38.4	80.0 - 96.0
30	16.0 - 20.8	32.0 - 41.6	80.0 - 104.0
40	16.0 - 22.4	32.0 - 44.8	80.0 - 112.0
50	16.0 - 24.0	32.0 - 48.0	80.0 - 120.0

Table 12. Clean Room Process distribution parameters (min, mode, and max) per percent above mean

Shifting the fitted continuous distributions used to model the process times for the Leak and Flow, Boresite, and Rate Table proved more problematic. We included them in the SRLM by taking the actual data sets for the processes, added the same incremental percentage to the data, and then fit a new distribution to the process.

This design of experiment (DOE) yielded 17 factors and five distinct simulation sets. Rather than run thousands of scenarios we decided to reduce the number by utilizing a nearly orthogonal Latin Hypercube (NOLH) experimental design. This DOE allows the modeler to efficiently explore the parameter space with a much smaller number of scenarios than a full experimental design. A Latin hypercube in fundamental form is a matrix (each column is an *n*-run and *k*-factor) permutation of the integers (1,2,…,*n*). The *n* integers represent the levels across the range of the factor. Latin hypercubes exhibit good all-purpose design, efficiency, "space-filling" properties, and are flexible for conducting analysis. Spreading the design points throughout the experimental region in a uniform manner leads to a good "space-filling" design and minimizes the unsampled space. By spreading the design points throughout the region, this design facilitates the analyst's ability to extract desired statistical information and insights. Cioppa and Lucas (2007) developed an algorithm for constructing such nearly orthogonal Latin hypercubes. NOLHs sacrifice orthogonality for better space filling properties. We used this algorithm, which led to a design with only 129 scenarios for the 17 factors.

The NOLH matrix also provides a method to investigate which factor (process time distributions) have the most impact on the response variable (mean cycle time). We regressed the 129 mean cycle times against the NOLH matrix to further investigate the relationship between the input variables (process time distributions) and the response variable (mean cycle time). The fitted model included both the linear terms and their two-way interactions (Cioppa & Lucas, 2007), in the form $g(x) = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k-1} \sum_{j>i}^{k} \beta_{i,j} x_i x_j$.

A regression tree, or partition tree, is a non-parametric approach to relating the associations between input variables (resources) and a response variable (mean cycle time). We utilized the statistical package JMP to conduct this analysis. JMP calculated the mean and standard deviation of the mean cycle time, and then decided on which input variable to split. The splits occurred at the input variables that lead to the best improvement in the fitted model. Trees can have multiple splits (leaves) and divide an input variable more than once (SAS Institute Inc., 2007). JMP conducted three splits in the Regression Trees with the simulation set based on a 10 percent increase in process times (Figure 23). The model obtained a minimum mean cycle time of 2.49 days with an r-squared value of 0.73. The upper bound for the Clean Room process time was the most significant factor; the mode value for the Clean Room time was the second most significant factor.

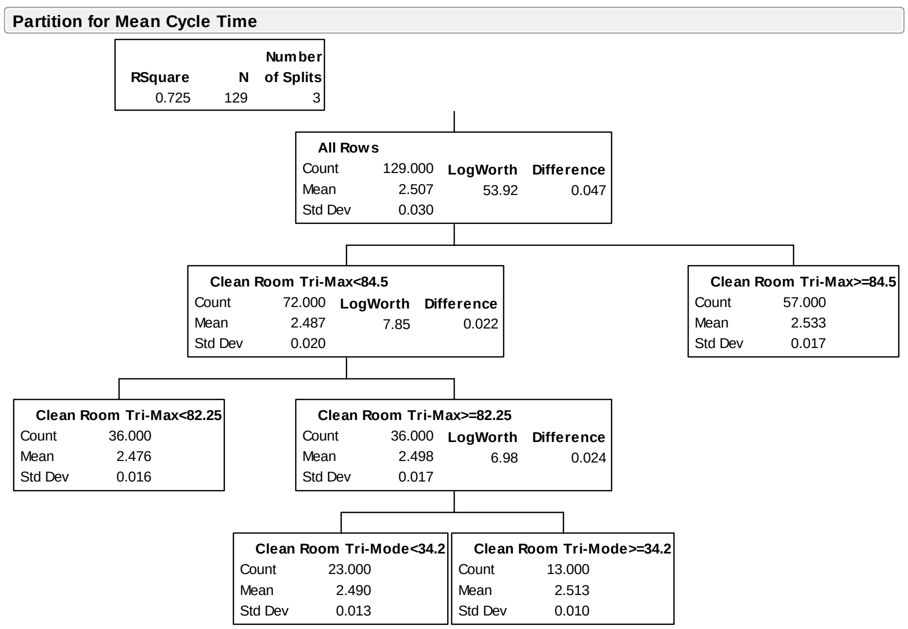

Figure 23. JMP Partition Tree with three splits for 10 percent increase simulation run.

JMP regressed the mean cycle times, obtained from the simulation set based on a 10 percent increase in process times, against the main effects and the two-way interactions of the input variables (process time distributions) in the simulation (Figure 24). The JMP output sorts the parameters in the resulting model by level of significance (SAS Institute Inc, 2007). The final model, obtained after conducting a multiple regression, had a mean cycle time of 2.51 days with an r-squared value of 0.91. The most significant factors were the three parameter values for the Clean Room triangular distribution.

Summary of Fit

RSquare	0.907
RSquare Adj	0.901
Root Mean Square Error	0.009
Mean of Response	2.507
Observations (or Sum Wgts)	129.000

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Clean Room Tri-Max	0.0110	0.00035	30.90	<.0001*
Clean Room Tri-Mode	0.0108	0.00089	12.17	<.0001*
Clean Room Tri-Min	0.0108	0.00177	6.11	<.0001*
Induction	0.0014	0.00038	3.69	0.0003*
Final RateTable	0.0011	0.00032	3.64	0.0004*
4044	0.0034	0.00114	3.03	0.0030*
(4044-26.2501)*(Final RateTable-94.5002)	0.0003	0.00043	0.66	0.5117

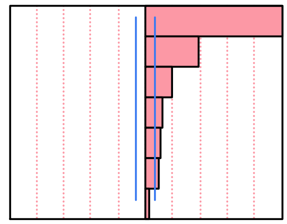

Figure 24. JMP Summary of Fit and Sorted Parameter regression estimates for 10 percent increase simulation run.

JMP conducted three splits in the Regression Trees with the simulation set based on a 20 percent increase in process times (Figure 25). The model had a minimum mean cycle time of 2.61 days with an r-squared value of 0.75. The upper bound for the Clean Room process time was the most significant factor.

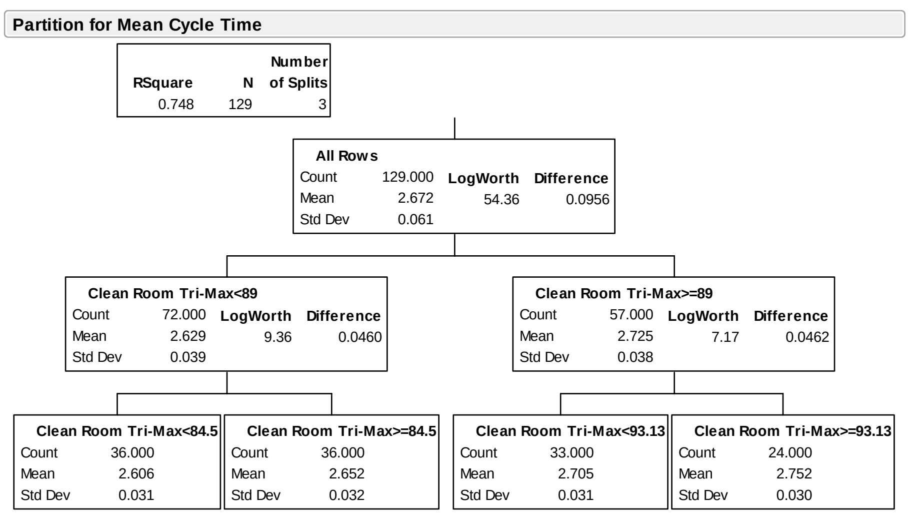

Figure 25. JMP Partition Tree with three splits for 20 percent increase simulation run.

JMP regressed the mean cycle times, obtained from the simulation set based on a 20% increase in process times, against the main effects and the two-way interactions of the input variables (process time distributions) in the simulation (Figure 27). The final model, obtained after conducting a multiple regression, had a mean cycle time of 2.67 days with an r-squared value of 0.95. The most significant factors were again the three parameter values for the Clean Room triangular distribution.

Summary of Fit	
RSquare	0.949
RSquare Adj	0.946
Root Mean Square Error	0.014
Mean of Response	2.672
Observations (or Sum Wgts)	129.000

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Clean Room Tri-Max	0.0114	0.00027	42.58	<.0001*
Clean Room Tri-Mode	0.0118	0.00067	17.62	<.0001*
Clean Room Tri-Min	0.0118	0.00134	8.80	<.0001*
Induction	0.0015	0.00029	5.34	<.0001*
Diagnostic RateTable	0.0011	0.00024	4.71	<.0001*
Final RateTable	0.0011	0.00024	4.55	<.0001*
(Diagnostic RateTable-99.0003)*(Final RateTable-99.0003)	0.0001	0.00004	1.22	0.2243

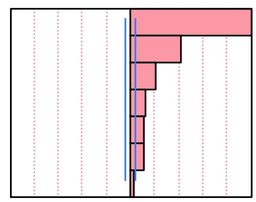

Figure 26. JMP Summary of Fit and Sorted Parameter regression estimates for 20 percent increase simulation run.

The additional increases of 30, 40, and 50 percent yielded similar results (see Appendix B). The three parameter values for the Clean Room process time distribution were the most significant factors effecting mean cycle time. However, the mean cycle time did not increase dramatically when the process time distribution were increased. Mean cycle time is not sensitive to the parameter estimates provided by the subject matter experts at TYAD.

E. RESOURCE FACTOR ANALYSIS

The baseline analysis identified that the utilization rates for the resources in the system were extremely low. Ten of the eleven resources had utilization rates below 30 percent. We decided to look closer at the resources in order to understand the relationship between the type of resources and mean cycle time, hoping to find ways to reduce the mean cycle time. We developed a design of experiments to measure the effect of varying the number of resources on the mean cycle time. We repeated the approach taken in the baseline analysis (Regression Trees and Regression Models) to identify the significant process time distributions. We varied the number of resources across a range of values (Table 13). The lower range value reflects the need to have at least one resource at each station. The upper range values reflect the space limitations on the repair line. We maintained the GCS arrival rates and numbers at the levels found in the base model.

	Induction Resource	4044 Machine	L and F Resource	Boresite Resource	Rate Table Resource	Clean Room Resource	Assembly Resource	Vib Resource	Final Assembly Resource	Final Inspection Resource
Low	1	1	1	1	3	3	1	1	1	1
High	2	3	3	4	6	6	2	2	2	2

Table 13. Process station Resource high and low bounds for NOLH matrix.

Executing this design of experiment would require running over 18,000 scenarios, an untenable number. We then decided to reduce the number of scenarios by a utilizing NOLH experimental design. The matrix reduced the number of simulations from 18,000 to 33. Table 14 displays the first ten scenarios of the NOLH matrix.

Scenario	Induction Resources	4044 Machine	L and F Resources	Boresite Resources	Rate Table Resources	Clean Room Resources	Assembly Resources	Vib Resources	Final Assembly Resources	Final Inspection Resources
1	2	1	2	2	6	5	2	1	2	2
2	2	3	1	2	4	4	2	1	2	1
3	2	2	3	1	3	5	2	1	1	2
4	2	3	3	2	6	3	2	1	1	1
5	2	1	2	2	5	5	1	2	1	1
6	2	3	2	2	4	4	1	2	1	2
7	2	2	3	2	3	5	1	2	2	1
8	2	2	3	2	6	4	1	2	2	2
9	2	2	1	3	5	4	1	1	2	2
10	2	2	2	3	4	5	1	1	2	1

Table 14. First ten scenarios (of 33) of the NOLH matrix for Resource factor analysis.

We ran these 33 scenarios through the SRLM, holding all other elements of the model at their base model values. The process rapidly reached stationarity, as in the base case, removing the need for a warm-up period. Summary statistics of the scenarios yielded a mean cycle time of 2.32 days per GCS with a standard deviation of 0.09 (Table 15). The mean cycle time exhibited very little variability across the scenarios. This lack of variability suggests that none of the factors (resources) effecting mean cycle time have much impact.

Mean Cycle Time (days)	2.316
Max Mean Cycle Time of Runs	2.528
Min Mean Cycle Time of Runs	2.225
Standard Deviation	0.086
95% Upper Confidence Level of true Mean	2.345
95% Lower Confidence Level of true Mean	2.286

Table 15. Summary statistics for the 33 resource factor scenarios.

We conducted a Regression Tree analysis in order to further explore the affect that the resources have on mean cycle time. We used an R-square threshold of 0.90 as an acceptable R-square value to stop the tree from splitting. JMP executed three splits before obtaining a model with an R-squared value in excess of 0.90 (Figure 27).

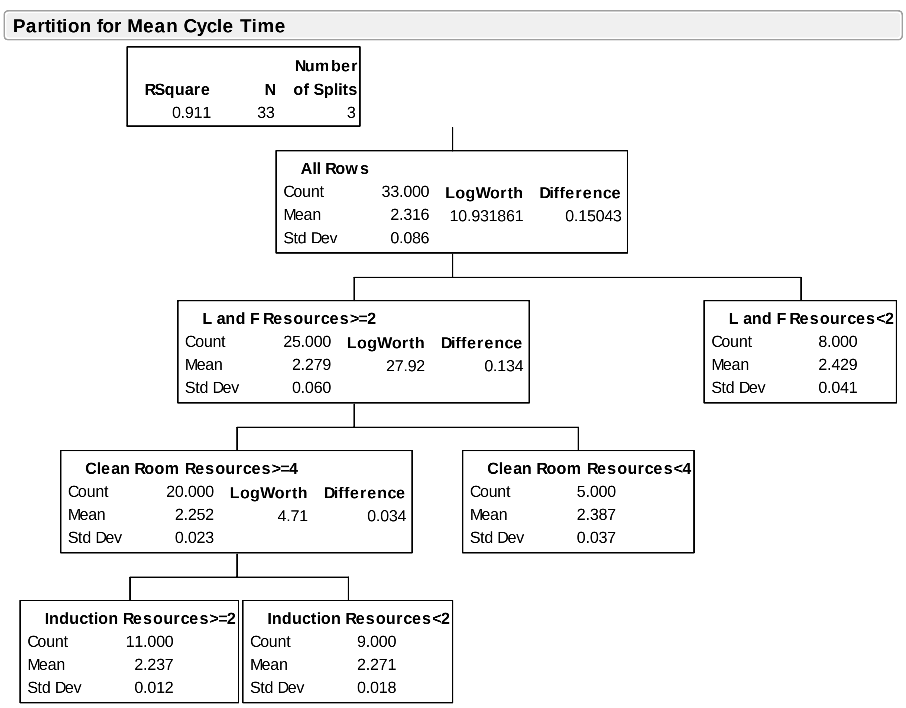

Figure 27. JMP Partition Tree with three splits of Leak and Flow, Clean Room, and Induction resources.

The first split occurred at the Leak and Flow resources. The mean cycle time drops from 2.32 to 2.28 days when the Leak and Flow has two or more resources (as it did in 25 out of 33 scenarios). The second split occurred at the Clean Room resources. The mean cycle time drops from 2.28 to 2.25 days when the Clean Room has four or more resources (as it did in 20 out of 33 scenarios). The third split occurred at the Induction resources. The mean cycle time drops from 2.25 to 2.24 days when the Induction has two or more resources (as it did in 11 out of 33 scenarios). The partition tree identified three major factors affecting mean cycle time. Yet mean cycle time remained largely insensitive to the number and allocation of resources. The last model from the Regression Tree analysis dropped mean cycle time only 3 percent from the baseline.

JMP regressed the mean cycle time against the main effects and the two-way interactions of the input variables (resources) in the simulation. The first model had a total of 55 terms. We then directed JMP to execute a stepwise regression, with a significance level $\alpha = 0.05$, to remove insignificant factors. JMP provided a summary of the fit and sorted parameter estimates as output (Figure 28).

Summary of Fit

RSquare	0.931
RSquare Adj	0.899
Root Mean Square Error	0.027
Mean of Response	2.316
Observations (or Sum Wgts)	33.000

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
L and F Resources	-0.071	0.0069	-10.20	<.0001*
Clean Room Resources	-0.049	0.0049	-9.88	<.0001*
(Vib Resources-1.51515)*(Final Assembly Resources-1.51515)	0.169	0.0284	5.93	<.0001*
(Induction Resources-1.51515)*(Clean Room Resources-4.51515)	-0.053	0.0100	-5.30	<.0001*
Induction Resources	-0.035	0.0100	-3.54	0.0019*
(Induction Resources-1.51515)*(L and F Resources-2.0303)	-0.071	0.0205	-3.48	0.0021*
4044 Machine	-0.014	0.0070	-2.07	0.0509
(4044 Machine-2.0303)*(Vib Resources-1.51515)	-0.027	0.0140	-1.90	0.0702
Vib Resources	-0.017	0.0097	-1.73	0.0977
Final Assembly Resources	-0.012	0.0096	-1.27	0.2158

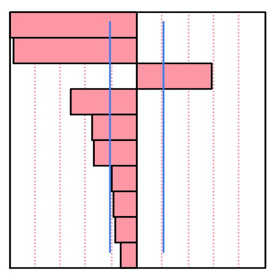

Figure 28. JMP Summary of Fit and Sorted Parameter regression estimates for resource factor regression model

The JMP output sorts the parameters in the resulting model by level of significance. The final model shows the Leak and Flow and Clean Room resources as the most significant factors. This confirms the findings from our earlier partition analysis.

We plotted an interaction profile plot to take a closer look at the significant interactions (Figure 29).

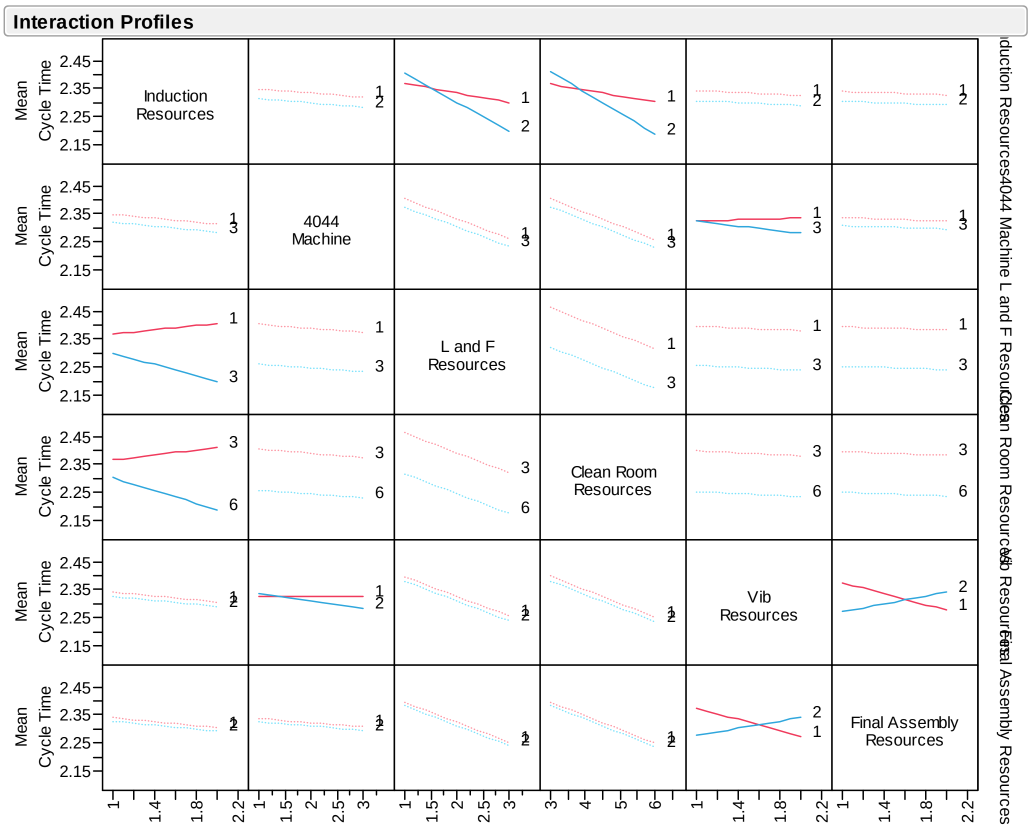

Figure 29. JMP Interaction Profiler for resource factor regression analysis. Circled in black is the most significant interaction.

Solid, non-parallel lines indicate interactions (SAS Institute Inc, 2007). The Final Assembly and Vibration (Vib) interaction, (circled in Figure 29) is the most significant two-way interaction. If we have two Final Assembly resources and One Vibration resource the predicted mean cycle time is the same as having the opposite configuration.

We also had JMP create a prediction profiler (Figure 30). The profiler is an interactive tool that allows the modeler to adjustment factor levels and computes the predicted response variable.

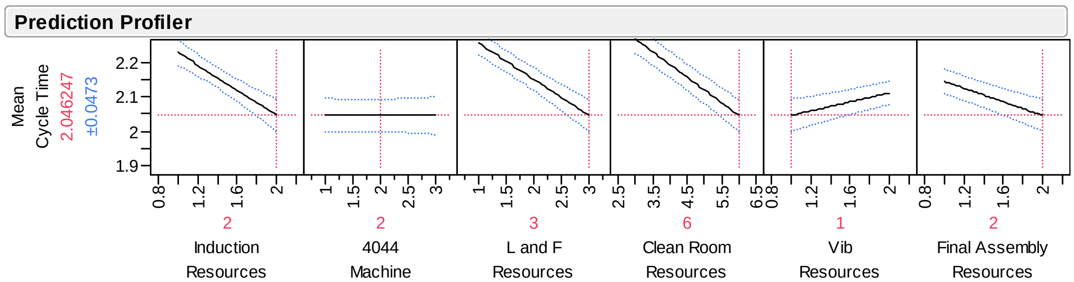

Figure 30. JMP Prediction Profiler for resource factor regression analysis.

We adjusted the resources in the profiler (only the significant factors are displayed) to achieve the minimum predicted mean cycle time. The model returned a mean cycle time of 2.05 days when the number of resources at Leak and Flow, Clean Room, and Induction were at their NOLH matrix upper bounds. Increasing the number of resources at the two most significant processes decreased the mean cycle time by only 11 percent, from 2.32 to 2.05 days. Neither an increase in the workforce nor a re-allocation of the current workers will make significant reductions in mean cycle time on the repair line.

F. INCREASE ARRIVALS

The baseline analysis identified that the repair line operates far below maximum capacity. This insight led us to seek the arrival rate that would drive the system to full capacity. Under normal operating conditions, the Sidewinder Repair Line inducts between one and twenty GCSs per week. The base model modeled the number of daily arrivals with a triangular(1,2,4) distribution. We developed an experimental design that increased the number of arrivals per day, while keeping all other parameters at their base model values (Table 16).

Scenario	Arrivals per Day Distribution
Base	*TRI(1,2,4)*
1	*TRI(1,3,5)*
2	*TRI(1,3,6)*
3	*TRI(1,4,7)*
4	*TRI(1,4,8)*
5	*TRI(1,4,9)*
6	*TRI(1,5,10)*
7	*TRI(1,5,11)*
8	*TRI(1,6,12)*

Table 16. Scenarios for GCS increase arrival distribution per day.

Arena conducted 20 replications for each of these eight scenarios and calculated our metrics for each scenario (Table 17).

	TRI(1,2,4)	TRI(1,3,5)	TRI(1,3,6)	TRI(1,4,7)	TRI(1,4,8)	TRI(1,4,9)	TRI(1,5,10)	TRI(1,5,11)	TRI(1,6,12)
Mean Cycle Time	2.35	2.53	2.68	3.65	14.47	370.73	907.77	1101.86	1347.92
Standard Deviation	0.01	0.01	0.01	0.11	3.76	20.06	17.17	16.99	17.07
Throughput per Year	476.70	649.87	736.47	909.53	995.49	1052.09	1154.93	1208.24	1311.22
WIP	4.32	6.31	7.59	12.76	55.40	1500.17	4032.37	5120.42	6797.76

Table 17. Base statistics (mean cycle time, standard deviation of mean cycle time, throughput per year, and WIP) for increased arrival distributions.

Mean cycle time increased in a linear manner as we shifted the arrival rate from a triangular(1,2,4) to a triangular(1,4,8) distribution. Interestingly, mean cycle time exploded to more than 370 days when the arrival rate distribution shifted to a triangular(1,4,9) distribution. The repair line appears to reach full capacity at this arrival rate (Figure 31).

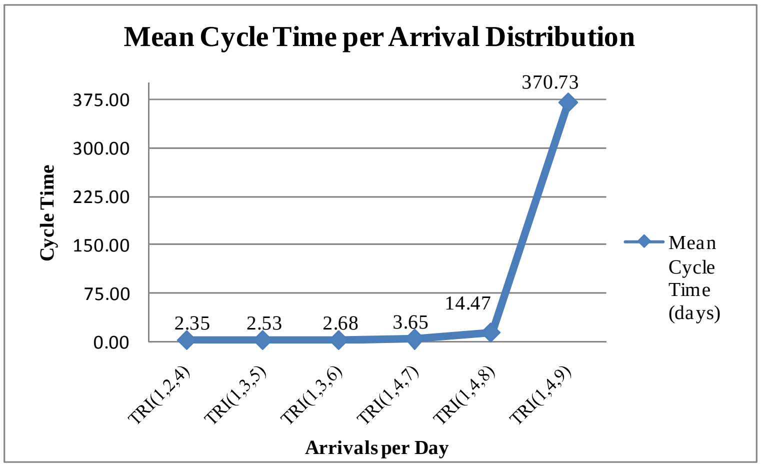

Figure 31. Mean cycle time per increased arrival distributions.

Earlier analysis revealed that the Clean Room process time to have the most effect on the mean cycle time, particularly the maximum value for the triangular distribution. Arena calculated the utilization rates for the Clean Room resources for each of the arrival rate distributions (Figure 32).

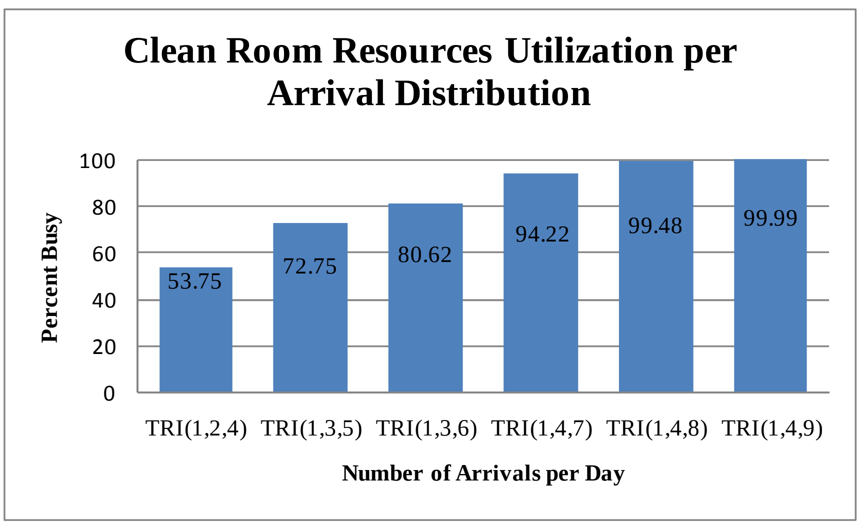

Figure 32. Clean Room utilization rates per increased arrival distributions.

The Clean Room utilization rate approached 100 percent as the arrival rate distribution shifted to triangular(1,4,9). Only perfect repair lines, without variability, can achieve 100 percent utilization (Hopp & Spearman, 2008). The Clean Room queue also had the longest GCS wait time for repair in the base SRLM analysis. Arena also provided the Clean Room queue lengths over time (see Figure 33) and the mean cycle times (Figure 34) for each of the arrival rate distributions.

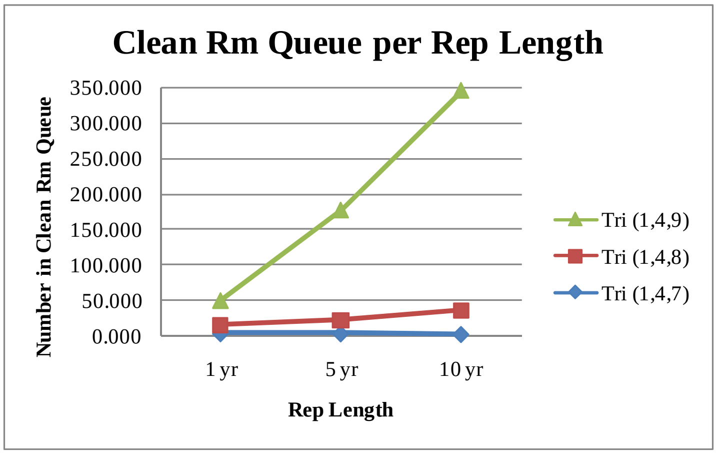

Figure 33. GCSs in the Clean Room queue per replication length (at one, five and ten years) highlighting triangular (1,4,7), (1,4,8), and (1,4,9) distributions.

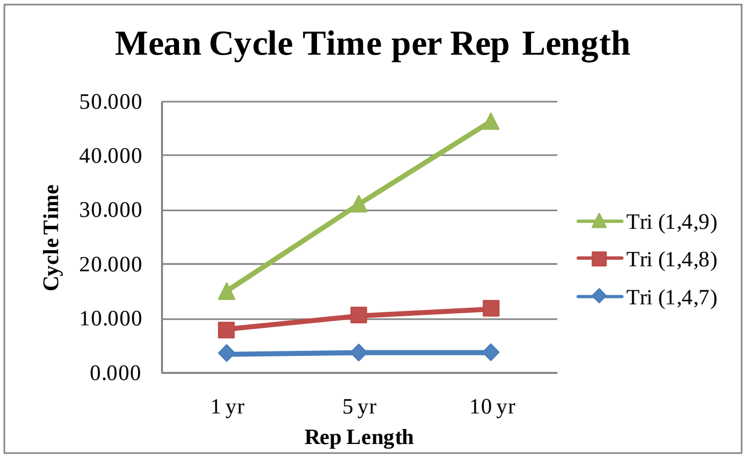

Figure 34. GCS mean cycle time per replication length (at one, five and ten years) highlighting triangular (1,4,7), (1,4,8), and (1,4,9) distributions.

The repair line reaches full capacity when the arrival rate is triangular(1,4,9). The Clean Room resources are fully utilized at this rate, limiting the ability of the repair line to reduce cycle time. The arrival rate of GCSs would need to double for the repair line to reach full capacity.

G. SIMULATION OPTIMIZATION

The baseline analysis identified that the utilization rates for the resources in the system were extremely low. This insight led us to investigate the impact reductions in the workforce would have on mean cycle time and the other metrics. We also sought to determine the resource allocation plan that would minimize mean cycle time. Arena provides an optimization capability (OptQuest) that we utilized to conduct a simulation optimization. The optimization sought to minimize mean cycle time subject to constraints on the number of resources at different stations.

OptQuest is a tool that uses a simulation model constructed in Arena to search for optimal solutions to a user-defined problem. When trying to evaluate the performance of a system using various resources, one must first decide the inputs for the various resources and then evaluate the performance for that particular arrangement of resources. This provides a baseline for the performance of the system, but to see the effects of varying the resources to increase the performance of the system, one must manually change the number of resources and then run the simulation again. This method is a repetitive and cumbersome task depending on the number of changes that are required, and it can result in a poor search for ways to improve the performance of the system. OptQuest performs this search for an optimal solution based on the performance variable the user selects. OptQuest updates and changes user-controlled variables within the Arena simulation and evaluates the user-defined performance parameter, then repeats until finding an optimal solution (Rockwell Automation, 2005). OptQuest uses the heuristics of tabu search, neural networks, and scatter search, and combining these heuristics into a single fused algorithm to locate the optimal solution (Jie & Li, 2008). Controls, responses, objectives, and constraints are the four main inputs required by QptQuest. Controls are variables or resources defined in the Arena model. OptQuest automatically assigns a control value to the resources defined in the model. The user selects a low and high bound for the controls. Responses can be included in the objective function or constraints and they are outputs of the simulation. Objective is the function that OptQuest is trying to minimize or maximize, based on the defined performance of the system. The objective function will include a selected response variable. Constraints define relationships between controls and responses to assist in the efficiency of the optimization (Rockwell Automation, 2005)

OptQuest used the SRLM to determine the number of resources per process station that minimizes the mean cycle time. The baseline SRLM had the normal operating conditions resource configuration (Table 18). Note that schedules do not bind these resources in OptQuest; rather, the resource capacity remains constant (there are no break times) throughout the optimization.

Resource	Maximum Capacity
Induction Station	1
4044 Machine	2
Clean Room Station	5
L and F Station	2
Boresite Station	3
Rate Table Station	5
Assembly Station	1
Vib Station	1
Final Assembly Station	1
Final Inspection Station	1
Painter	1

Table 18. Baseline SRLM resource configuration (22 total resources + one Painter).

We modeled the Paint Room resource (Painter) as having fixed capacity in the optimization. The Sidewinder Repair Line management does not have any direct influence on the TYAD Industrial Facility operations, and requested that we omit this worker from the analysis. We developed upper and lower bounds for the capacity of the remaining controls, fixing all lower bounds at one and setting all upper bounds equal to one more than the base model value (Table 19).

Control	Suggested Value	Lower Bound	Upper Bound
Induction Station	1	1	2
4044 Machine	2	1	3
L and F Station	2	1	4
Boresite Station	3	1	4
Rate Table Station	5	3	6
Clean Room Station	5	3	6
Assembly Station	1	1	2
Vib Station	1	1	2
Final Assembly Station	1	1	2
Final Inspection Station	1	1	2

Table 19. Current, lower and upper resources bounds for optimization.

The response selected for this optimization was a user-specified tally value of cycle time. The tally value was the mean GCS cycle time throughout all replications. The constraint for the optimization scenarios was the resource total. We discovered the resource utilization rates in the base analysis and determined to constrain the optimization both above and below the current capacity (22). We began with a resource total of no more than 16 for the first scenario and then incremented the total to 18, 20, 22, then 24. The objective function was to minimize the response of tally time (Tally 1, mean cycle time in days). Summarized below is the simulation optimization model in standard Naval Postgraduate School (NPS) format (Brown & Dell, 2007).

Sets & Indices: [cardinality]

i index number of process station [$i = 1, 2, \ldots, 10$]

c sum of resources upper bound [16,18,20,22,24]

k resources (superscript) [k=1,2,…,6]

Model Inputs: [units]

t_i^k service time at station i with resources k [time]

$lower_i$ resource lower bound per i [integer]

$upper_i$ resource upper bound per i [integer]

Decision Variables: [units]

V	mean cycle time (objective)	[days]
X_i^k	k resources assigned to station i	[binary]

Formulation:

Objective:

$$\min V$$

subject to:

$$\sum_{i,k} t_i^k X_i^k \leq V$$

$$\sum_{i,k} kX_i \leq c$$

$$\sum_k X_i^k = 1 \ \forall i$$

where:

$$X_i^k \in \{0,1\} \ \forall i,k$$

$$X_i^k \equiv 0 \quad \forall k < lower_i, \ \forall k > upper_i$$

The optimization ran three replications (based on time restrictions), 100 years per replication. Arena identified the top ten permutations and ran an additional seven replications, to estimate mean cycle time for each permutation. We show the results for these ten permutations, with the sum of resources constraint "no more than 16," below (Table 20).

Induction Station	4044 Machine	L and F Station	Boresite Station	Rate Table Station	Clean Room Station	Assembly Station	Vib Station	Final Assembly Station	Final Inspection Station	Sum of Resources	Tally 1 (days)
1	1	2	1	3	4	1	1	1	1	16	2.2968
1	1	2	2	3	3	1	1	1	1	16	2.4010
2	1	2	1	3	3	1	1	1	1	16	2.4095
1	1	3	1	3	3	1	1	1	1	16	2.4120
1	1	2	1	4	3	1	1	1	1	16	2.4147
1	1	2	1	3	3	2	1	1	1	16	2.4193
1	1	2	1	3	3	1	1	1	1	15	2.4194
1	1	1	1	3	5	1	1	1	1	16	2.4238
1	1	2	1	3	3	1	1	1	2	16	2.4247
1	2	2	1	3	3	1	1	1	1	16	2.4249

Table 20. Top 10 resource allocations, based on lowest mean cycle time and sum of resources "no more than 16."

We repeated this approach four more times, increasing the maximum number of resources allowed by two each time (see Appendix C top 50 allocations). OptQuest rank-ordered the resulting twenty outputs by mean cycle time (Table 21). The yellow highlighted row identifies the configuration of resources with the lowest mean cycle time, while the gray highlighted row identifies the optimal configuration of resources for the base case resource capacity.

Induction Station	4044 Machine	L and F Station	Boresite Station	Rate Table Station	Clean Room Station	Assembly Station	Vib Station	Final Assembly Station	Final Inspection Station	Sum of Resources	Tally 1 (days)
2	2	2	2	5	5	2	1	2	1	24	2.2261
2	2	2	2	5	5	2	1	1	1	23	2.2288
2	2	2	3	5	5	2	1	1	1	24	2.2294
2	2	2	2	3	5	2	2	2	2	24	2.2296
2	2	2	3	3	6	2	1	2	1	24	2.2312
2	1	3	2	3	5	2	2	2	2	24	2.2326
2	3	2	2	3	5	2	1	2	1	23	2.2333
2	2	2	2	3	5	2	1	1	1	21	2.2342
2	2	2	3	3	5	2	1	2	1	23	2.2344
2	2	2	2	6	5	2	1	1	1	24	2.2345
1	1	2	4	4	6	1	1	1	1	22	2.2532
2	2	2	1	3	6	1	2	2	1	22	2.2537
1	2	2	3	5	5	1	1	1	1	22	2.2548
1	1	2	3	5	6	1	1	1	1	22	2.2565
2	2	2	1	3	6	1	1	2	2	22	2.2565
1	2	2	2	6	5	1	1	1	1	22	2.2567
1	2	2	2	3	6	1	2	1	1	21	2.2587
2	2	2	1	3	5	1	2	2	2	22	2.2606
2	1	2	2	3	4	2	2	1	1	20	2.2610
1	1	2	4	3	6	1	1	1	1	21	2.2611

Table 21. Top 20 resource allocations based on lowest mean cycle time and sum of resources "no more than 24."

Not surprisingly, utilizing 24 resources yielded the minimum mean cycle time. More surprisingly, the addition of two additional resources did not result in a significant reduction in mean cycle time. The optimal configuration with 24 resources reduced mean cycle time slightly more than 1 percent, from 2.25 to 2.23 days. OptQuest also provided insights into which resource allocation plans, constrained by the base case number of resources (22), minimized mean cycle time (Table 22).

Induction Station	4044 Machine	L and F Station	Boresite Station	Rate Table Station	Clean Room Station	Assembly Station	Vib Station	Final Assembly Station	Final Inspection Station	Sum of Resources	Tally 1 (days)	Percent Change from Baseline
2	2	2	2	5	5	2	1	2	1	24	2.2261	-1.27
2	2	2	2	5	5	2	1	1	1	23	2.2288	-1.15
2	2	2	3	5	5	2	1	1	1	24	2.2294	-1.12
2	2	2	2	3	5	2	2	2	2	24	2.2296	-1.12
2	2	2	3	3	6	2	1	2	1	24	2.2312	-1.05
2	1	3	2	3	5	2	2	2	2	24	2.2326	-0.98
2	3	2	2	3	5	2	1	2	1	23	2.2333	-0.95
2	2	2	2	3	5	2	1	1	1	21	2.2342	-0.91
2	2	2	3	3	5	2	1	2	1	23	2.2344	-0.90
2	2	2	2	6	5	2	1	1	1	24	2.2345	-0.90
1	1	2	4	4	6	1	1	1	1	22	2.2532	-0.07
2	2	2	1	3	6	1	2	2	1	22	2.2537	-0.05
1	2	2	3	5	5	1	1	1	1	22	2.2548	0.00

Table 22. Top resource allocations above (lower mean cycle time) base case allocation highlighted in gray

Twelve resource allocation plans yielded smaller mean cycle times than the base model. We obtained a mean cycle time of 2.23 days with only 21 resources. The repair line could reduce mean cycle time from 2.25 to 2.23 days with one less resource (Table 22 yellow highlight). OptQuest also provided insights into which resource allocation plans, constrained by fewer resources than in the base case (22), minimized mean cycle time (Table 23).

Induction Station	4044 Machine	L and F Station	Boresite Station	Rate Table Station	Clean Room Station	Assembly Station	Vib Station	Final Assembly Station	Final Inspection Station	Sum of Resources	Tally 1 (days)	Percent Change from Baseline
1	2	2	3	5	5	1	1	1	1	22	2.2548	0.00
1	1	2	3	5	6	1	1	1	1	22	2.2565	0.07
2	2	2	1	3	6	1	1	2	2	22	2.2565	0.08
1	2	2	2	6	5	1	1	1	1	22	2.2567	0.08
1	2	2	2	3	6	1	2	1	1	21	2.2587	0.18
2	2	2	1	3	5	1	2	2	2	22	2.2606	0.26
2	1	2	2	3	4	2	2	1	1	20	2.2610	0.27
1	1	2	4	3	6	1	1	1	1	21	2.2611	0.28
2	1	2	1	3	5	1	1	1	1	18	2.2642	0.42
1	1	3	1	3	5	1	1	1	1	18	2.2742	0.86
1	1	2	1	4	5	1	1	1	1	18	2.2757	0.93
1	1	2	1	3	5	1	1	1	2	18	2.2758	0.93
1	1	2	1	3	6	1	1	1	1	18	2.2762	0.95
2	1	3	1	3	4	1	1	1	1	18	2.2778	1.02
1	1	2	1	3	5	1	2	1	1	18	2.2785	1.05
1	1	2	1	3	5	1	1	1	2	18	2.2786	1.06
2	1	2	1	3	4	1	2	1	1	18	2.2791	1.08
2	1	2	1	3	4	1	1	2	1	18	2.2791	1.08
1	1	2	1	3	4	1	1	1	1	16	2.2968	1.86

Table 23. Resource allocations below (higher mean cycle time) base case allocation highlighted in gray. Yellow highlights are best allocations with two or less resources from the base case of 22.

The optimal resource allocation plan with 20 resources yielded a mean cycle time of 2.26 days, a 0.27 percent increase from the base case. The optimal resource allocation plan with 18 resources yielded a mean cycle time of 2.26 days, a 0.42 percent increase from the base case. The optimal resource allocation plan with 16 resources yielded a mean cycle time of 2.30 days, a 1.86 percent increase from the base case. The repair line could reduce the number of resources from 22 to 16 (27 percent) and experience an increase in mean cycle time of only 1.86 percent.

V. CONCLUSIONS AND FUTURE RESEARCH

The mean cycle time for the TYAD Sidewinder repair line under current operating conditions is 2.35 days. The repair line should repair 476 GCSs per year. The repair line operates far below maximum capacity. Workers at ten of the eleven stations have a less than 30 percent utilization rate. Workers at the Clean Room have the highest utilization rate at 54 percent. The process times at the Clean Room have the greatest impact on the mean cycle time and reductions in these times would lead to the greatest decrease in the mean cycle time in the simulation. The repair line does not achieve full operating capacity until the GCS arrival rate doubles. Re-allocation of the current workforce to an optimal configuration will reduce mean cycle time by less than 1 percent. TYAD could reduce the workforce at the repair line by 27 percent and only experience a 1.9 percent increase in mean cycle time.

We briefed this thesis to three organizations (TYAD, Army Material Command (AMC) Fort Belvoir,VA, and the Army Material Systems Analysis Activity (AMSAA) Aberdeen Proving Grounds, MD). TYAD is looking at the results to further improve the Sidewinder Repair line, apply DES to depot lines of the future, and apply DES to an existing remodel of a current repair facility. AMC (headquarters for all Army Depots) immediately requested assistance and guidance with one of their ammunition depots that manufacture mortar rounds. AMSAA, one of the three major analytical organizations in the Army, is using this thesis as a template for future applications of DES to repair, overhaul, deployment, and redeployment operations.

Several additions to the work discussed in this thesis could prove useful to TYAD. Follow-on work could include better collection of process time data at TYAD to further enhance the station process time distributions. Building a sub-model of the Clean Room station to gather summary statistics and determine significant factors effecting Clean Room process time could guide the implementation of time saving measures. Expanding the SRLM to include the entire GCS repair process, from customer identification of faults to the return of a repair GCS, would provide TYAD better understanding of how they support their customers. Expanding the model to include wait time for repair parts not on-hand and failure times for machines and equipment would provide a more accurate picture of the repair line. Conducting a cost-benefit analysis that considered the lost/gain of cycle time against the addition/deletion of resources would better inform TYAD on the budgetary implications of their policies for the repair line.

APPENDIX A. SRLM ANIMATION

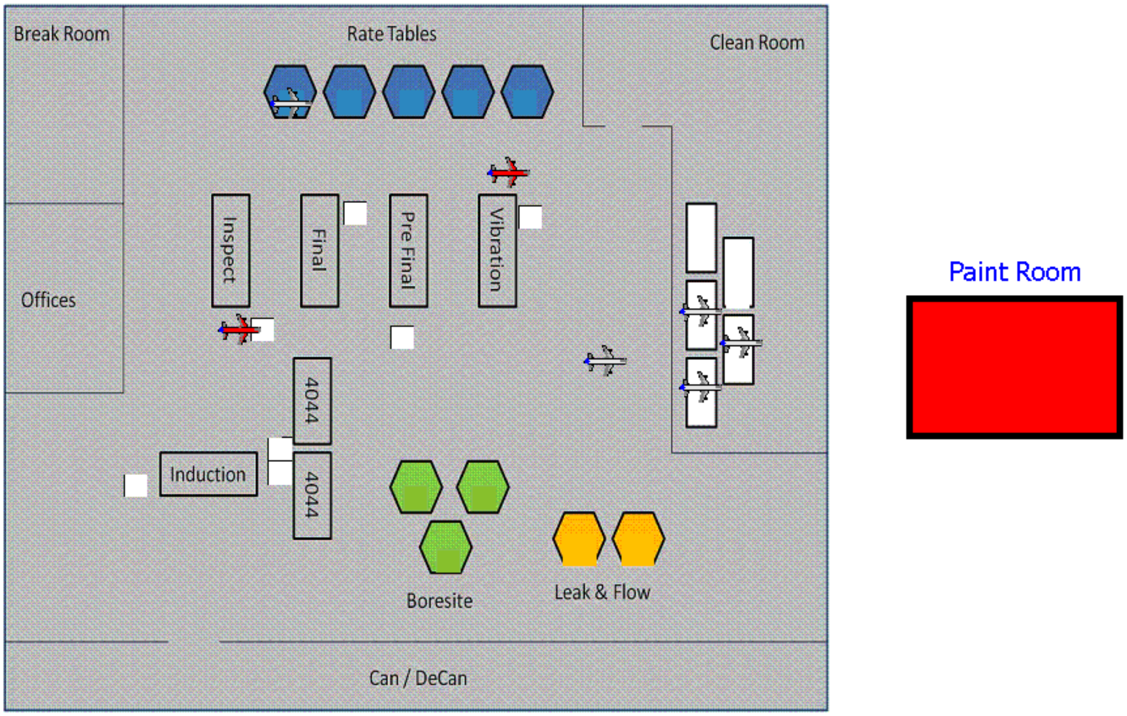

Figure 35. SRLM animation screen shot from Arena. Mimics Sidewinder floor layout with GCSs (silver and red) moving through the repair process. Red GCSs signify the GCS shell visited the Paint Room.

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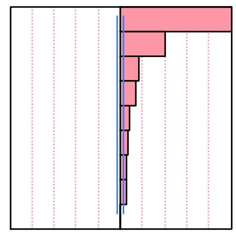
APPENDIX B. TREES AND REGRESSION MODELS

Summary of Fit

RSquare	0.978924
RSquare Adj	0.97733
Root Mean Square Error	0.014251
Mean of Response	2.841829
Observations (or Sum Wgts)	129

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Clean Room Tri-Max	0.0120378	0.00018	66.98	<.0001*
Clean Room Tri-Mode	0.012231	0.000449	27.22	<.0001*
Clean Room Tri-Min	0.0102384	0.000899	11.39	<.0001*
Induction	0.0018194	0.000192	9.49	<.0001*
Final RateTable	0.000837	0.00016	5.24	<.0001*
Diagnostic RateTable	0.0008146	0.00016	5.10	<.0001*
Diagnostic Boresite	0.001339	0.000319	4.19	<.0001*
Diagnostic Leak and Flow	0.0013029	0.000319	4.08	<.0001*
(Diagnostic Leak and Flow-51.7501)*(Diagnostic Boresite-51.7501)	-2.079e-5	7.589e-5	-0.27	0.7846



Partition for Mean Cycle Time

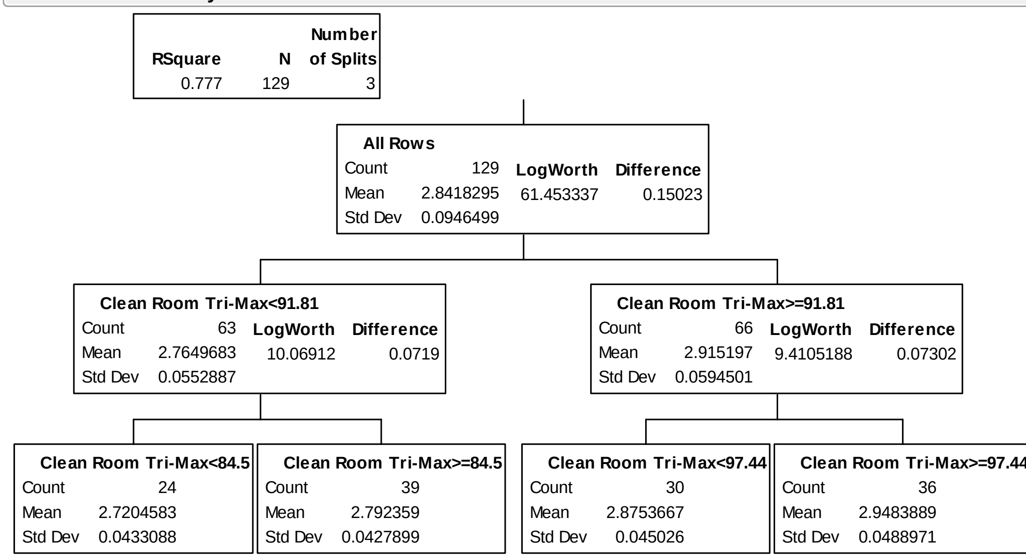


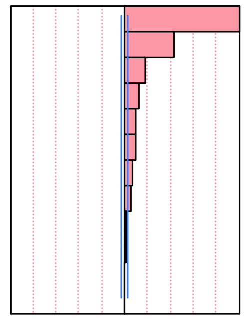
Figure 36. Summary of Fit, Sorted Parameter regression estimates, and Partition Tree for 30 percent increase simulation run. Mean cycle time of 2.8 days, R-square of 0.98, and the Clean Room triangular distribution parameters of max, mode, and min are the most significant factors effecting mean cycle time.

Summary of Fit

RSquare	0.984603
RSquare Adj	0.98301
Root Mean Square Error	0.017325
Mean of Response	3.012853
Observations (or Sum Wgts)	129

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Clean Room Tri-Max	0.0125559	0.000164	76.63	<.0001*
Clean Room Tri-Mode	0.0134875	0.00041	32.92	<.0001*
Clean Room Tri-Min	0.0115271	0.000819	14.07	<.0001*
Induction	0.0017772	0.000175	10.17	<.0001*
Final RateTable	0.0011627	0.000146	7.98	<.0001*
Diagnostic RateTable	0.0011058	0.000146	7.59	<.0001*
Final LeakFlow	0.0014271	0.000291	4.90	<.0001*
Diagnostic Boresite	0.0013614	0.000291	4.67	<.0001*
(Clean Room Tri-Mode-38.4)*(Clean Room Tri-Max-96)	6.7423e-5	4.535e-5	1.49	0.1398
(Diagnostic RateTable-108.001)*(Final RateTable-108.001)	1.535e-5	0.000013	1.18	0.2421
(Induction-90.0003)*(Clean Room Tri-Min-19.2)	2.9671e-5	9.381e-5	0.32	0.7524
(Diagnostic Boresite-54.0003)*(Final LeakFlow-54.0003)	7.9032e-7	0.000051	0.02	0.9876



Partition for Mean Cycle Time

RSquare	N	Number of Splits
0.729	129	3

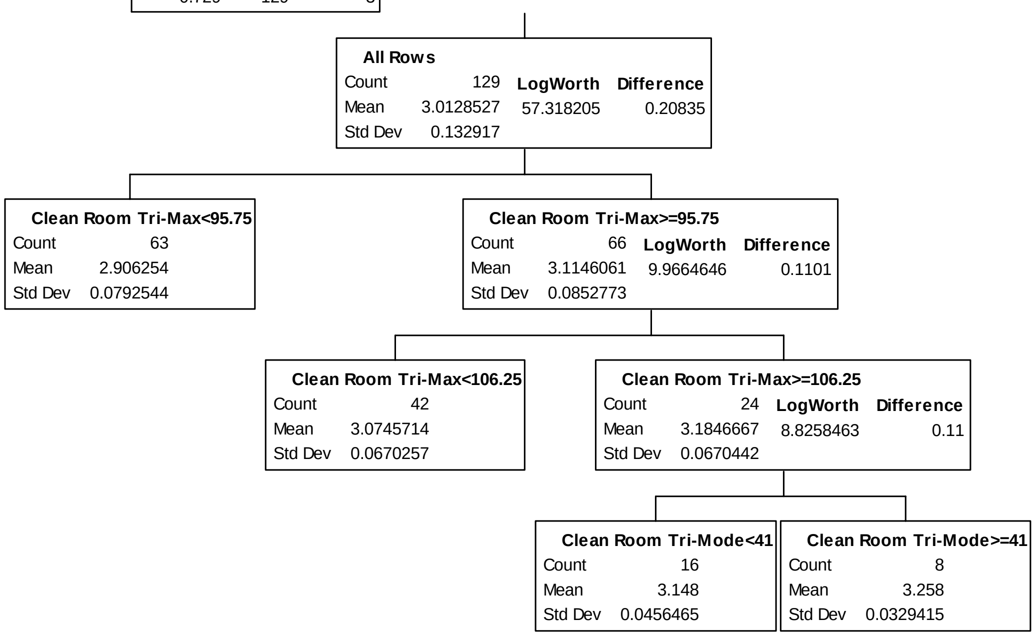


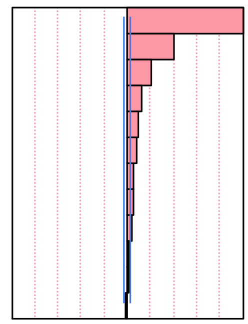
Figure 37. Summary of Fit, Sorted Parameter regression estimates, and Partition Tree for 40 percent increase simulation run. Mean cycle time of 3.0 days, R-square of 0.98, and the Clean Room triangular distribution parameters of max, mode, and min are the most significant factors effecting mean cycle time.

Summary of Fit

RSquare	0.984745
RSquare Adj	0.983167
Root Mean Square Error	0.022692
Mean of Response	3.195984
Observations (or Sum Wgts)	129

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Clean Room Tri-Max	0.0133462	0.000172	77.73	<.0001*
Clean Room Tri-Mode	0.0133038	0.000429	30.99	<.0001*
Clean Room Tri-Min	0.0138442	0.000858	16.13	<.0001*
Induction	0.0017208	0.000183	9.40	<.0001*
Final RateTable	0.0011143	0.000153	7.30	<.0001*
Diagnostic RateTable	0.0009982	0.000153	6.54	<.0001*
Final Boresite	0.0013771	0.000305	4.51	<.0001*
Final LeakFlow	0.001209	0.000305	3.96	0.0001*
(Clean Room Tri-Mode-40.0025)*(Clean Room Tri-Max-100.001)	0.0001052	3.839e-5	2.74	0.0071*
(Induction-93.7501)*(Clean Room Tri-Min-20.0012)	0.0001055	7.839e-5	1.35	0.1811
(Diagnostic RateTable-112.5)*(Final RateTable-112.5)	1.1432e-5	0.000011	1.04	0.2983
(Final LeakFlow -56.2501)*(Final Boresite-56.2501)	-3.478e-5	4.522e-5	-0.77	0.4433



Partition for Mean Cycle Time

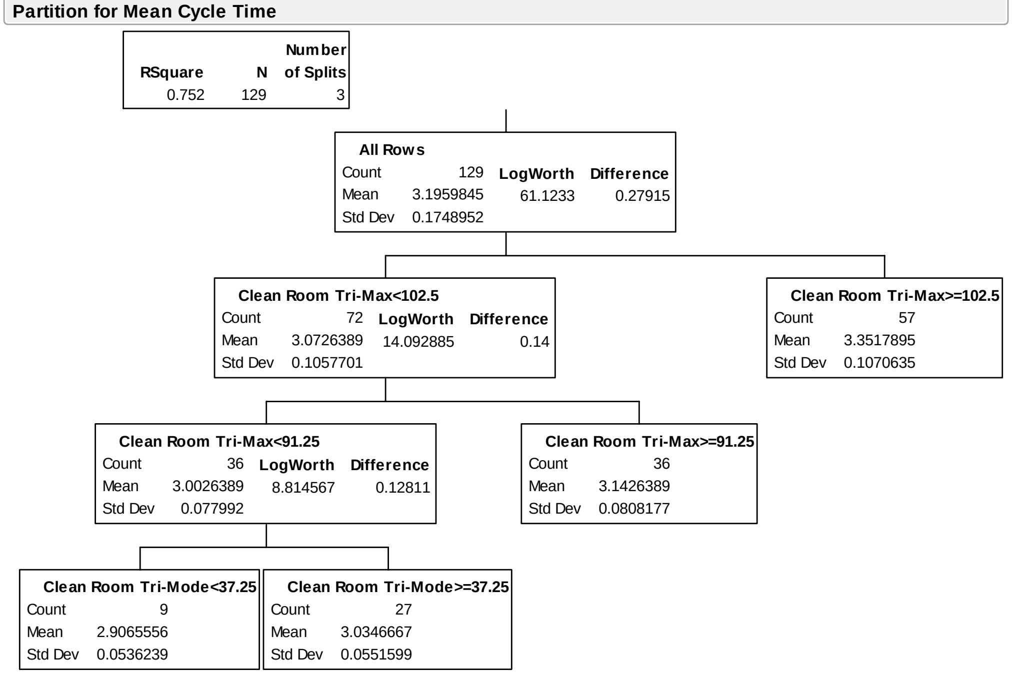


Figure 38. Summary of Fit, Sorted Parameter regression estimates, and Partition Tree for 50 percent increase simulation run. Mean cycle time of 3.2 days, R-square of 0.98, and the Clean Room triangular distribution parameters of max, mode, and min are the most significant factors effecting mean cycle time.

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APPENDIX C. OPTQUEST RESULTS

Induction Station	4044 Machine	L and F Station	Boresite Station	Rate Table Station	Clean Room Station	Assembly Station	Vib Station	Final Assembly Station	Final Inspection Station	Sum of Resources	Tally 1 (days)	Percent Change from Baseline
2	2	2	2	5	5	2	1	2	1	24	2.2261	-1.27
2	2	2	2	5	5	2	1	1	1	23	2.2288	-1.15
2	2	2	3	5	5	2	1	1	1	24	2.2294	-1.12
2	2	2	2	3	5	2	2	2	2	24	2.2296	-1.12
2	2	2	3	3	6	2	1	2	1	24	2.2312	-1.05
2	1	3	2	3	5	2	2	2	2	24	2.2326	-0.98
2	3	2	2	3	5	2	1	2	1	23	2.2333	-0.95
2	2	2	2	3	5	2	1	1	1	21	2.2342	-0.91
2	2	2	3	3	5	2	1	2	1	23	2.2344	-0.90
2	2	2	2	6	5	2	1	1	1	24	2.2345	-0.90
1	1	2	4	4	6	1	1	1	1	22	2.2532	-0.07
2	2	2	1	3	6	1	2	2	1	22	2.2537	-0.05
1	2	2	3	5	5	1	1	1	1	22	2.2548	0.00
1	1	2	3	5	6	1	1	1	1	22	2.2565	0.07
2	2	2	1	3	6	1	1	2	2	22	2.2565	0.08
1	2	2	2	6	5	1	1	1	1	22	2.2567	0.08
1	2	2	2	3	6	1	2	1	1	21	2.2587	0.18
2	2	2	1	3	5	1	2	2	2	22	2.2606	0.26
2	1	2	2	3	4	2	2	1	1	20	2.2610	0.27
1	1	2	4	3	6	1	1	1	1	21	2.2611	0.28
2	1	2	1	3	5	1	1	1	1	18	2.2642	0.42
1	1	3	1	3	5	1	1	1	1	18	2.2742	0.86
1	1	2	1	4	5	1	1	1	1	18	2.2757	0.93
1	1	2	1	3	5	1	1	1	2	18	2.2758	0.93
1	1	2	1	3	6	1	1	1	1	18	2.2762	0.95
2	1	3	1	3	4	1	1	1	1	18	2.2778	1.02
1	1	2	1	3	5	1	2	1	1	18	2.2785	1.05
1	1	2	1	3	5	1	1	1	2	18	2.2786	1.06
2	1	2	1	3	4	1	2	1	1	18	2.2791	1.08
2	1	2	1	3	4	1	1	2	1	18	2.2791	1.08
1	1	2	1	3	4	1	1	1	1	16	2.2968	1.86
2	1	3	1	4	3	1	1	2	1	19	2.3944	6.19
2	1	3	1	4	3	1	2	2	1	20	2.3949	6.22
2	1	3	1	5	3	1	1	2	1	20	2.3967	6.30
2	1	3	1	5	3	1	1	1	2	20	2.3970	6.31
2	1	2	1	6	3	1	2	1	1	20	2.3973	6.32
2	1	2	1	3	3	1	2	1	1	17	2.3980	6.35
2	1	3	1	3	3	1	1	2	1	18	2.3981	6.36
2	1	3	1	6	3	1	1	1	1	20	2.3987	6.38
2	1	3	1	3	3	1	1	1	2	18	2.3993	6.41
2	1	2	1	4	3	1	1	1	1	17	2.3994	6.41
1	1	2	2	3	3	1	1	1	1	16	2.4010	6.49
2	1	2	1	3	3	1	1	1	1	16	2.4095	6.86
1	1	3	1	3	3	1	1	1	1	16	2.4120	6.97
1	1	2	1	4	3	1	1	1	1	16	2.4147	7.09
1	1	2	1	3	3	2	1	1	1	16	2.4193	7.30
1	1	2	1	3	3	1	1	1	1	15	2.4194	7.30
1	1	1	1	3	5	1	1	1	1	16	2.4238	7.50
1	1	2	1	3	3	1	1	1	2	16	2.4247	7.53
1	2	2	1	3	3	1	1	1	1	16	2.4249	7.54

Table 24. Top 50 resource allocation results from OptQuest optimization (base case highlighted in gray).

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