SYSC 4005 A

Winter 2023

Project Deliverable #3

Completed By:

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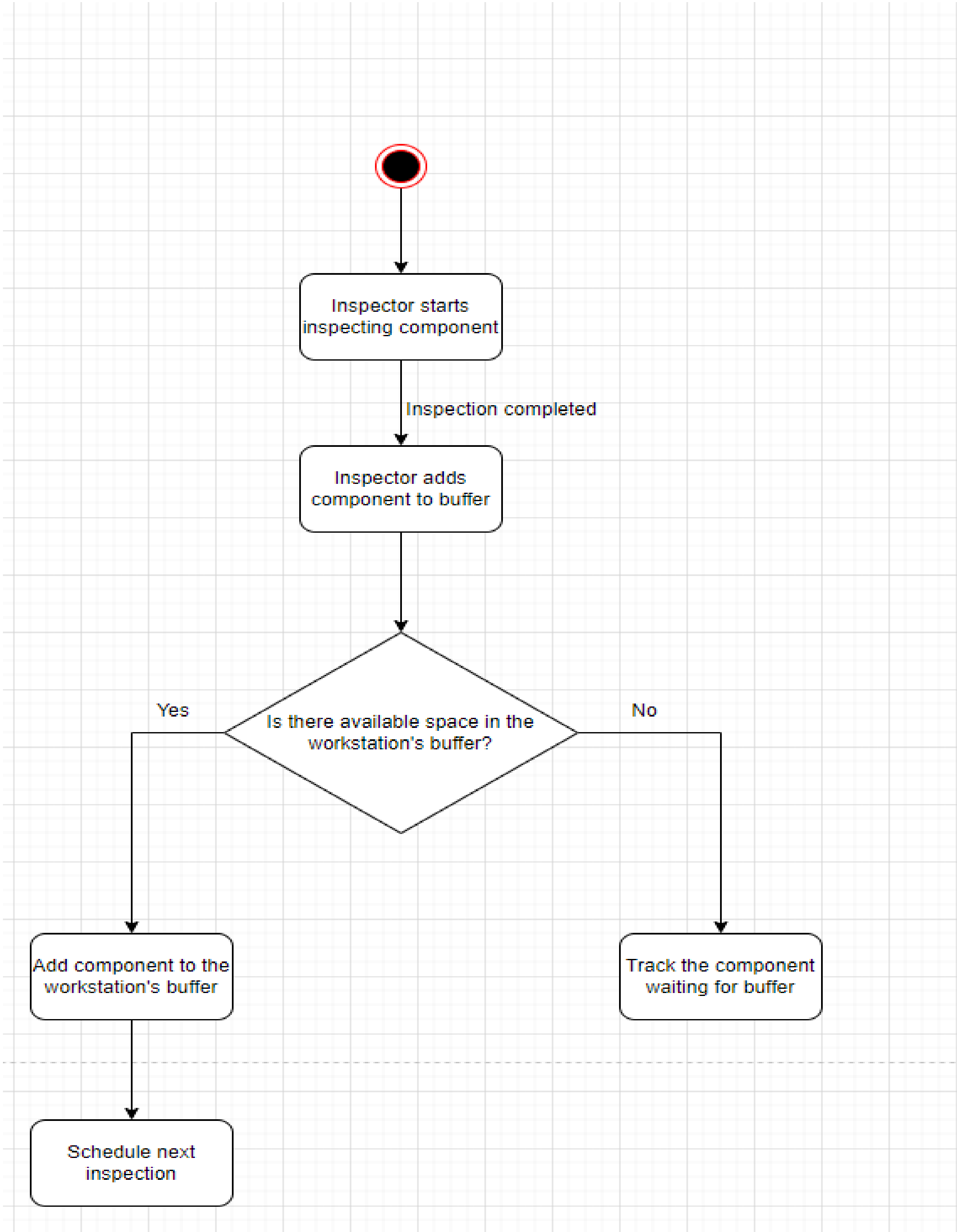
1. Verification

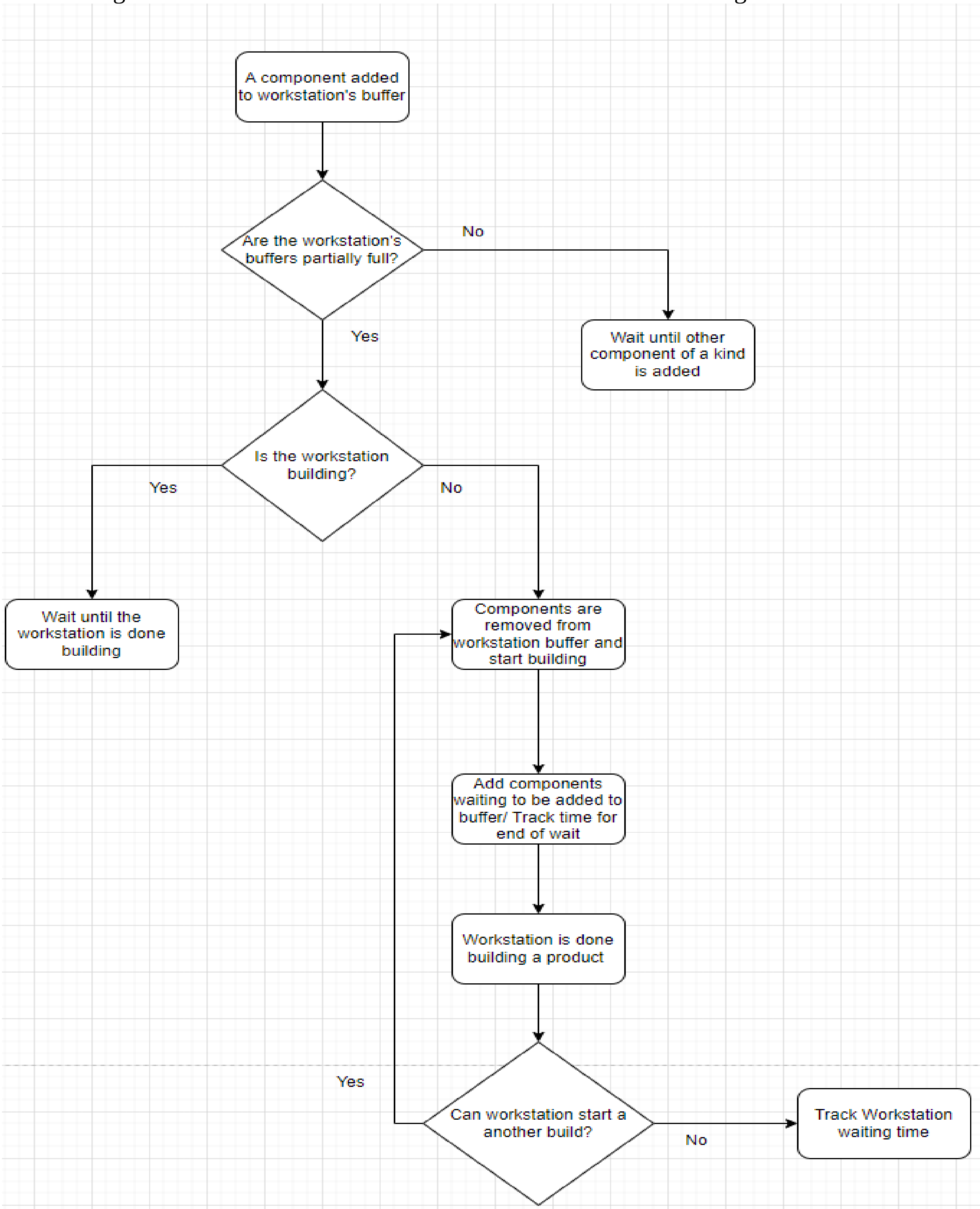
Model verification was done to ensure the conceptual model is reflected accurately in the operational model. This is to verify that the simulation is operating as intended. The conceptual model and operational model will be independently verified to ensure that the model accurately represents the manufacturing process described in the project description.

The first verification technique is having the model reviewed independently. This was accomplished by having each team member verify that the model was implemented correctly in the python code by reviewing the parts written by other team members. This helped to eliminate any discrepancies while developing the model.

To verify the conceptual model, a flowchart has been created to show how future simulation events shall be generated based on the initial events, and this flowchart can be found below. The figure below shows the flow of execution on the side of the inspector:


Inspector starts inspecting component
Inspection completed
Inspector adds component to buffer
Is there available space in the workstation's buffer?
Yes
No
Add component to the workstation's buffer
Track the component waiting for buffer
Schedule next inspection

The next figure below shows the flow of execution of the workstation logic of the simulation:



Once the flowchart's process, assumptions, abstractions, simplifications, and parameters are conceptually verified, we shall proceed to the operational model verification process. This was done by running the simulation and analyzing the line-by-line execution of event handling to make sure that the progression of the simulation program is consistent with the conceptual model flow chart.

2. Validation

The process of validating a simulation model involves comparing the model outputs to real-life observations. This determines if the model is a consistent and accurate representation of the real system. The project models a manufacturing facility, with the given collections of sets of historical data for component inspection and product build times, it can be assumed that the manufacturing facility can be used to obtain a historical dataset that corresponds with the output variables of interest in the simulation model.

A group of simulation generated output variables can be used to calculate a simulation mean & standard deviation given the reported real values for the desired output variables. In order to match the output variables' confidence intervals to the measured values, this is done. The model can be approved if the computed confidence range from the simulation contains the observed value and the worst-case error is less than or equal to the epsilon error level. More simulation replications will be needed to reach a determination if the worst-case error is higher than the epsilon error cutoff value with the confidence interval comprising the real value.

Since the actual version of the manufacturing process detailed in this project is hypothetical, there is currently no way to know the actual observed values of the output variables, thus the above method of using simulation confidence intervals to reach a validation conclusion will only be partially possible. The simulation output variable confidence intervals will still be generated, but the validation will be done by ensuring that the output variables are reasonably close to each other between different simulation runs. This will ensure the output variables are reasonably accurate and accessing it could be deferred to a later task when the actual output variables are known. Given a confidence interval of the simulation output parameters, the width can provide insight into what epsilon error threshold values can lead to accepting the model's implementation. The confidence intervals for the simulation's output variables with the standard operating policy can be found in the below section comparing the standard and alternate operating policies.

3. Production Runs and Analysis

Following the assumption that the implementation of the simulation has been verified and validated, we can then proceed to run multiple simulation replications so that confidence intervals for the output.

Number of Replicants:

To determine the appropriate number of replications, after 100 replications for each component, the means and standard deviations of the waiting times were determined for each component and the following equation was used to estimate the ideal number of replications, R for this simulation.

$$R \geq \left(\frac{z_{\alpha/2} S_0}{\epsilon} \right)^2$$

Where R is the number of replications, z is the z-value at alpha divided by 2, alpha is 0.05, So is the standard deviation of the data and epsilon is the error threshold of the data. This equation was applied to the mean and standard deviation of the blocked times of the simulation and given a 10% error value. It was concluded that the maximum replication value needed for this simulation has an estimated value of 632.

Initialization Phase:

While initializing a simulation, there may be a bias as a result of the initial conditions of the simulation being an unreliable representation of the model's actualities. To mitigate this bias, the simulation is divided into an initialization phase and a data collection phase. Data is not gathered during the initialization process, which is when the simulation can build up to the regular operation. Data gathering can be relied upon to start once the process has ramped up to steady-state circumstances. To implement this initialization phase, an event could be handled at the precise moment the initialization phase ends and the production phase begins to reset all of the output variables and exclude all events that occurred during the initialization phase from consideration for any subsequent adjustments.

As the duration of each simulation repetition grows, the effect of initialization bias on the output variables becomes less important, it was determined that for this project the effort and time funding needed to execute such a system would have limited value. Currently, a single simulation replication stops after 50,000 products are made, and given that the maximum difference between the initial condition of 5 empty buffers and the max capacity condition of 10 items across all buffers is very small by comparison. The initialization period was deemed unnecessary for the simulation.This design decision might result in wider confidence intervals for the output variables due to a higher degree of output variable variance, but the breadth of the confidence interval can be decreased by raising the number of replications.

Confidence Interval:

We evaluated the length of the initialization phase and the number of replications needed to achieve 95% confidence intervals with widths that did not exceed 20% of the predicted values in to determine the steady-state estimations of the variables of interest. After that, we carried out the production runs and determined the 95% confidence interval for the desired attributes.