

Qualcomm Capstone

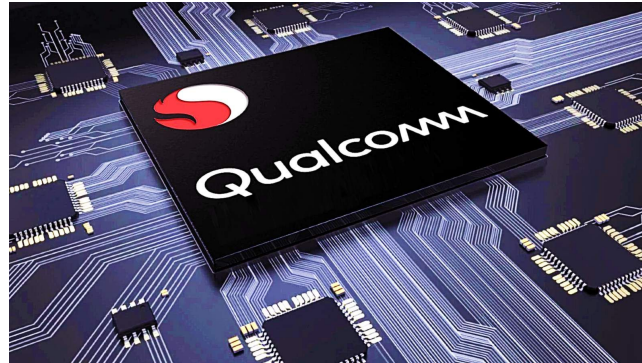
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Contents

- 1 Qualcomm Background
- 2 Project Overview
- 3 Solution Design
- 4 Methodology and Workflow
- 5 Exploratory Analysis and Predictive Model
- 6 Deliverables and Progress
- 7 Conclusion and Final Work

Qualcomm Background

- Founded in 1985 and headquartered in San Diego, California
- World leader in the development and commercialization of foundational technologies for the wireless industry, specifically semiconductors
- Helped shape modern smartphone era and driving advancements in areas like Internet of Things, automotive technology, and AI



Project Overview

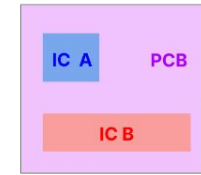
Problem Statement

Qualcomm's product development teams currently rely heavily on intuition-based planning, leading to potential inaccuracies in timeline estimates and and inefficient resource allocation.

The goal is to create a data-driven model that predicts development cycle times with greater accuracy, enabling proactive decision-making and improving time-to-market for new semiconductor products.

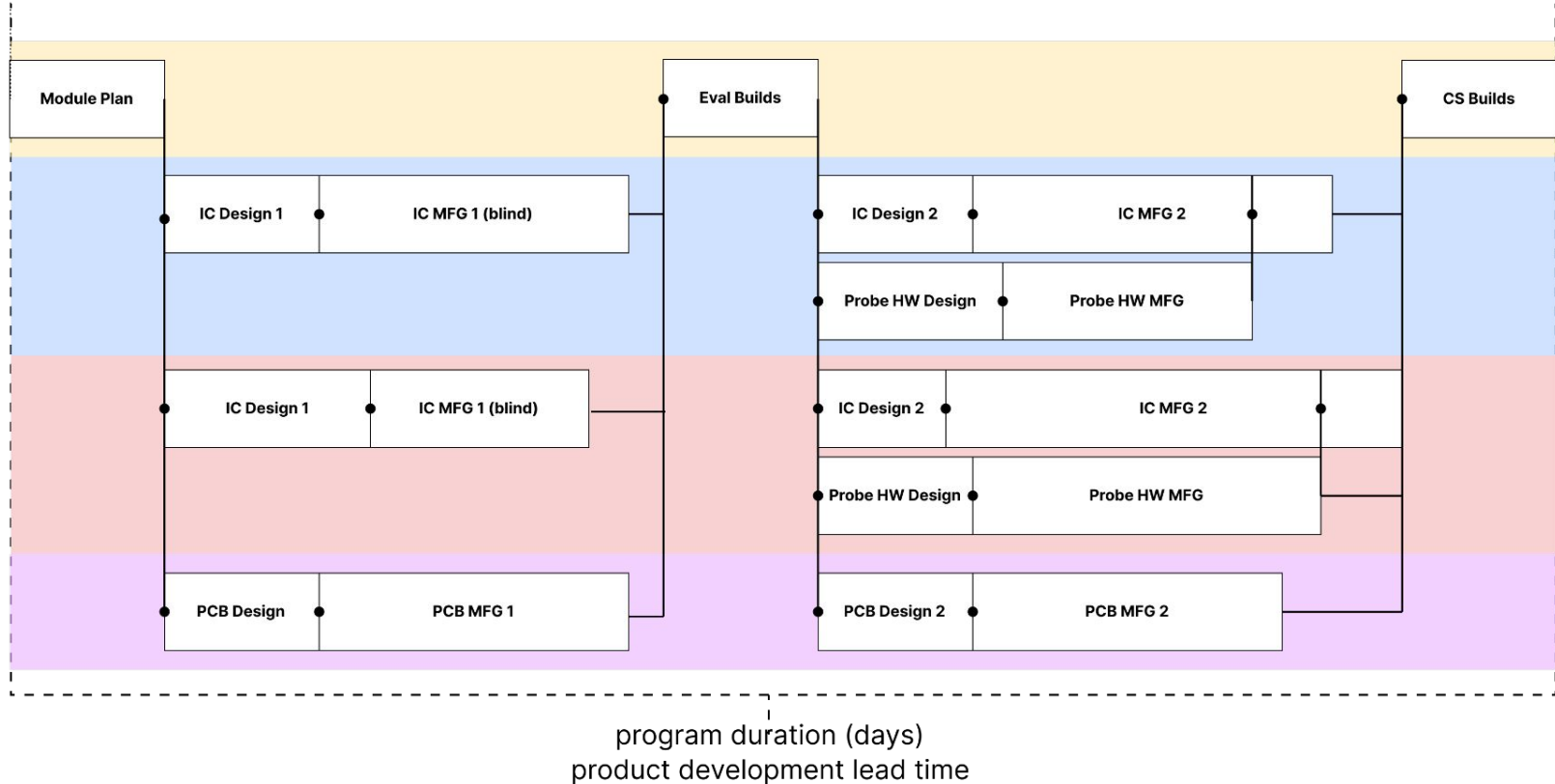
Problem: Complicated Lead Times

Program Start
(Specs Published)



Finished Product

Customer Delivery

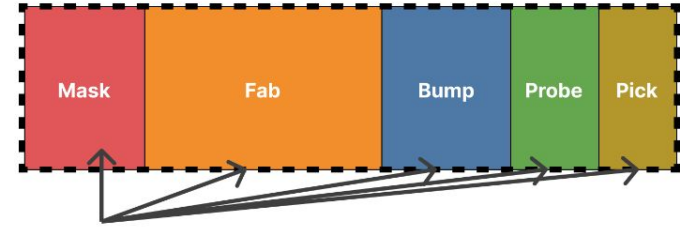


Challenge: Lots of Subcycles and Variation

Program Start
(Specs Published)



IC MFG



Varying suppliers and
processes used at each
stage

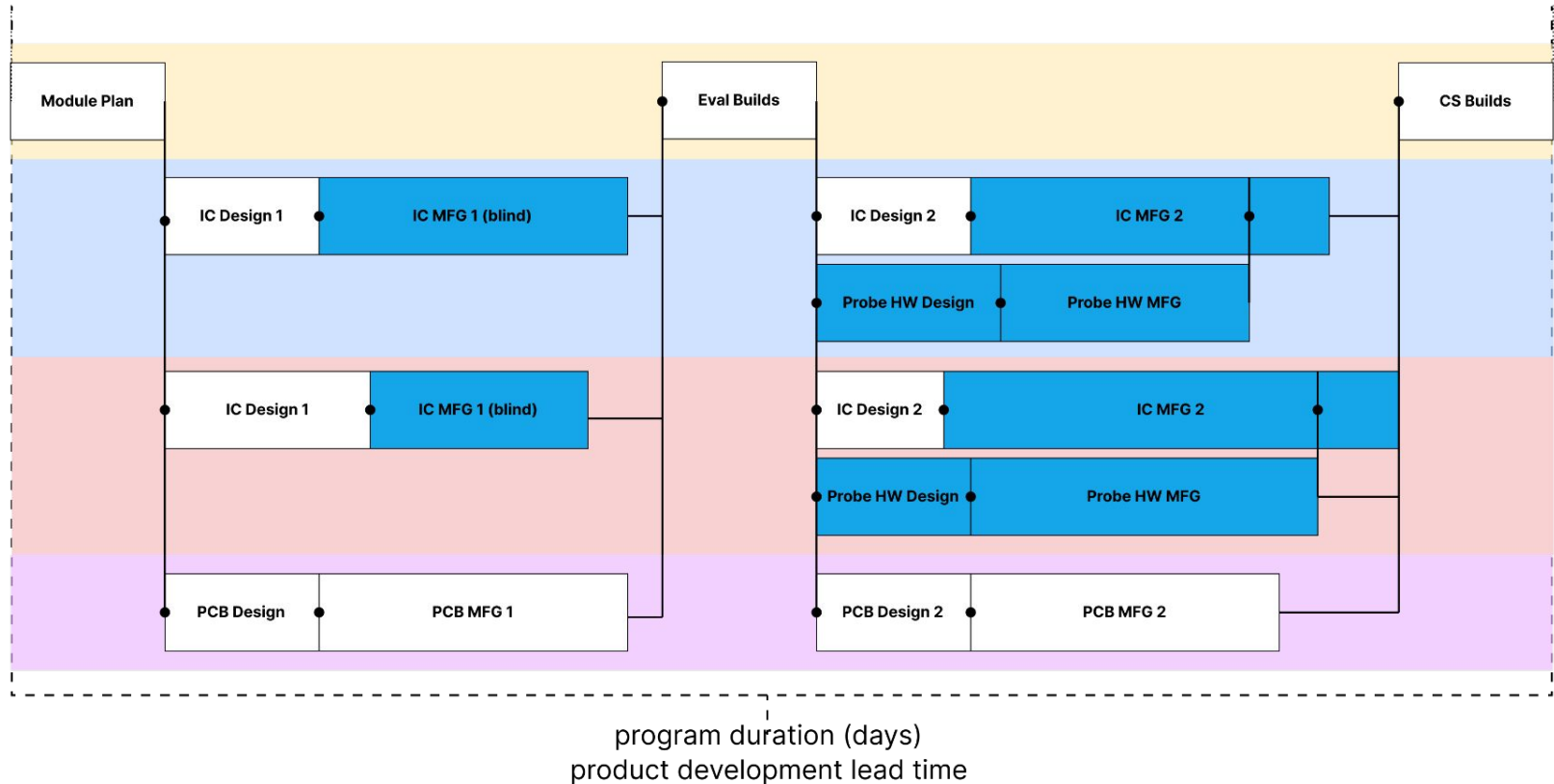
program dura
product develop

Challenge: Dynamic Simulation

Pass through changing device and supplier parameters to pick from unique, more accurate distributions

Program Start
(Specs Published)

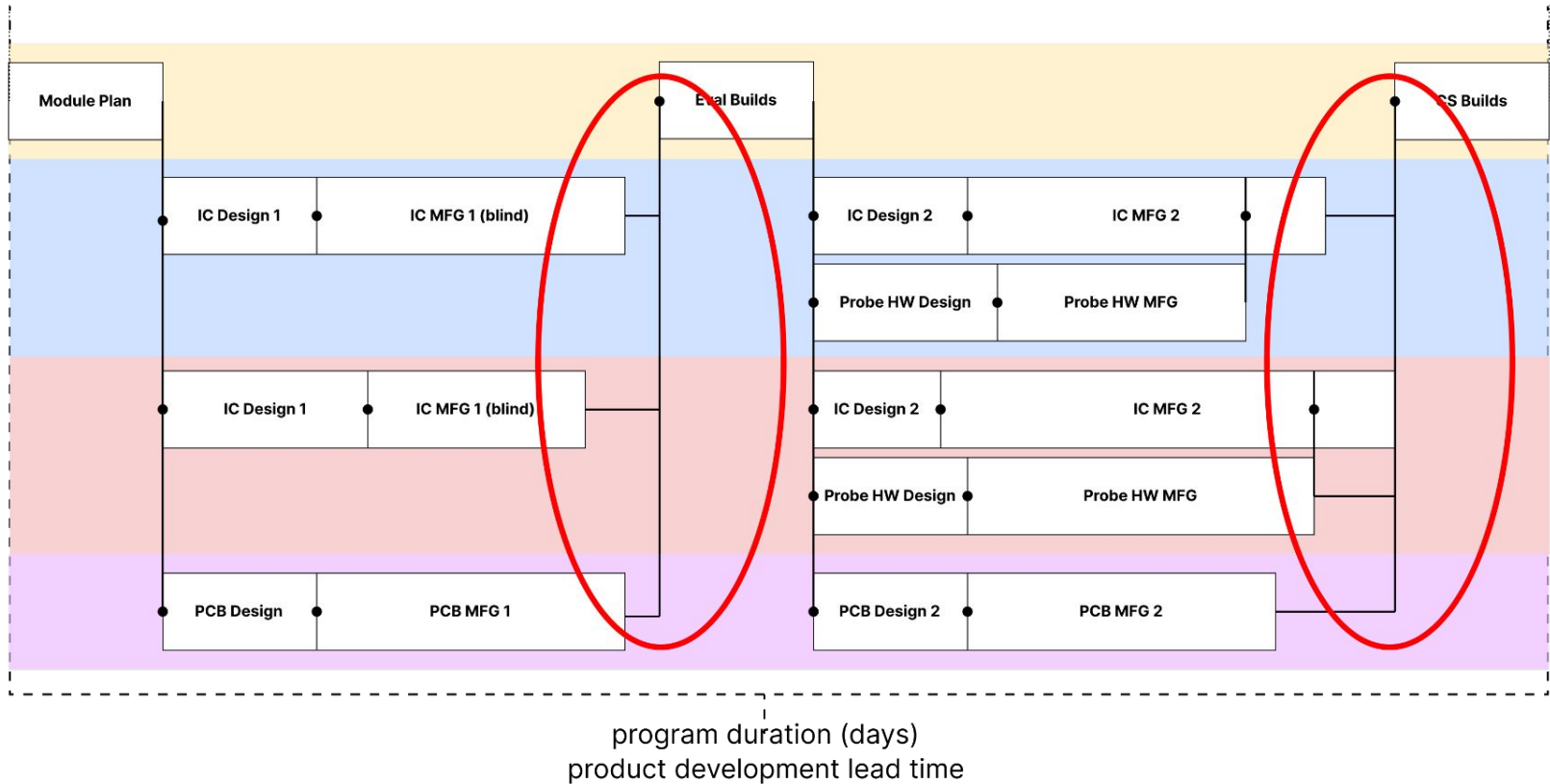
Customer Delivery



Challenge: Changing Critical Paths

Program Start
(Specs Published)

Customer Delivery



Solution Design Overview

Objective:

- Estimate development lead time for semiconductor module products using a Python-based simulation model.

Key Solution Features:

- Simulate lead time using stacked probabilities from various cycle times.
- Output: Probability distribution of development duration and sensitivity analysis.

Benefits:

- Provides accurate estimates for lead times.
- Highlights bottlenecks and high-risk areas.
- Informs better decisions to optimize product development.

Methodology & Workflow

Data Preparation

- Clean historical datasets for tasks, lead times, and dependencies
- Exploratory analysis, familiarity with the data

Simulation Framework:

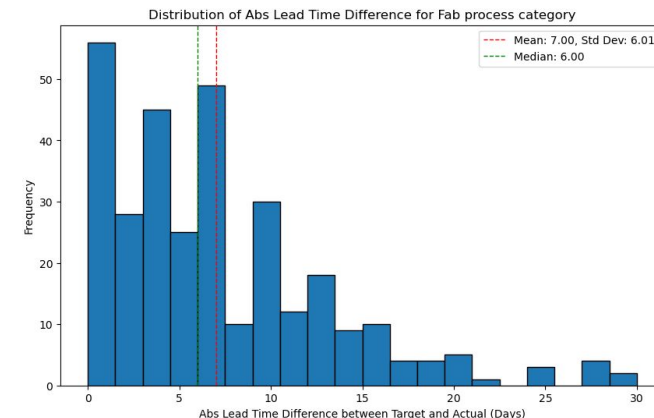
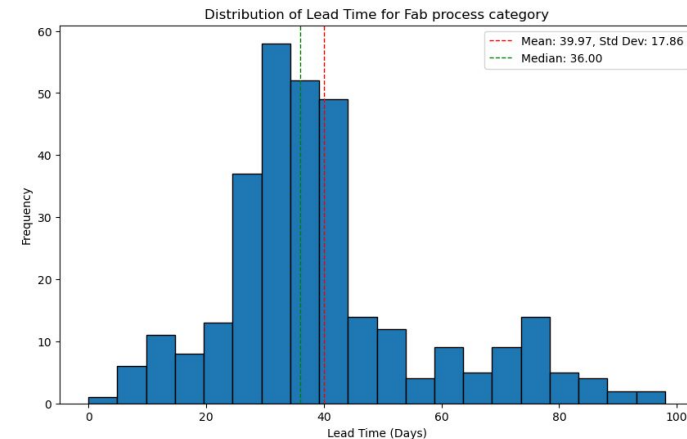
- Test different predictive models
- Tasks modeled with probabilistic distributions
- Directed Acyclic Graphs (DAG) for dependencies that show a defined direction for the procedures

User Interaction:

- GUIs were created to allow the user to input desired deadlines and measure the probabilities of meeting them

Exploratory Data Analysis

- Visualized Lead time (dependent variable) and lead time difference (Target vs Actual) against features
 - Lead time difference absolute value also reviewed
- 4 Process Categories:
 - Maskset
 - Fabrication
 - Bump
 - DPS
- Fabrication process had largest mean and standard deviation for lead time and lead time difference



Predictive Model

Goal: Simulation to recommend timelines and determine feasibility

- Bayesian Ridge selected: output includes mean and SD

End State

- Predictive model not used due to inaccuracy compared to historical grouping distributions

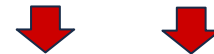
Model Type	R ²
Linear	0.80
Random Forest	0.86
Bayesian Ridge	0.80

$$\text{Simulated Cycle Time} \sim \mathcal{N}(\hat{y}_{\text{mean}}, \hat{y}_{\text{std}}^2)$$

Historical Data



Predictive Model



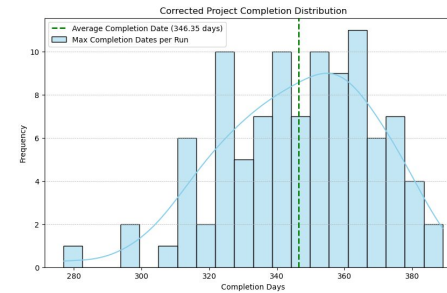
	site	platform	stage	expedite	wafertype	mean	std	count	pred_mean	pred_std_dev
0	site_2	platform_1	maskset	nl	spw	12.625000	2.714021	56	17.192267	6.287239
1	site_2	platform_1	fab	shl	spw	37.878049	4.411321	41	17.192267	6.287239
2	site_3	platform_1	dps	shl	spw	5.600000	2.206573	30	16.941030	6.416689
3	site_1	platform_1	bump	nl	spw	10.758621	5.110599	29	15.634206	6.333009
4	site_16	platform_8	maskset	nl	mpw >10 variants	8.272727	2.271601	22	9.335825	6.297020

Deliverables and Progress

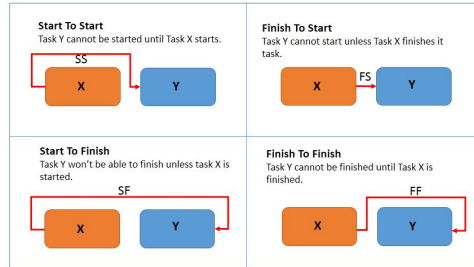
1 GUI for user input

The screenshot shows a 'Feature Input GUI' window. It contains several input fields organized into sections. The 'IC' section has 'IC A' and 'IC B'. The 'Stage' section has 'Masket', 'Fab', 'Bump', and 'DPS'. The 'Platform' section has 'platform_5' and 'platform_8'. The 'Site' section has 'site_12' and 'site_15'. The 'Expedite' section has 'hi', 'ni', and 'shl'. The 'Wafer type' section has a dropdown menu. At the bottom, there are fields for 'Target Start Date (MM/DD/YYYY):' and 'Target End Date (MM/DD/YYYY):', and a 'Submit' button.

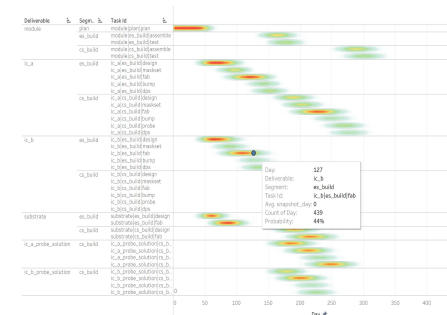
3 Monte Carlo Simulation Model



2 Data Structure and Task Dependencies



4 Tableau Dashboard for dynamic visualizations



Dashboard/GUI Development

Purpose: Allows users to easily select the task features for each stage of the IC Manufacturing Build phases

- Dynamic Filtering of subsequent features based user selections and historical data
- Error Messages for incomplete or invalid field inputs

The screenshot shows a window titled "Feature Input GUI" with a table for selecting features for two ICs (IC A and IC B) across different stages (Maskset, Fab, Bump, DPS). The columns are IC, Stage, Platform, Site, Expedite, and Wafertype. Each cell contains a dropdown menu. At the bottom, there are input fields for "Target Start Date (MM/DD/YYYY):" and "Target End Date (MM/DD/YYYY):", and a "Submit" button.

IC	Stage	Platform	Site	Expedite	Wafertype
IC A	Maskset	platform_5	site_12	nl	spw
	Fab	platform_8	site_16		
	Bump			hl nl shl	
	DPS				
IC B	Maskset				
	Fab				
	Bump				
	DPS				

Target Start Date (MM/DD/YYYY):

Target End Date (MM/DD/YYYY):

Data Structure

The purpose of structuring the data allows to connect all key data needed for simulations, like task details, timelines, and dependencies.

Historical Data:

- Stores information like task durations, wafer counts, and priority levels.
- Tracks how actual lead times compare to targets to highlight variability.

Task Dependencies:

- Uses a Directed Acyclic Graph (DAG) to show how tasks depend on each other.
- Includes parallel workflows (e.g., IC A, IC B, PCB) to reflect real manufacturing processes.

Relational Database:

- Links tasks, workflows, and dependencies in a single system.
- Helps identify critical paths and bottlenecks.

How It Helps:

- Ensures simulations use clean, well-structured data.
- Adapts to new inputs, like deadlines or task priorities, for flexible planning.
- Supports tools like Gantt charts to visualize workflows.

Simulation

Key features include:

Probabilistic Task Durations

- Using historical data to model durations, provide variability and probabilities

Task Dependencies

- Simulates the workflow and ensures task follow their logical order

Predictions

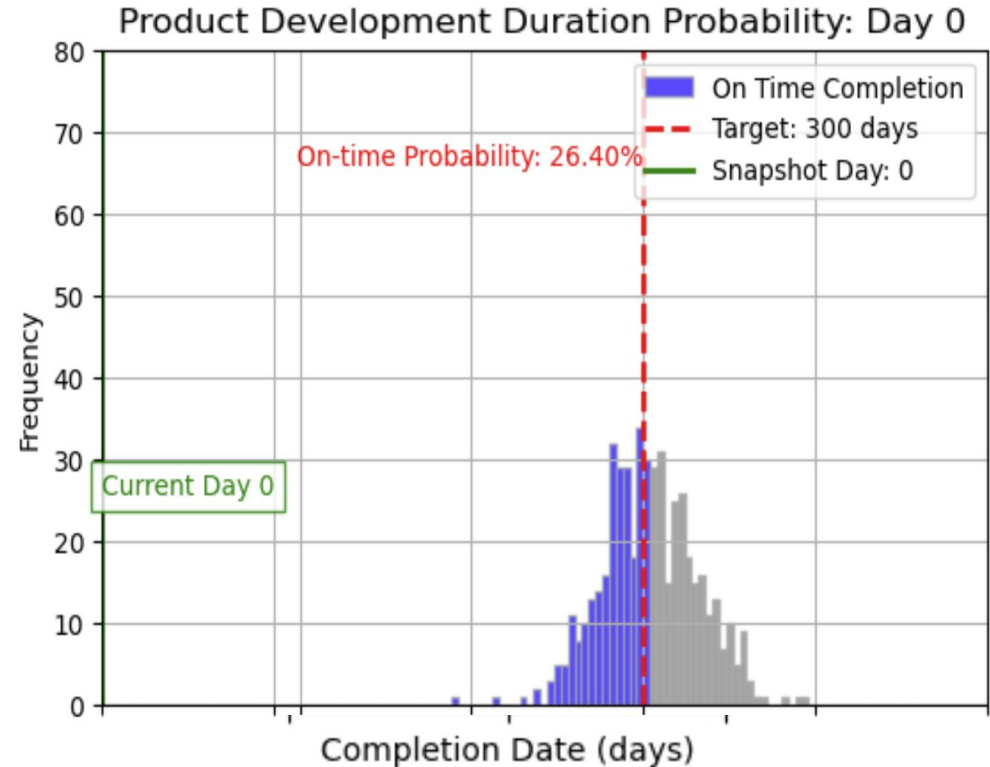
- Improvement is seen as completed tasks reduce uncertainty for the remaining tasks and stages

Takeaways

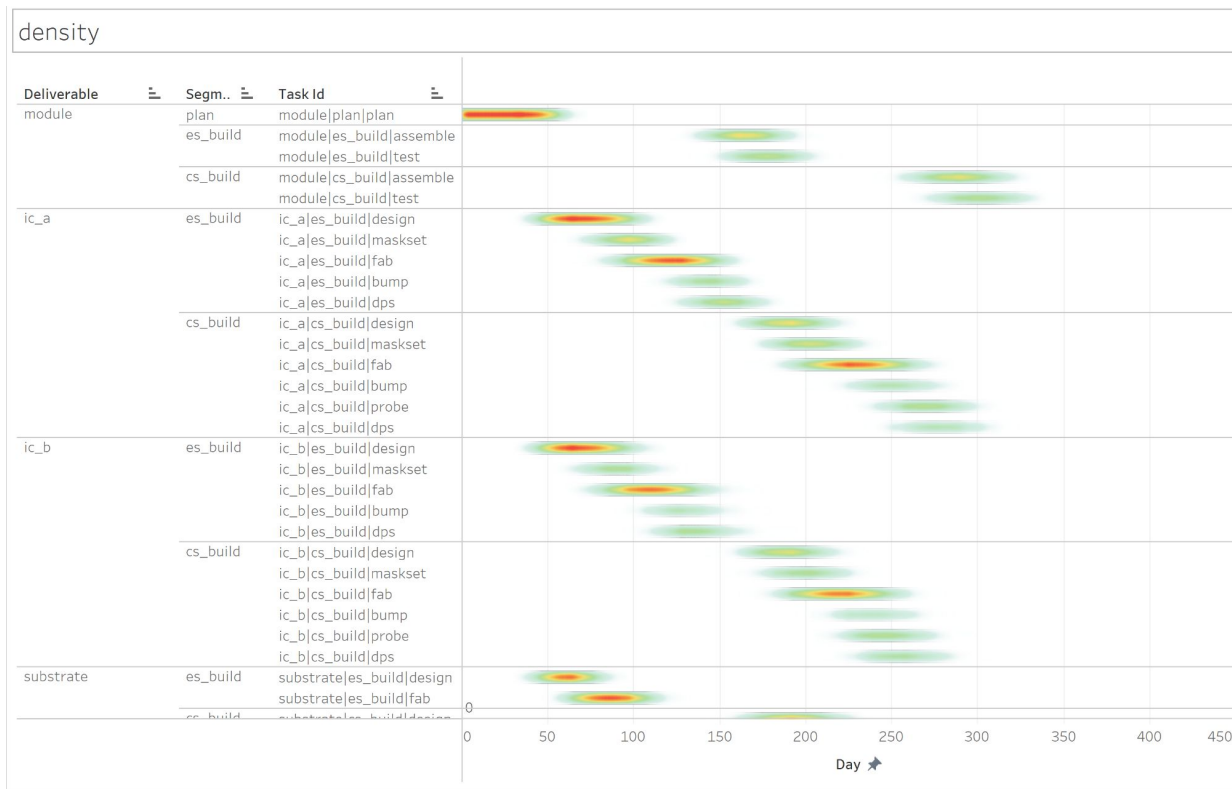
- Identification of bottlenecks in those stages with high variability (like DPS and FAB)
- Probability distribution of meeting deadlines, enabling “what if “ scenarios

Simulation

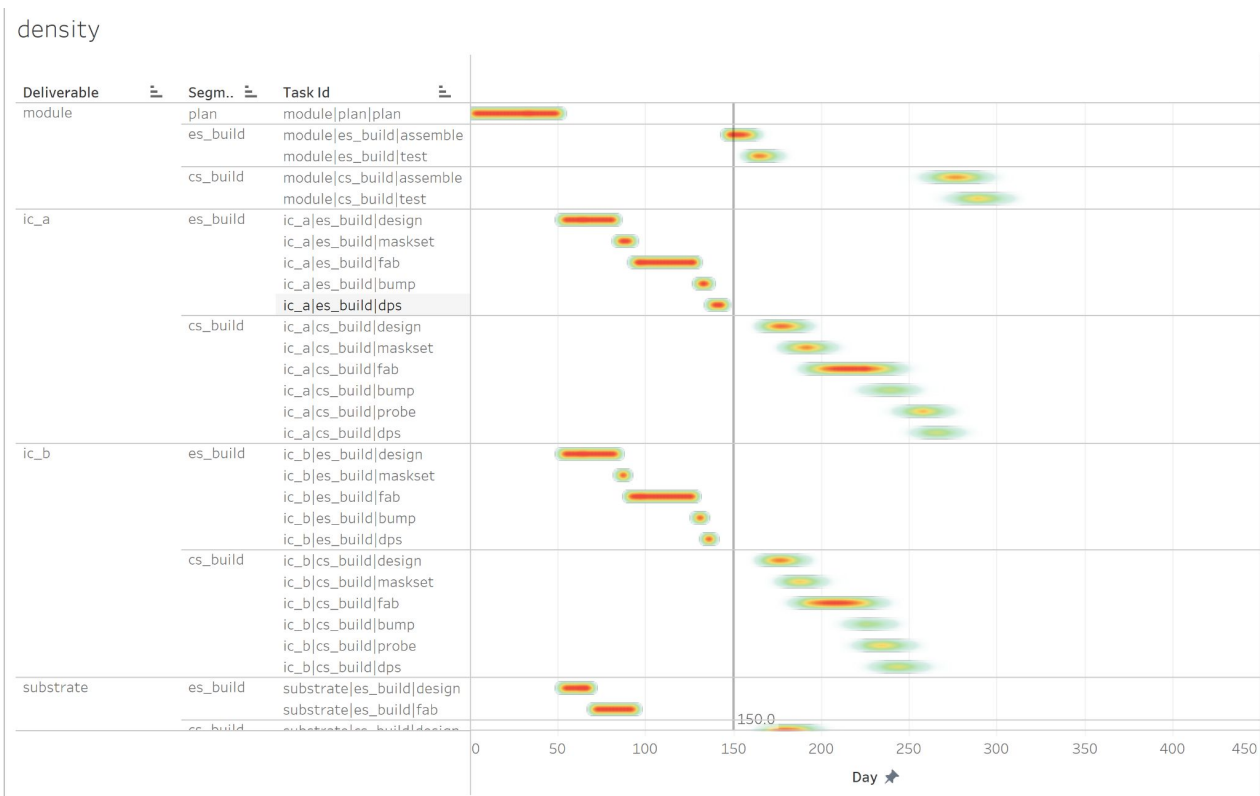
- Found through EDA, most lead time distributions for each cycle are normally distributed
- Will not have access to resource capacity data for project
- Two Main phases in simulation:
 - IC1 & IC2/Probe Solution
 - IC1/IC2 predictive lead times are input to simulation
 - Probe Solution data not obtained yet



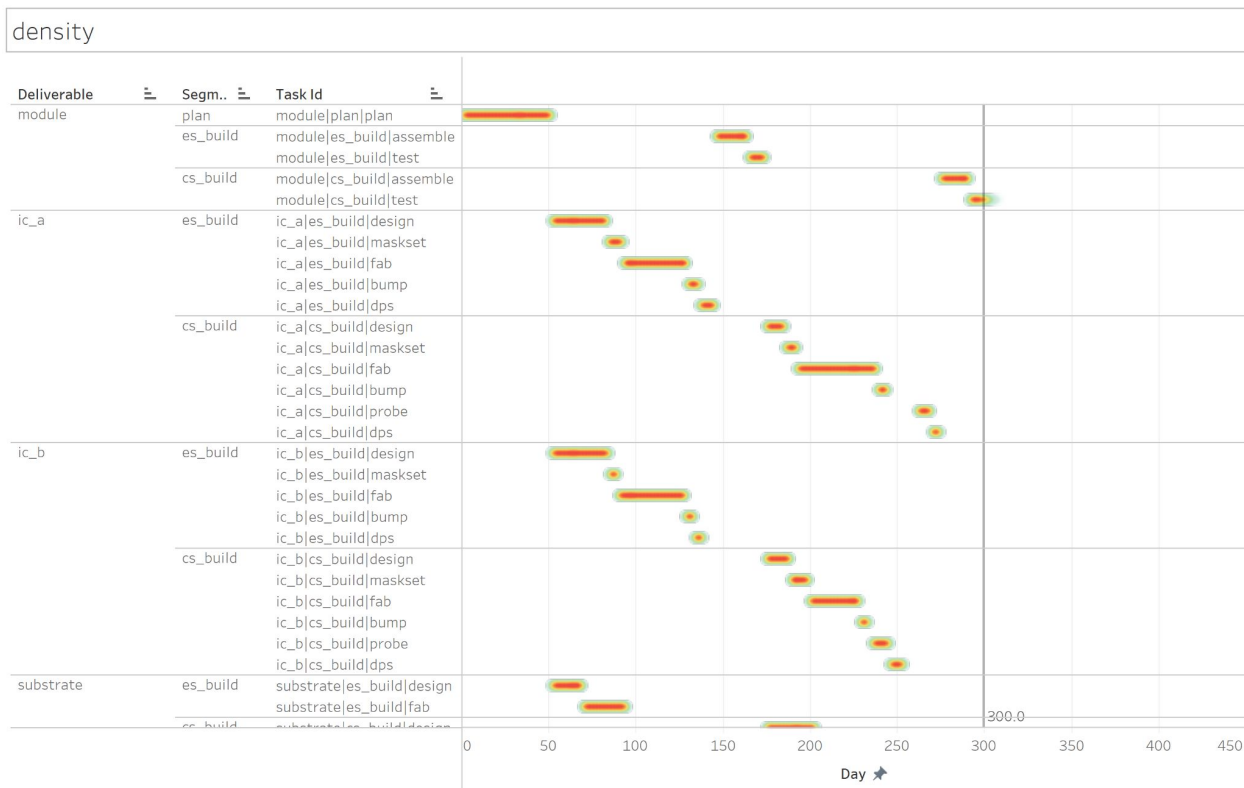
Day 0



Day 150



Day 300



Key Insights and Metrics

Bottlenecks Identified:

- Fab and DPS stages exhibit high variability (Standard dev: 7.09 & 11.21 days respectively)

Timeline Accuracy:

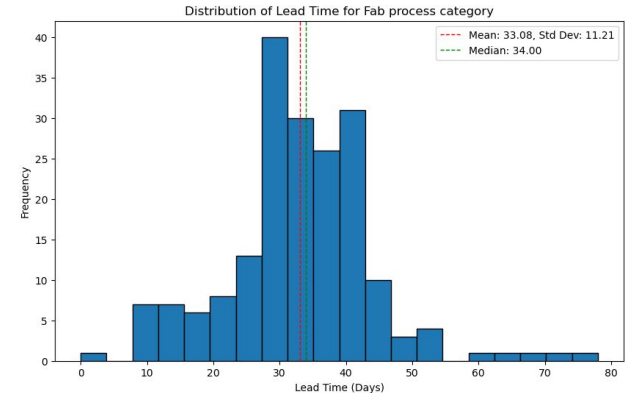
- Data-driven planning approach for internal timelines

Cost Savings:

- Increased monetary savings due to accurate planning

Improved Workflow:

- Reduced idle time at the IC stages via parallel processing



Future Work and Model Improvements

- **Tony - Describe future state of our work and potential improvements at Qualcomm**

Conclusion

Achievements:

- Developed a scalable, data-driven solution for timeline prediction
- Demonstrated improved accuracy and actionable insights

Future Directions:

- Explore Bayesian modeling for rare scenarios.
- Incorporate resource capacity constraints for better scheduling.
- Extend the solution to other industries.

Q&A

Questions and Discussion