PURDUE UNIVERSITY | The Data Mine

PROCESS FLOW INTERCONNECTION TOOL

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TESLA

INTRODUCTION

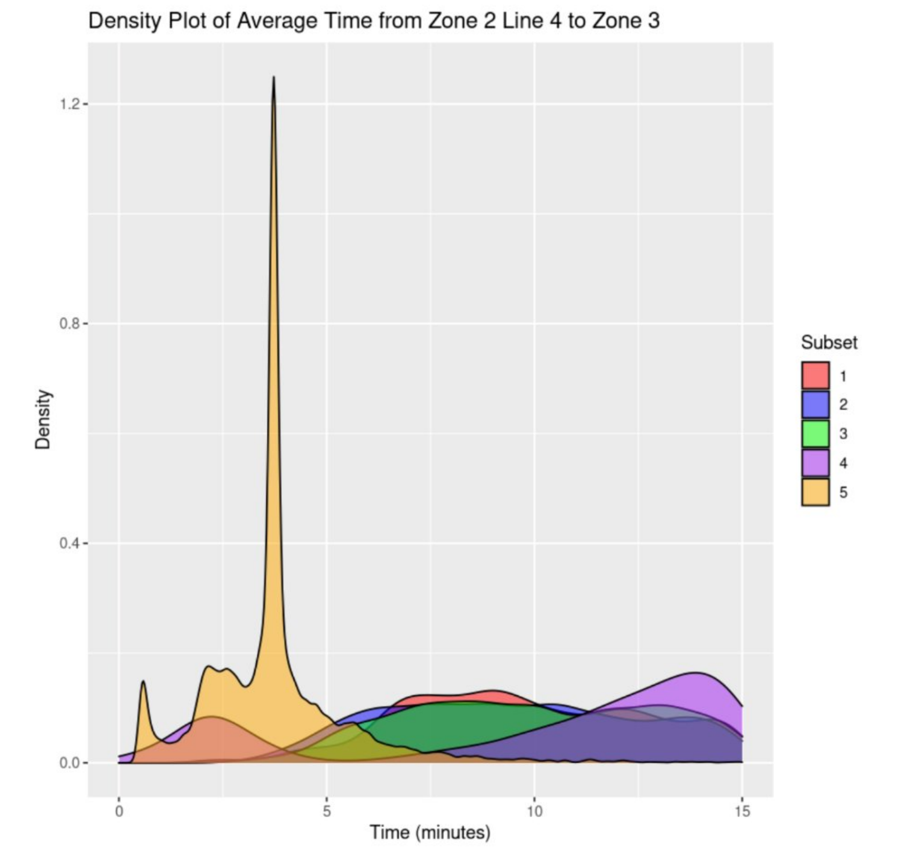
This project was proposed to develop a Process Flow Interconnection Tool, and the impact for Tesla will be the ability to forecast downtime opportunities based on the line conditions. We are tasked to create and manage the process flow using the manufacturing operations system database. In the first semester, we determined the flow rate of parts from the individual production stations and analyzed visualizations. This semester, we aim to discover various starvations and blockage scenarios across all production stations. Our project aims to identify potential areas of improvement, which allows Tesla to further enhance its operational efficiency by minimizing bottlenecks and optimizing resources throughout various stations.

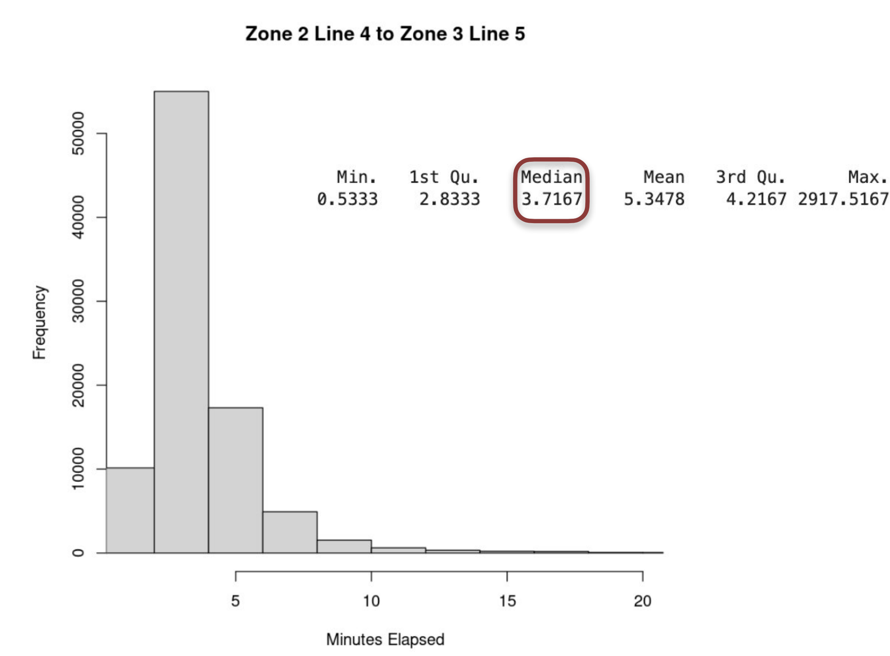
ANALYSIS

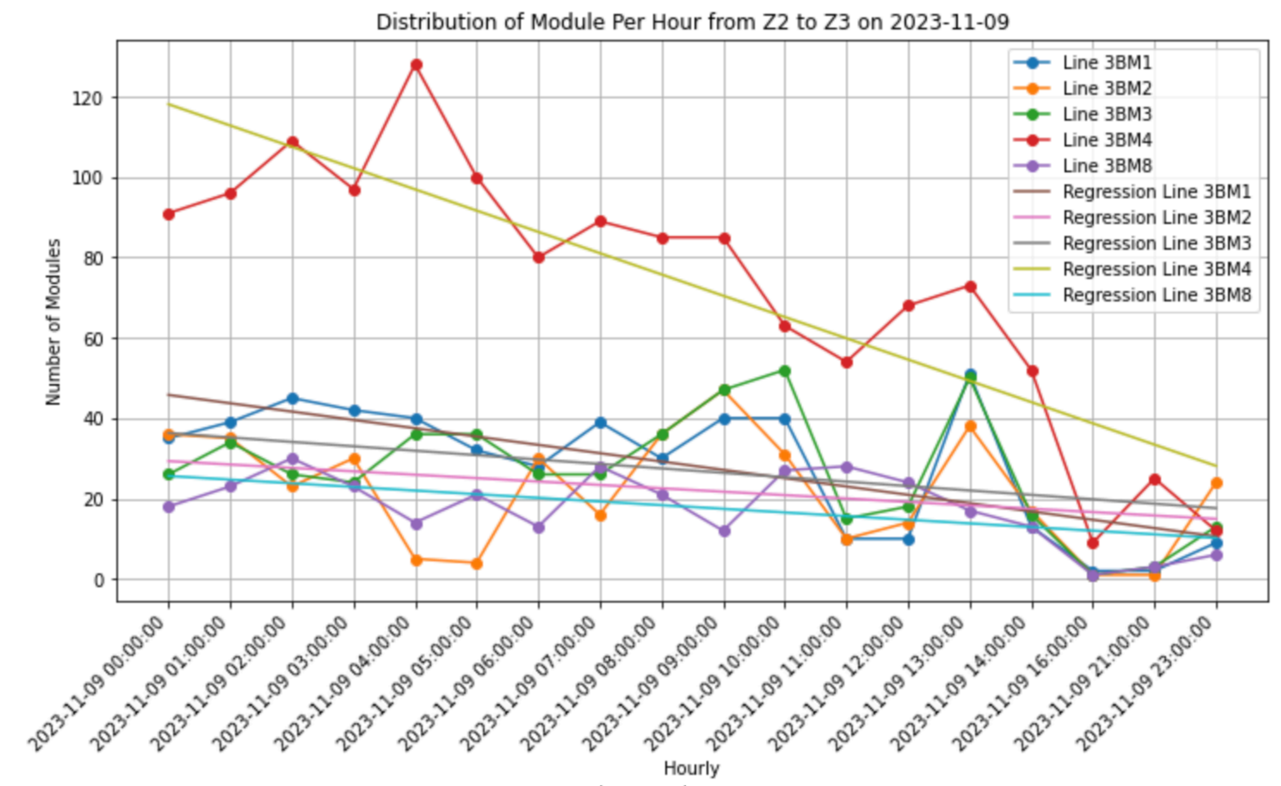
Starvation occurs when a downstream activity is idle with no inputs to process because of upstream delays. Blocking occurs when an activity becomes idle because the next downstream activity is not ready to take it. Further external factors resulting in delays in transition times have to be considered which might result in possible delays. Based on the team's original dataset available, Zone 2 Line 4 to Zone 3 Line 5 has the best transition time ~3.7 minutes

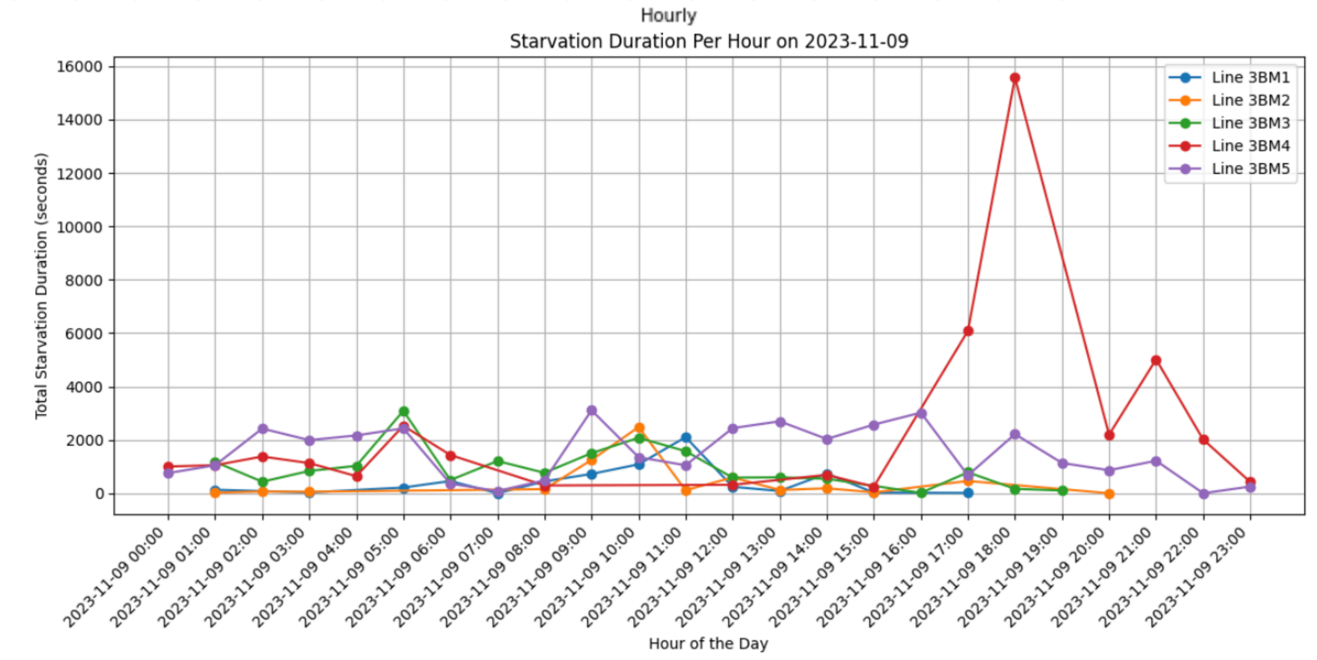
- Zone 2 Line 123 performed the best overall, because Zone 3 Lines 1, 2, 3, and 5 averaged around 7 minutes
- Combination with Line 4 always had highest transition time due to the physical location of the line in factory layout

In addition, we have found that the relationship between the volume of modules per hour and the starved time (by hour) is inversely related, which means that when the volume decreases at a certain point in the day, the starved time increases and vice versa. In addition, when we performed statistical linear regression on our dataset, we also found a negative slope on the line-of-best-fit for each line in Zone 2 to 3, which verified our observations on the two inverse relationships.







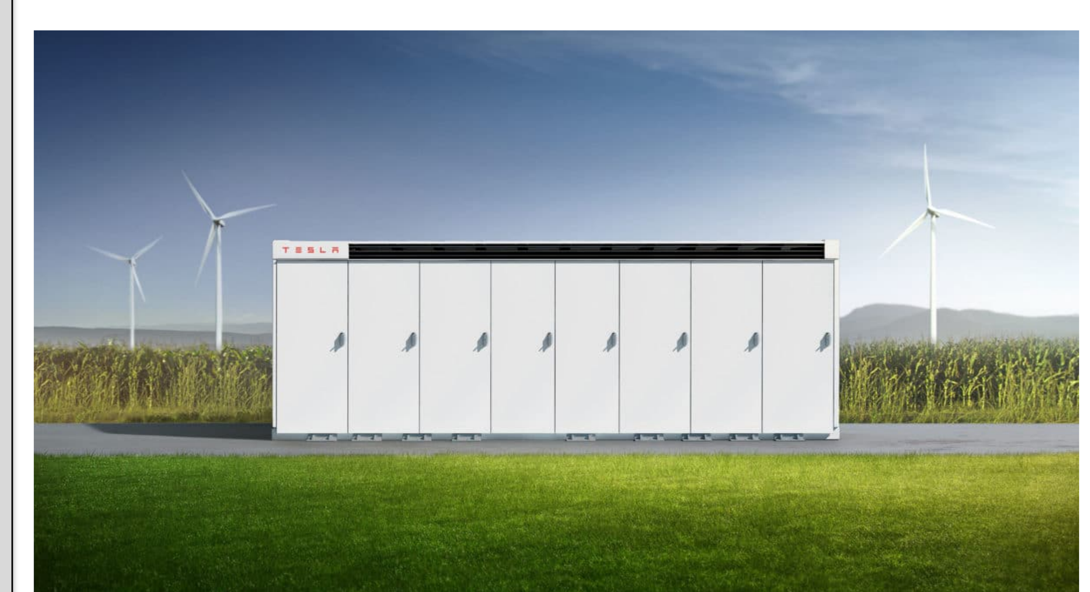


METHODOLOGY

The team was provided with numerical datasets in the fall semester, each with over 800,000 data points that helped the team draw conclusions on transition times on different line combinations. In the spring semester, the team was given a few more datasets with the overall starved times and the total modules produced in a set period of time.

Using R, and Python on Anvil, the team was able to clean out the invalid data entry points (which included missing values and errors present in a few entries). This helped clean out the data in order to perform our analysis more thoroughly.

The team used Statistical Tests, and Data Visualizations in order to draw conclusions based on our prompt, which was to understand transition time between different zone – line combinations to find the optimal pair. Using histograms, boxplots, density plots and statistical summaries, our team was able to find that Zone 2 Line 4 to Zone 3 Line 5 had the best transition time. We also found that the relationship between the volume of modules per hour and the starved time (by hour) is inversely related. Some of the limitations that need to be considered was the irregularities and outliers in the data that made it hard to plot the data. As well as the difficulties in understanding of factory layout to exactly depict the viable combinations to be considered



CONCLUSION & FUTURE GOALS

After analyzing data on modules per hour and starvation duration for parts, we gained a better understanding of how to forecast future module outputs and potential bottlenecks, wherever they may occur. We reached our goal of being able to identify where things could be improved and by how much. Furthermore, through numerous data visualizations, we were able to make sense of trends, extrapolate meaningful conclusions in the dataset, and see how and why they may occur given the layout of the Tesla Gigafactory.

Our future goal is to explore other factors that may delay processing time, such as blocked scenarios. Blocking occurs when an activity becomes idle because the next downstream activity is not ready to take it, and we would like to predict processing times even when specific lines undergo blocked situations. This specific strategy is to help overcome more potential bottlenecks that occur not as a result of line starvations, but as a result of idleness.

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