Simulation of a Manufacturing Process for Aerospace Parts to Optimize Process Utilization

SIE 431 - Final Report

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1.0 Background & Introduction

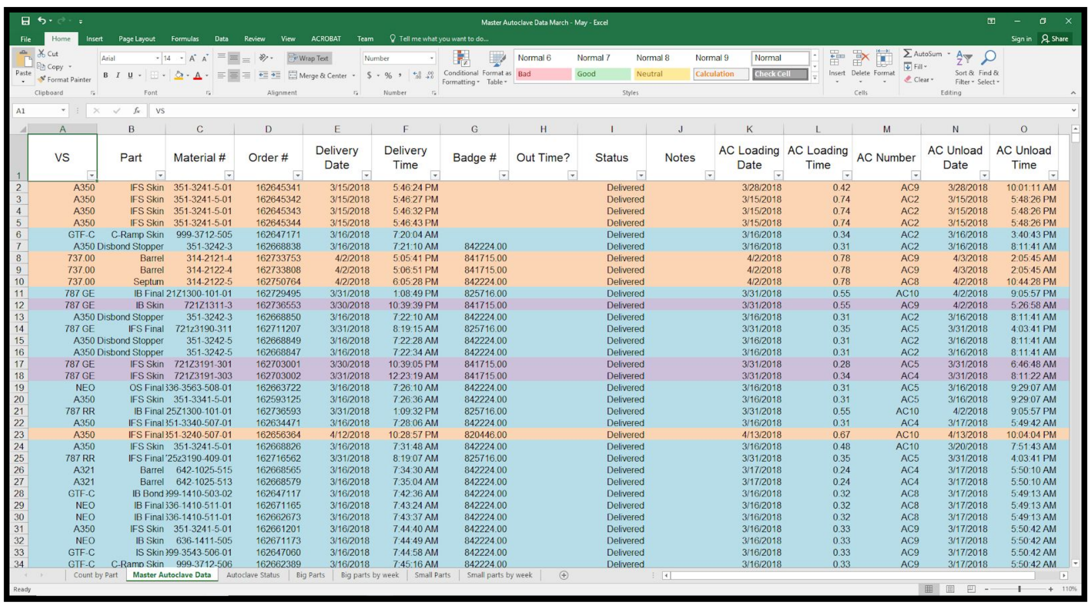
An autoclave is most commonly used in industry for curing composite materials in both a mechanical and chemical process. In the mechanical process pressure is applied to remove trapped air to help mold individual fibers and plies together. In the chemical process a crosslink reaction is initiated to complete a rigid mold, this process is initiated through the heat or ultraviolet exposure. The autoclave forms a process in which heat and pressures are applied in a cylindrical atmosphere. Each part process is slightly different do to dimension constraints so the cure cycles for a specific application varies since it is determined by using calculations to derive empirical data to develop cure cycles for parts or materials to ensure desired properties.

The average autoclave cure cycle is broken down into a two-step process.The first process consists of creating a vacuum and then pressurized environment while temperature gets heated up to a moderate level and held depending on the part model and size (boeing 787, airbus a320, gridlock/military), small parts are in the autoclave for 4 hours and large parts for 8 hours. The heat reduces the viscosity of resin materials to flow and reach trapped air pockets. After the first curing cycle is done, it was moved to the next value stream where a had to be opened from the sealed plastic bag it was in, then a layer of metallic "chicken wire" was placed on top of it. Then another layer of polymer composite was placed on top. Then be re-bagged, then goes back to the autoclave for 2nd curing cycle.In the second stage of the process the temperature is ramped up to a final curing temperature and held there up to 12 hours for bigger parts to complete the cure cycle. What happens in between process? Andrew.

We plan on using the simulation approach because the manufacturing process has many queues and process that can be modeled using probability distributions for service and interarrival times. This approach will allow us to improve waiting times, make the process more efficient to save on final manufacturing costs through the manipulation of parameters. The simulation approach allows us to rn many replications on the outcomes and perform statistical analysis for the purpose of improving the overall process without making changes to the actual implemented queuing system.

2.0 Input Data Analysis

The data used for this project contains arrival times for parts going into the UTC Aerospace manufacturing process that our simulation models. We obtained this data by asking a contact that works at UTC Aerospace. We have this contact because one of our group members was an intern for this company last summer. Fortunately, the arrival times for this system are well documented as it is automatically captured in an excel spreadsheet when an part arrives on site. The data used for the simulation is from this excel spreadsheet. Therefore, there were no issues collecting data on our part. It can also be assumed that the reliability of the data is high because the procedure for capturing the data is automated and not prone to human error.



VS	Part	Material #	Order #	Delivery Date	Delivery Time	Badge #	Out Time?	Status	Notes	AC Loading Date	AC Loading Time	AC Number	AC Unload Date	AC Unload Time
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737.00	Septum	314-2122-5	162750764	4/2/2018	6:05:28 PM	842224.00		Delivered		4/2/2018	0.78	AC8	4/2/2018	10:44:28 PM
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NEO	IB Final	36-1410-511-01	162662673	3/16/2018	7:43:37 AM	842224.00		Delivered		3/16/2018	0.32	AC8	3/17/2018	5:49:13 AM
A350	IFS Skin	351-3241-5-01	162661201	3/16/2018	7:44:40 AM	842224.00		Delivered		3/16/2018	0.33	AC9	3/17/2018	5:50:42 AM
NEO	IB Skin	636-1411-505	162671173	3/16/2018	7:44:49 AM	842224.00		Delivered		3/16/2018	0.33	AC9	3/17/2018	5:50:42 AM
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Figure1. Arrival Data for parts entering the system provided by UTC Aerospace

For our ARENA model, the interarrival times from the big parts and the small parts were needed to use for the Input Analyzer tool so that we could estimate the interarrival distributions that we would use for the model. In order to get the necessary data, the parts were separated into big parts and small parts. The spreadsheet did not include this label, so a pivot table was used to separate the parts by value stream (VS). From there, each value stream was determined to be either big or small from memory from our team member who participated in the internship with UTC. After that, we separated the data by big parts and small parts and copied the partitioned data into their own spreadsheets. Now that the data was separated by large and small parts, the next step was to convert the arrival times into the correct format. The original arrival times had a date column and a time column, but we needed it to start at some time zero and count up by a specified time interval, such as minutes. In order to do this, the date and time columns were combined, then changed to the number format in the spreadsheet, then the numbers were scaled to be in terms of minutes, then the data was offset by the first data point and finally, the difference between each arrival was calculated to get the interarrival times in minutes. Each of these steps were repeated for the small part arrival times too.

After the data was formatted correctly, a text file was created for each part size. From there, the Input Analyzer was ready to be used. Each file was read into the Input Analyzer and the Fit All feature was used to calculate the estimated distribution for the simulation. The result for the big parts was an exponential distribution with the expression -0.001 + EXPO(47.8) and squared error 0.000147. The result for the small parts was a weibull distribution with the expression -0.001 + WEIB(64.2, 0.289) and squared error 0.002359. Our team was satisfied with the low squared error meaning that the distribution is very similar to the data. Although we felt like the distribution was good enough for our simulation, it was not optimal. According to the KS test, both distributions resulted in p-values less than 0.01. This means that the data point that is the furthest distance away from the distribution is statistically different than expected for both cases. Although the KS test shows evidence against the estimated distributions, we know that this test only takes into account the data point with the most error and due to the complexity of the arrival times, we think that this result was only to be expected. We are confident that the low squared error shows that the estimated distributions are close enough for this project.

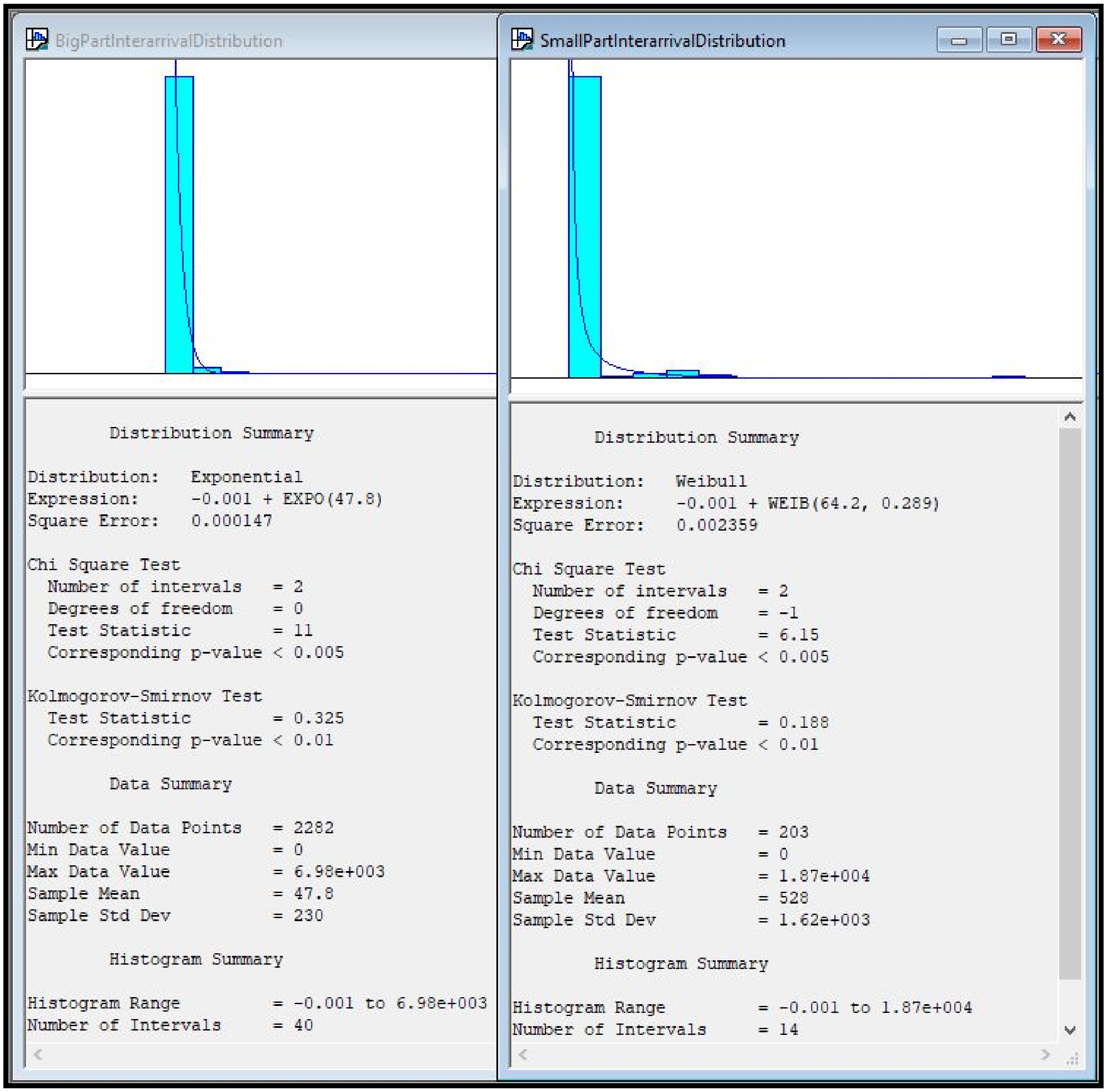


Figure 2. Input Analyzer results for the big and small part interarrivals

3.0 Conceptual Logic & Arena Overview

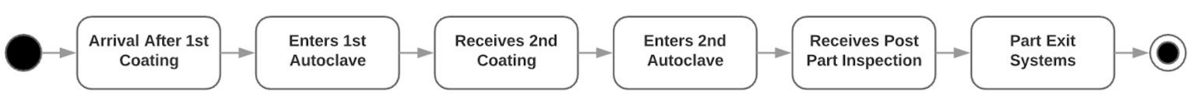


Figure 3: Activity Diagram for Modelled Process

3.1 Walkthrough

This models shows and models the flow of parts after the first coat. The team is modeling after the first coat application because this is the data that was available and the main problem lies in the utilization of the autoclaves and the processes that are not the coat application. The arena model is broken up into the following sections modeling the flow of parts through the UTC Aerospace facility:

- Arrival of small and large parts after first coating
- Batching the parts and baking them in the respective autoclave
- Transport of parts back for second coat
- Second coat application
- Second batch and bake in respective autoclave
- Final inspection
- Exit from system

The system begins with the arrival of parts. Here there are two arrival modules that each have an arrival rate based on either the large or small parts data from UTC. There are two record modules following each of the arrival modules to count how many of each part are entering the system. The use of routes and stations is prevalent in the model so the model may not seem as linear as it is. Following the arrival of the parts and their count, the part travels to the batching of the parts and into the autoclave. An attribute is assigned to differentiate first coated parts from final coated parts in the autoclaves and post autoclave. Then a decide module is used to send the part to the respective autoclave. The small autoclave can service two parts, while the large autoclave services eight parts simultaneously. Thus in batching the parts there must be at least two parts and then this batch continues into the queue for the autoclave, then into the autoclave itself. The small autoclave has a constant bake time of four hours, while the large autoclave uses the DISC(0.75, 8, 1.0, 12) expression to model that 75% of the recipe cook times are 8 hours, while 25% of the recipe cook times are 12 hours. This is treated as a seize, delay, release as the part is within the autoclave during the process and cannot leave until the time is completed. Following the autoclaves, a decide module separates the batches based on their coat (first or final). Sending to either the first coat going to final coat or the final coat going to inspection. The first coat going to second coat path then uses a decision module to split large and small parts. The large and small parts are transported and this time is transported into the route module. They then go to the coat application step where the small coat takes 6 hours, while the large is 8 hours. These parts then enter the autoclave path once again, but the attribute for first coat is changed to final coat and a splitter separates the batches into individual parts. The other path at the decide module that splits based on coat is the final coat path, which goes onto the final inspection. Final inspection is separate for large and small parts. The resources for the inspection are shared with the coating process. There is not a rejection or pass for the final inspection, simply a check. The parts then pass through a separator to break the batches into individual parts and then exit the system.

4.0 Verification and Validation

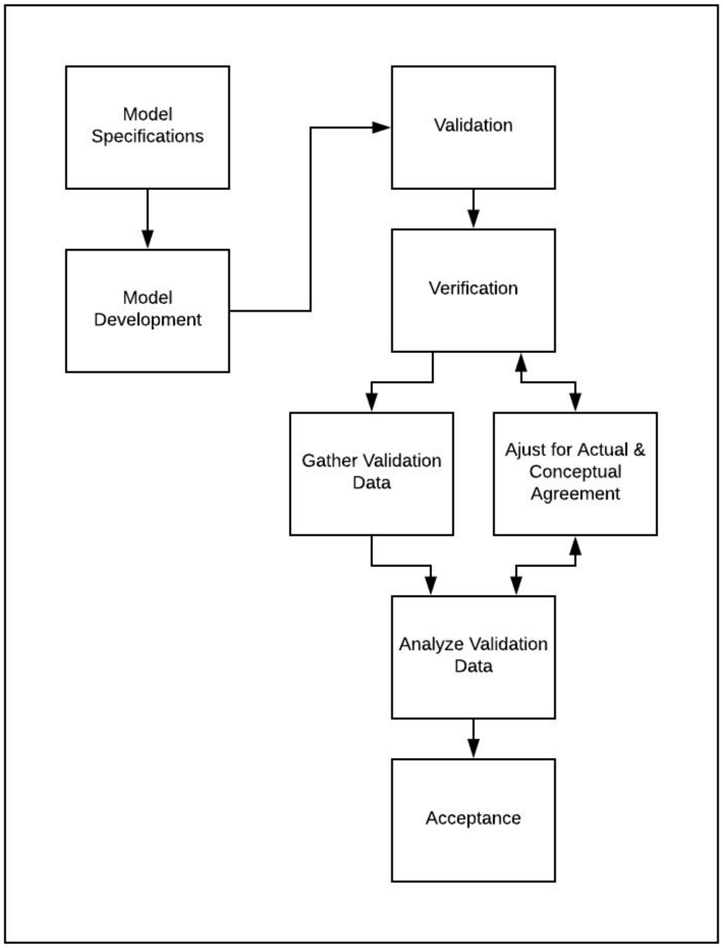


Figure 4: Activity Diagram for Modelled Process

Computerized model verification methods are essential to ensure that proper computer programming and simulation intermediate steps are implemented in the conceptual model to meet the complexity of the actual system being modeled. We reached optimal model correctness by implementing a static and dynamic approach when analyzing the simulation software. In our static approach we analyzed the model by analyzing UTC's Aerospace data provided from an internship co-op. In our dynamic approach we manipulated our established model to accommodate various conditions and properties to determine the correct implementation of the model. By doing a dynamic approach we were able to take note of the effects of inputs and outputs in relation to the different variances.

4.1 Verification

The first step in ensuring our model performed as expected was making sure all of the error messages were taken care of and the modules were providing numbers that were in the ballpark. This problem was encountered after a first attempt at using the arrival data to estimate the interarrival distribution for the system. Instead of using the interarrival times for the Input Analyzer, we put the arrival times and the resulting distribution had a range that was much larger than it should have been. After putting the incorrect estimated interarrival time into our model, we had a small number of arrivals. After testing the input analyzer with test data, we realized the mistake and used the interarrival times for the Input analyzer. The result was that the number of arrivals from the simulation was nearly identical to the actual number of arrivals from our data set.

Another way we verified our model was by going through each module and double-checking each parameter to make sure it reflected the actual system and performed like how we expected it to. We go through and justify each individual module in the Conceptual Logic & ARENA Overview, but for other modules that we were not familiar with, small proof-of-concept experiments were done to make sure they worked. For example, we created a simple ARENA model to test the batch and separate modules. The result of that experiment was that we learned that when a batch of entities enter a process, one resource is required for one batch, not one resource per one entity. We also learned to only temporarily separate the entities in the batch module because we separated them later in the model. The experiment allowed us to figure out the separate module, which was pretty straight forward.

The last verification method we used was animation. By including the Station and Route modules, we were able to incorporate the travel times between each station and animate the model. This made it much easier to visualize our model and identify how the interactions were between the interarrival times, queues and resources. This also allowed us to encompass all of the major sources of time in the system so that later we could validate the results of the model with the actual system.

4.2 Validation

One of the ways we made sure the simulation was an accurate representation of the actual system was by comparing our assumptions to the actual system. This is similar to the walkthrough for each module, but instead of making sure each module performs what we tell it to, we compare the parameters of the modules to the actual system. For example, the actual interarrival times were compared to the estimated interarrival distribution using the squared error and the KS test. From that we know that the distribution is a good fit for the data because both of the squared errors were low (0.000147 and 0.002359). We also know that the estimated distributions were not great in terms of their largest error, but this was to be expected due to the complex nature of the arrival times. Another comparison was between the simulated service and transfer times and the actual service and transfer times. This was simple in our case because the autoclaves heat the parts for specific times so they will generally be well simulated using constant service times. Similarly, the transfer times were very consistent and small compared to the service times, so the simulation performed well when the transfer times were kept constant.

The more critical way we validated our simulation was by comparing the results from the simulation to the actual system as much as possible. For example, the total number of parts that entered the actual model was 2,485. Fortunately, the average total number of parts that entered the model was 2,484.81. This shows an incredible amount of precision for our interarrival times. Similarly, we compared the average total times in the system by part. On average, the large parts spent 30 hours in the system and the small parts spent 27 hours in the system. These results seem to support what we expect from our memory of the actual system. The other way we validated the model was by reading the actual arrival times and comparing those responses to the responses from the model with estimated interarrival times. Again, the results were near identical, giving our team confidence in assuming that our simulation is an accurate model of the actual system. We called this model the base scenario.

Table 4.2.1

Arena model	**In**
large	2319.76
small	165.05
Total (Average)	**2484.81**

Table 4.2.2

Actual Data	**In**
large	2282
small	203
Total	**2485**

** Data that was modeled did not have exit values for small and large parts. Therefore parts exiting system were not displayed.

5.0 Assumptions, Experimentation, and Results

5.1 Assumptions

1. There are only two kinds of parts, small and large parts, that flow through the system.
2. The transfer and service times are constant for the parts not matter the size. The only different from this is that the large parts are 75% 8 hours bake in the autoclave and 25% 12 hours bake.
    a. This was done to better mimic the recipes in the autoclave for different large parts.
3. The arrival data is only from 2.5 months worth of data.
    a. Therefore there may be outliers that could not be seen in this period, but a larger period would be needed.

5.2 Experimentation and Results

After the model for the base scenario was verified and validated, we analyzed the results of the simulation to see where we could optimize the waiting times in the queues. From the category overview report, we noticed that the waiting times for the large parts were virtually zero and the utilization rates for the processes involving the large parts were very low. This meant that the large parts did not wait to be put inside an autoclave or to get a second coat or to be inspected. Similarly, the resources for all of these processes were not very busy. This meant that there was room for improvement in the system by decreasing the capacity for the processes involved with the large parts which would improve the utilization of the resources.

In order to test this, the Process Analyzer was used to run the model for different scenarios to find the capacity combination with the best results. The controls for the Process Analyzer included all four of the resources in our model (large autoclaves, small autoclaves, large part coaters/inspectors and small part coaters/inspectors). Even though we were only interested in changing the capacity for the resources involved with the large parts, we included the ones for the small parts as well just to monitor the full picture in terms of the capacity allocation. For the responses, we kept track of the average time in the system, average waiting time, average time in each of the queues, and utilization rates for each of the resources. From this setup, we could monitor what each scenario's capacity consisted of, the effect on the total waiting time, the effect on each waiting time in the queues and the effect on the resource utilization.

The first scenario consisted of the base scenario with 100 replications. From there, the capacity of the large resource was decreased by one until the limit of that single parameter was reached. It turns out that the model would not run when the capacity was set below 4 autoclaves. We believe this result is due to the limitations of the student version of the ARENA Software. As the resources are being utilized more, more entities remain in progress and the student version of ARENA only allows 150 entities at one time to be in the system. Even though we were limited by the simulation software, we believe we have enough results to make a recommendation for this system (see section 6.0). After we reached the limit for the autoclave resource, we did the same thing with the coater/inspector resource by keeping the other parameters constant and only changing the one as much as possible. Again, we were not able to run the replication when the capacity went below 2 teams (of 3 people), or 6 resources. From there, we kept the number of teams at its limit and lowered the number of autoclaves until we hit the limit again. The optimal result was having two teams or 6 resources for the coater/inspector and 4 autoclaves. This was the limit that we were able to utilize the resources for the large parts as much as possible.

	Scenario Properties				Controls				Responses													
	S	Name	Program File	Reps	Large Coating	Small Coating Resource	Large Resource	Small Resource	Large Part.TotalTim	Small Part.TotalTim	Large Part.WaitTim	Small Part.WaitTime	Group Large Parts.Queue.	Group Small Parts.Queue.	Apply Second	Apply Second	Final Inspection	Final Inspection	Large Coating	Small Coating Resource.Util	Large Resource.Utili	Small Resource
1		Scenario 0	1 : 431Proj_1	100	21.0000	6.0000	7.0000	2.0000	30.552	27.386	2.790	12.098	1.400	2.954	0.000	1.071	0.000	0.844	0.185	0.136	0.400	0.177
2		Scenario 1	1 : 431Proj_1	100	21.0000	6.0000	6.0000	2.0000	30.552	27.369	2.791	12.082	1.401	2.988	0.000	1.055	0.000	0.837	0.185	0.136	0.467	0.177
3		Scenario 2	1 : 431Proj_1	100	21.0000	6.0000	5.0000	2.0000	30.563	27.907	2.818	12.615	1.404	3.358	0.000	1.048	0.000	0.818	0.185	0.139	0.560	0.181
4		Scenario 3	1 : 431Proj_1	100	21.0000	6.0000	4.0000	2.0000	30.825	27.935	3.083	12.643	1.404	3.396	0.000	1.026	0.000	0.802	0.185	0.149	0.699	0.194
5		Scenario 4	1 : 431Proj_1	0	21.0000	6.0000	3.0000	2.0000	---	---	---	---	---	---	---	---	---	---	---	---	---	---
6		Scenario 5	1 : 431Proj_1	0	21.0000	6.0000	2.0000	2.0000	---	---	---	---	---	---	---	---	---	---	---	---	---	---
7		Scenario 6	1 : 431Proj_1	0	21.0000	6.0000	1.0000	2.0000	---	---	---	---	---	---	---	---	---	---	---	---	---	---
8		Scenario 7	1 : 431Proj_1	0	21.0000	6.0000	8.0000	2.0000	---	---	---	---	---	---	---	---	---	---	---	---	---	---
9		Scenario 8	1 : 431Proj_1	0	21.0000	6.0000	9.0000	2.0000	---	---	---	---	---	---	---	---	---	---	---	---	---	---
10		Scenario 9	1 : 431Proj_1	0	21.0000	6.0000	10.0000	2.0000	---	---	---	---	---	---	---	---	---	---	---	---	---	---
11		Scenario 0	1 : 431Proj_1	0	21.0000	6.0000	7.0000	2.0000	---	---	---	---	---	---	---	---	---	---	---	---	---	---
12		Scenario 11	1 : 431Proj_1	100	18.0000	6.0000	7.0000	2.0000	30.552	27.386	2.790	12.098	1.400	2.954	0.000	1.071	0.000	0.844	0.216	0.136	0.400	0.177
13		Scenario 12	1 : 431Proj_1	100	15.0000	6.0000	7.0000	2.0000	30.552	27.386	2.790	12.098	1.400	2.954	0.000	1.071	0.000	0.844	0.259	0.136	0.400	0.177
14		Scenario 13	1 : 431Proj_1	100	12.0000	6.0000	7.0000	2.0000	30.552	27.419	2.791	12.134	1.401	2.992	0.000	1.063	0.000	0.836	0.324	0.136	0.400	0.176
15		Scenario 14	1 : 431Proj_1	100	9.0000	6.0000	7.0000	2.0000	30.569	28.074	2.838	12.781	1.400	3.240	0.011	1.104	0.036	0.846	0.431	0.136	0.399	0.177
16		Scenario 15	1 : 431Proj_1	100	6.0000	6.0000	7.0000	2.0000	31.697	26.929	3.949	11.626	1.402	2.581	0.331	1.122	0.828	0.872	0.647	0.150	0.400	0.195
17		Scenario 16	1 : 431Proj_1	0	3.0000	6.0000	7.0000	2.0000	---	---	---	---	---	---	---	---	---	---	---	---	---	---
18		Scenario 0	1 : 431Proj_1	0	4.0000	6.0000	7.0000	2.0000	---	---	---	---	---	---	---	---	---	---	---	---	---	---
19		Scenario 0	1 : 431Proj_1	0	5.0000	6.0000	7.0000	2.0000	---	---	---	---	---	---	---	---	---	---	---	---	---	---
20		Scenario 0	1 : 431Proj_1	100	6.0000	6.0000	7.0000	2.0000	31.697	26.929	3.949	11.626	1.402	2.581	0.331	1.122	0.828	0.872	0.647	0.150	0.400	0.195
21		Scenario 0	1 : 431Proj_1	100	6.0000	6.0000	6.0000	2.0000	31.688	26.906	3.948	11.602	1.402	2.591	0.329	1.115	0.827	0.866	0.647	0.149	0.466	0.193
22		Scenario 0	1 : 431Proj_1	100	6.0000	6.0000	5.0000	2.0000	31.682	26.622	3.961	11.327	1.405	2.570	0.325	1.076	0.830	0.846	0.646	0.150	0.558	0.194
23		Scenario 0	1 : 431Proj_1	100	6.0000	6.0000	4.0000	2.0000	31.831	26.087	4.088	10.779	1.406	2.576	0.271	1.002	0.787	0.801	0.646	0.156	0.698	0.202
24		Scenario 0	1 : 431Proj_1	0	6.0000	6.0000	3.0000	2.0000	---	---	---	---	---	---	---	---	---	---	---	---	---	---

Figure 5. Experimentation of different capacities using Process Analyzer

Table 5.2.1 - Utilization of resources (scenario 0 vs number 23)

Utilization				
Scenario/Section	Large Coating	Small Coating	Large Resource (Autoclave)	Small Resource (Autoclave)
Base	0.185	0.136	0.400	0.177
Recommended	0.646	0.156	0.698	0.202

Table 5.2.2 - Time values of different scenarios (scenario 0 vs number 23)

Times through system				
[hours]	Base Scenario		Recommended Scenario	
Part	Wait time	Total Time	Wait Time	Total Time
Small	12.098	27.386	10.779	26.087
Large	2.790	30.552	4.088	31.831

6.0 Recommendation

As mentioned in the previous section, the limitations of the student version of ARENA have somewhat limited our recommendation. Although we may not be able to provide the best recommendation possible, we still have enough results to make a significant improvement to the system. The base scenario contained 7 large autoclaves and 7 teams of 3 people applying the second coat or doing the final inspection. From our experimentation, the recommended scenario contains two teams of 3 people applying the second coat or doing the final inspection and only 4 large autoclaves. After reaching this scenario, we used the Output Analyzer to show the statistical significance of the results. The first response is for the average total time in the system for the large part. From figure 6 we see that the 95% confidence intervals are mutually exclusive, so the increase in the recommended scenario is statistically verified at this level of significance. Even though there is a significant increase in the total time in the system, it only changed from 30.6 hours to 31.8 hours. We believe this small change in the total time in the system is worth the increase in resource utilization that will be seen later.

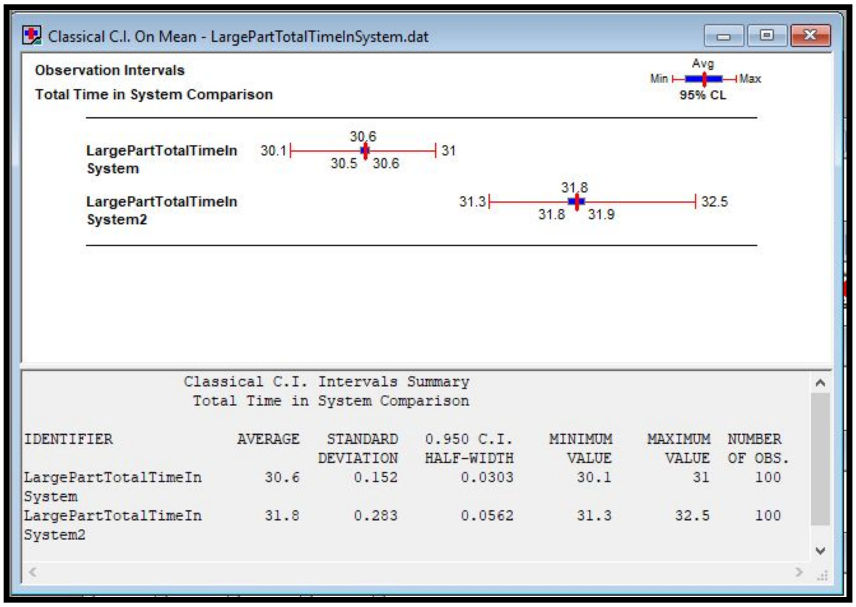


Figure 6. Average Total Time in the System Comparison of base scenario and recommendation

Similar to the Average total time in the system, the average waiting time in the system was the more direct response that we were affecting with our recommendation. From figure 7 we see that the difference is much larger than the average total time in the system going from 2.79 hours to 4.09 hours. This makes sense because our service times are constant and do not change from the base scenario to the recommended scenario, so the changes in the average total time in the system are coming from the average waiting time in the system. Again, even though the waiting times for the queues are going up, we still recommend decreasing the capacity for the large part resources.

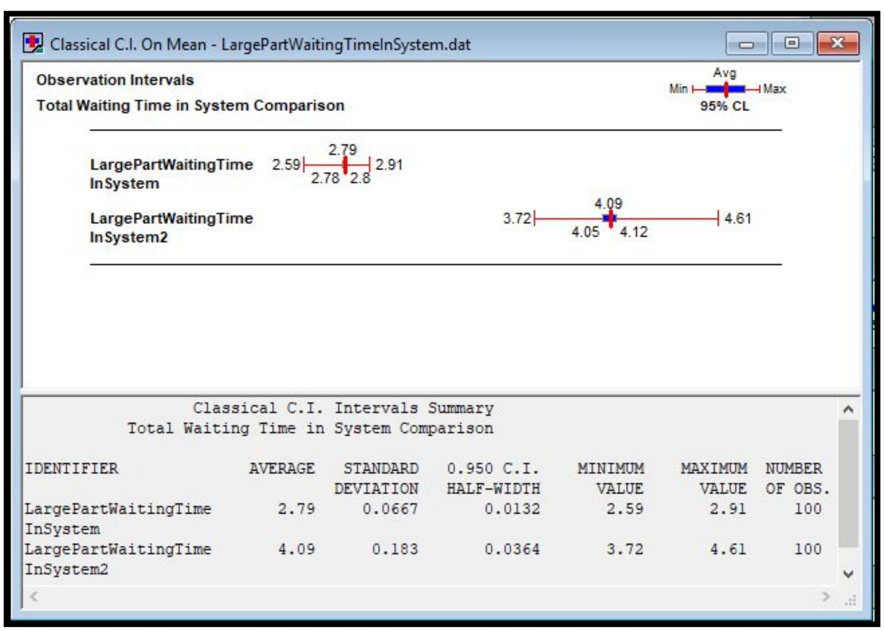
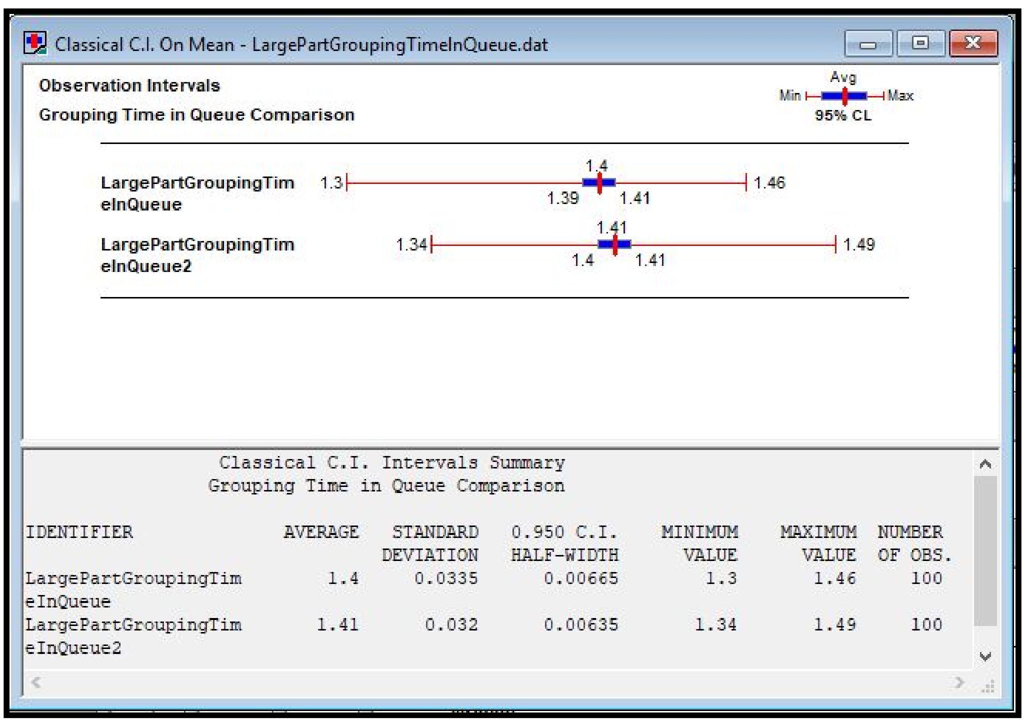


Figure 7. Waiting Time in the System Comparison of base scenario and recommendation

After seeing the increase in the average waiting time in the system, it is helpful to see which queues are experiencing these changes. From figure 8, we see that the queue for grouping the large parts does not show a statistically significant change. This makes sense because changing the resource capacity does not directly affect the batch size or the big part arrival rate so it should stay about the same. The next queue is waiting to apply the second coat for the large parts. From figure 9, we see how the queue goes from not being used to being used on average 0.271 hours. This is good because we have passed the point where the full capacity for the second coat/inspection station is being utilized. If the ARENA application allowed us to further decrease the capacity we would have an even bigger queue here, but the utilization of the resources would have been better too. Similarly, the average waiting time for the inspection queue goes from never having a queue to waiting 0.787 hours per large part (see figure 10). This makes sense because both queues for the application of the second coat and the inspection use the same resources and if all of the resources are in use then both queues will be affected. The last responses we looked at were for the resource utilization. From figures 11 and 12, we see a huge increase in utilization. The autoclave utilization went from 0.4 to 0.698 and the second coat/inspection utilization went from 0.185 to 0.646. This huge increase in utilization for both the autoclave and second coat/inspection resource while only slightly increasing the waiting times in the queues is the main reason why we recommend this scenario over the base scenario.



IDENTIFIER	AVERAGE	STANDARD DEVIATION	0.950 C.I. HALF-WIDTH	MINIMUM VALUE	MAXIMUM VALUE	NUMBER OF OBS.
LargePartGroupingTimeInQueue	1.4	0.0335	0.00665	1.3	1.46	100
LargePartGroupingTimeInQueue2	1.41	0.032	0.00635	1.34	1.49	100

Figure 8. Grouping Time in Queue Comparison of base scenario and recommendation

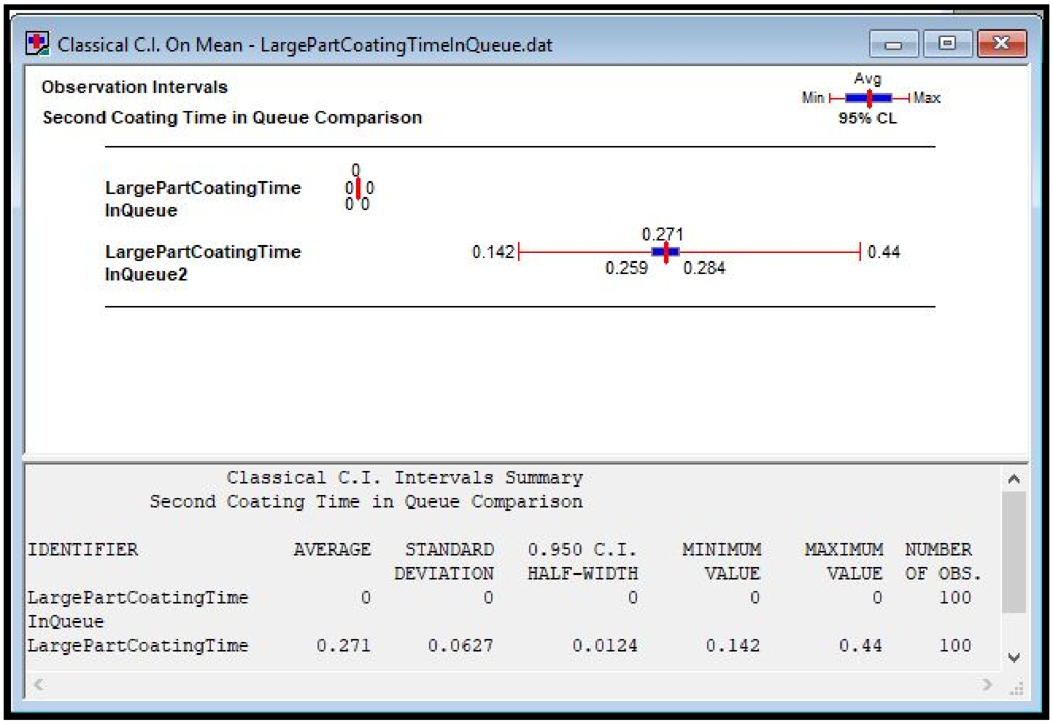


Figure 9. Second Coat Time in Queue Comparison of base scenario and recommendation

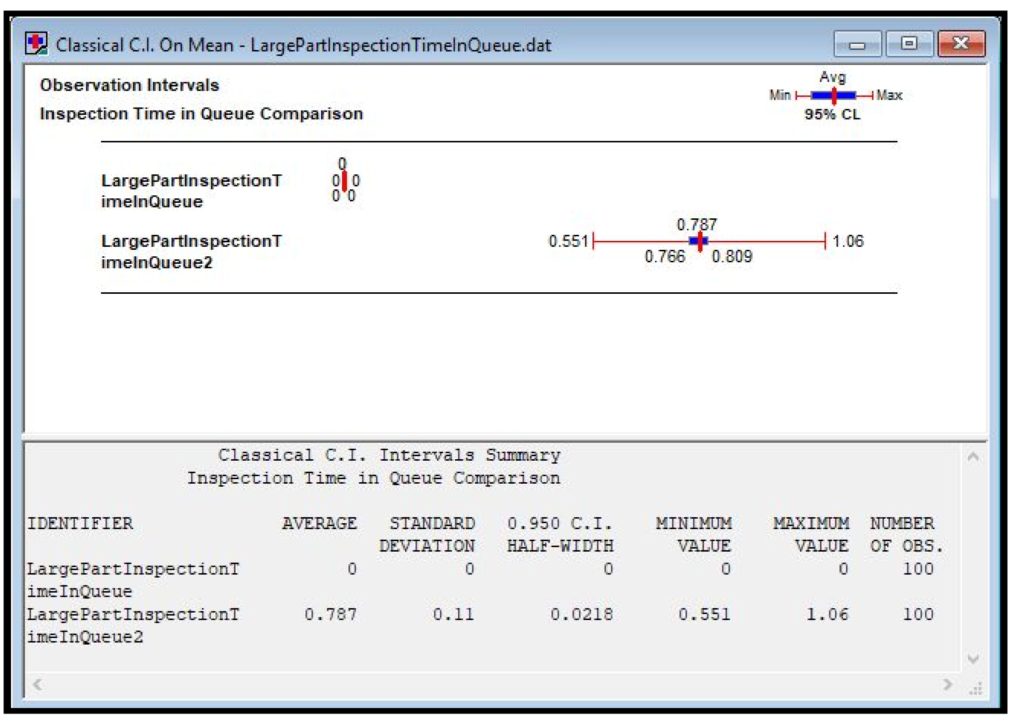
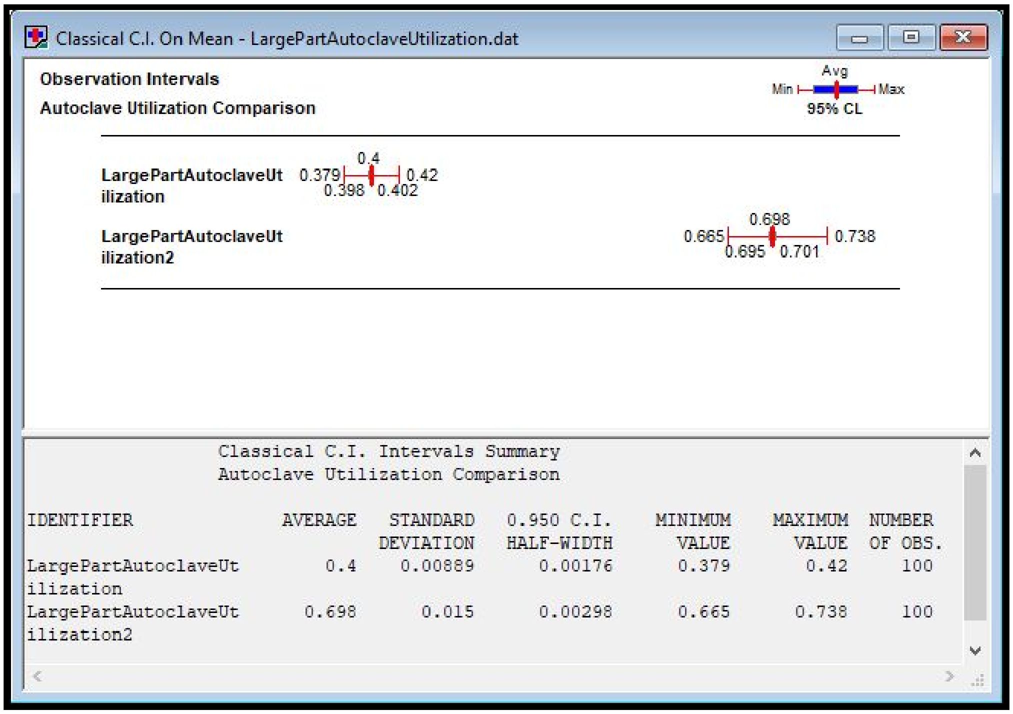
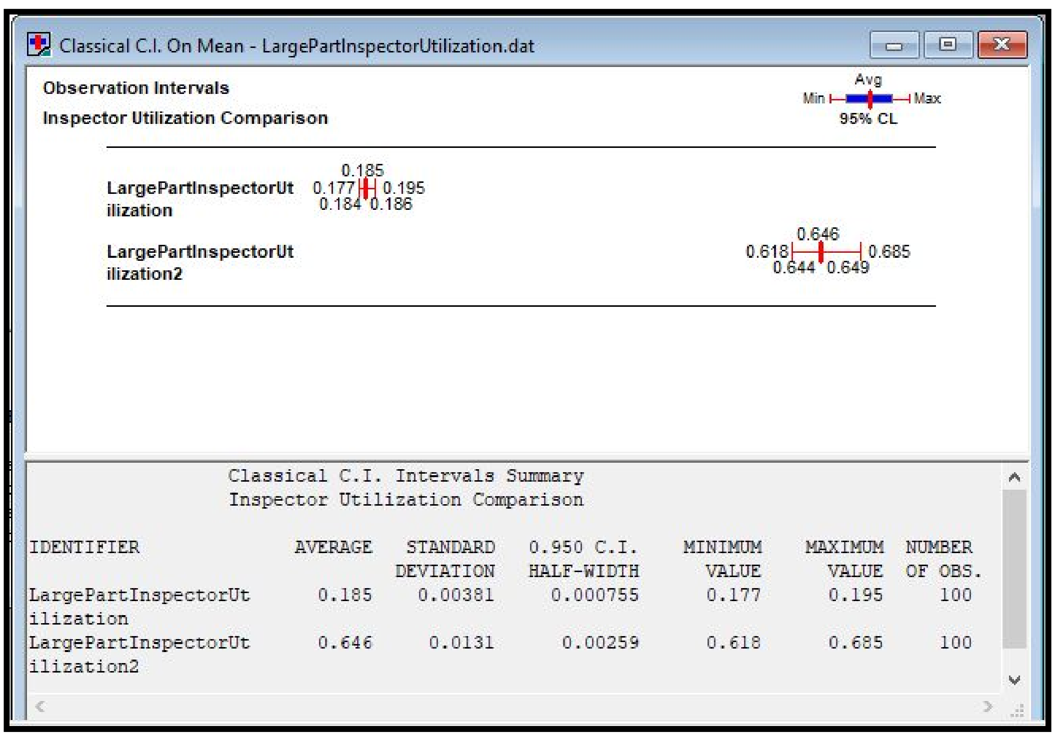


Figure 10. Inspection Time in Queue Comparison of base scenario and recommendation



IDENTIFIER	AVERAGE	STANDARD DEVIATION	0.950 C.I. HALF-WIDTH	MINIMUM VALUE	MAXIMUM VALUE	NUMBER OF OBS.
LargePartAutoclaveUtilization	0.4	0.00889	0.00176	0.379	0.42	100
LargePartAutoclaveUtilization2	0.698	0.015	0.00298	0.665	0.738	100

Figure 11. Autoclave Utilization Comparison of base scenario and recommendation



IDENTIFIER	AVERAGE	STANDARD DEVIATION	0.950 C.I. HALF-WIDTH	MINIMUM VALUE	MAXIMUM VALUE	NUMBER OF OBS.
LargePartInspectorUtilization	0.185	0.00381	0.000755	0.177	0.195	100
LargePartInspectorUtilization2	0.646	0.0131	0.00259	0.618	0.685	100

Figure 12. Coater/Inspector Utilization Comparison of base scenario and recommendation

7.0 Summary and Conclusion

Modeling and Simulations are an integral part of the development process early on in the engineering life cycle, by optimizing early on you can explore the design trade space and make appropriate design decisions in conjunction with testing and analysis to make the system perform as intended. The goal of this project was to find solutions to mitigate the issue of backed up parts near the autoclaves. The solutions was to increase utilization of the autoclaves. The recommended scenario contains two teams of 3 people applying the second coat or doing the final inspection and only 4 large autoclaves, while the current staffing is 7 large autoclaves and 7 teams of 3 people applying the second coat or doing the final inspection. The utilization was increased dramatically for the large parts and slightly increased for the small parts, as can be seen in table 5.2.1. The optimal scenario increased the total time by about one hour for the large, but cut the time for the small by about the same as can be seen in table 5.2.2. This may be unwanted as there is a magnitude difference in the number of large parts to small parts, but the utilization for the large was the true goal, not the total time.

On the topic of assumptions, all of the assumptions were reasonable and did not skew the results from what could be seen. More in depth analysis would be required to understand how the assumptions would skew the results, but the data very closely mimics the actual data arrival number to the ARENA arrival total number. This shows that the input to the model was very close and accurate, validating the assumption. The assumption for the 75%/25% 8/12 hours large autoclave service time was also rationale as it dealt with a more true value for the large parts as there had been different recipes for the large parts. The last assumption is that the model working with 2.5 months of data would mimic the true day to day operation of the UTC facility. This is unknown because of the limited amount of data available. The day to day operations may be similar to the ARENA model, but over longer periods of time outliers may not be incorporated as situations may occur that the model was not designed around, thus creating delays or other issues.