Department of Industrial Systems Engineering and Management (ISEM)
IE3100R Systems Design Project | AY 2023/2024

Wafer Loading Plan Optimization

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Overview

Company Background

Skyworks Solutions, Inc., a global **semiconductor manufacturing** leader, is committed to innovating its technology and industrial processes. Recognizing the need for **enhanced efficiency and accuracy in production planning**, Skyworks has embarked on a transformative journey towards **automation**.

One of Skywork's principal products is wafers where the daily manufacturing capacity is determined by its **loading plan**.

Problem Statement & Objectives

The current weekly loading plan takes into account demand data, production requirements, and the quantity of parts allowed for pre-building. It is currently **created and validated manually without the aid of intelligent systems**. This might result in **inefficiencies and inaccuracies** due to the potential for human error and the lack of real-time data integration.

As such, the objective of this project is to **formulate an intelligent algorithm and data driven solutions** which can be used to generate an optimal weekly loading plan that satisfies all parties' requirements.

Digitalisation of wafer loading planning → Mixed Integer Linear Programming; Reinforcement Learning

Solution Requirements

The intelligent algorithm should help automate the planning processes to optimize the allocation of wafer starts weekly, subject to factory constraints, e.g., SCM's operating plan, prebuild and tools' capacity limitation on certain processes.

Key Skill Sets

Programming Skills
- Python
- Excel VBA

Data Preprocessing & Modelling

System Design
Research & Design solutions

Modelling & Analytics
Machine Learning

Framework

Data Preprocessing	Mixed Integer Linear Programming	Reinforcement Learning Framework	Result Analysis	Recommendation
Raw data are extracted from various sources and combined for analysis	Aggregated level model + Part Level model	Q-Learning RL Algorithm	Prebuild & Shortage Analysis	Delivers actionable recommendations in terms of suitable models & strategies

Mixed Integer Linear Programming (MILP)

Parameters

w: Weeks

$m,n \in w$, where m indicates the production week, and n indicates the week pull-in from

p: Parts

k: Number of weeks

Input Data

PB_w : Total "required" pull-in (prebuild) quantity in week w to meet SCM guideline.

PL_w : Part candidates which can be pull in from week w

PC_{mn} : # of parts which can be pull in from week n to week m, where $n > m$

D_{pw} : Demand of part p in week w, where p in PL_w

Decision Variables

x_{mn}: average quantity of all potential candidates which can be pulled in

x_{mnp}: pulled in part p from week n to week m

y: 1 or 0 indicates pull in, 1 = pulled in and 0 r= cannot be pulled in

s : unsatisfied prebuild requirement

Aggregate Level Model

To determine the pull-in quantity for the week

$$\text{Minimize } \sum_{m,n}(n-m)y_{mn}/\,k + M\sum_w S_w$$

Subject to

$\sum_n PC_{wn}\cdot x_{wn} + x_{ww} >= PB_w - S_w$ for every m
Total required pull-in quantity needs to meet supply chain guidelines

$\sum_n PC_{mn}\cdot x_{mn} + x_{ww} = \sum_w D_w$ for every m
The overall demand = prebuild allowed + pulled in

$x_{mn} \le y_{mn}\cdot M$ for each m, n, where M is a big number
Quantity variable x can only be greater than 0 if y variable =1

$\sum_{m=1}^{n} x_{mn} \le D_{pn}$ for each p in week n
The pull-in quantity should be less than demand in the same week, and the part is qualified to pull in (n>1)

$x_{mn} = 0\ y_{mn} = 0$ if $PC_{mn} = 0$
$x_{mn} \ge 0$
y_{mn} = 0 or 1

Part Level Model

To determine the specific parts that can be pulled in

$$\text{Minimize } \sum_{m,n,p}(n-m)y_{mnp}/k + M\sum_m S_m$$

Subject to

$\sum_{n,p} x_{mnp} \ge PB_w - S_w$
Total pull-in quantity = Required pull-in quantity – unsatisfied prebuild

$x_{mnp} \le y_{mnp}\cdot M$ for each m, n, where M is a big number
Quantity variable x can only be greater than 0 if y variable =1 of part p

$\sum_{m=1}^{n-1} x_{mnp} \le D_{pn}$ for each p in week n
The pull-in quantity should be less than each part's demand

$x_{mn} \ge 0$
y_{mn} = 0 or 1

Reinforcement Learning – Q Learning

Q-Learning Goals

The model **can observe the state of a system and choose**. It rewards actions that are "good" and penalises actions that are "bad" according to the objectives, and then updates its priorities based on the results. **Trial-and-error style of iterating** helps it to learn the best actions to achieve its goal.

Model Objectives

1. Fulfil surplus production capacity
2. Discourage pulling demand from further weeks
3. Penalise invalid actions and reward valid actions

Q Updating Function

$$Q_{new}(A_t,S_t) \leftarrow (1-\alpha)\times Q(A_t,S_t) + \alpha\times(r_{t+1} + \gamma\times \max Q(a,S_t))$$

Agent Hyperparameters

Learning Rate (alpha) =0.6

Discount Factor =0.95

Episodes =25000

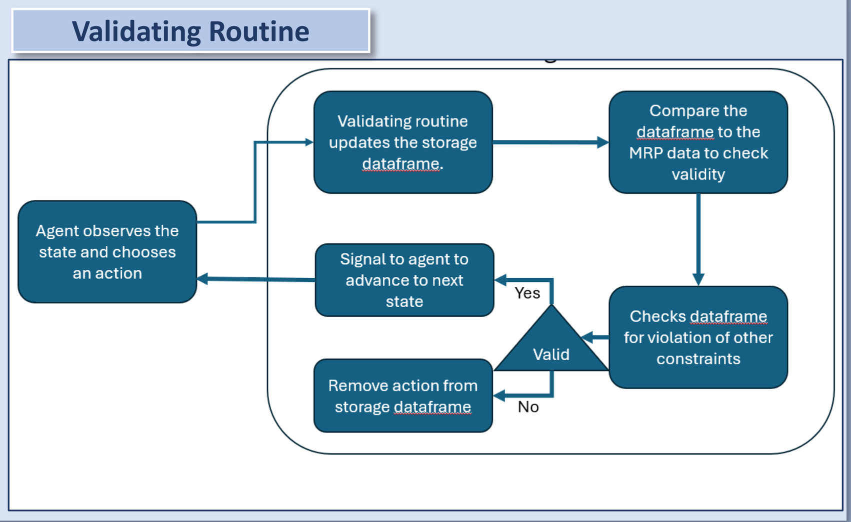
Invalid Penalty =2

Valid Reward =1.5

Completion Reward =10

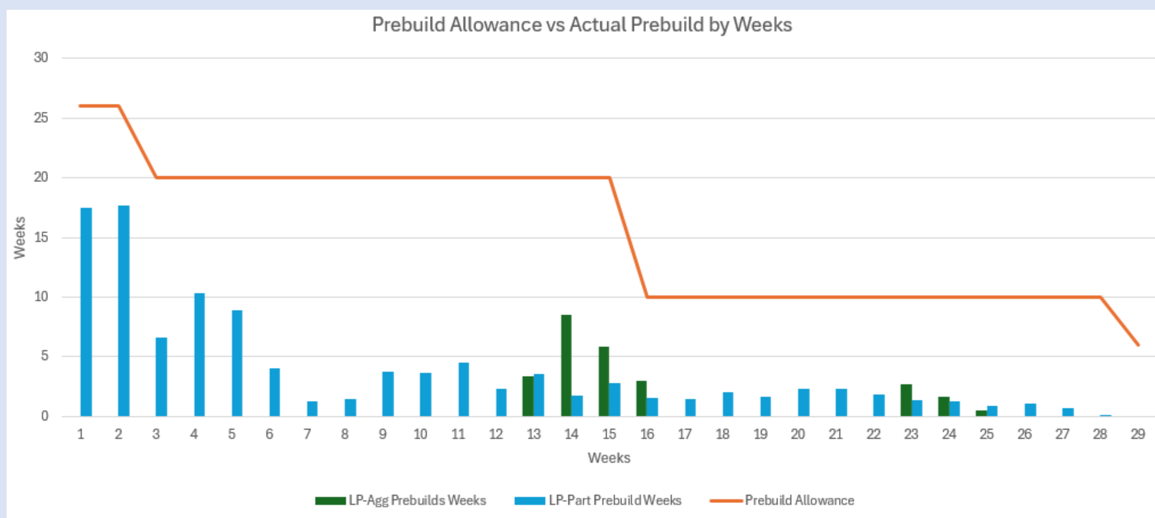
Further Week Penalty =0.4

Validating Routine



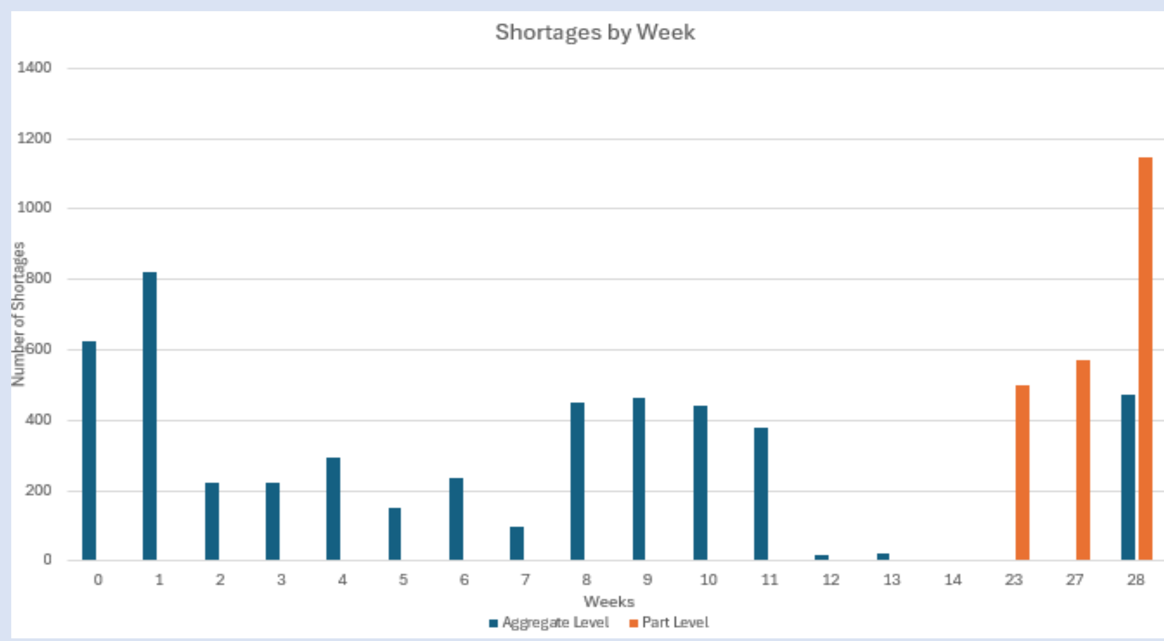
Modelling & Results

Overview of Prebuild Compliance



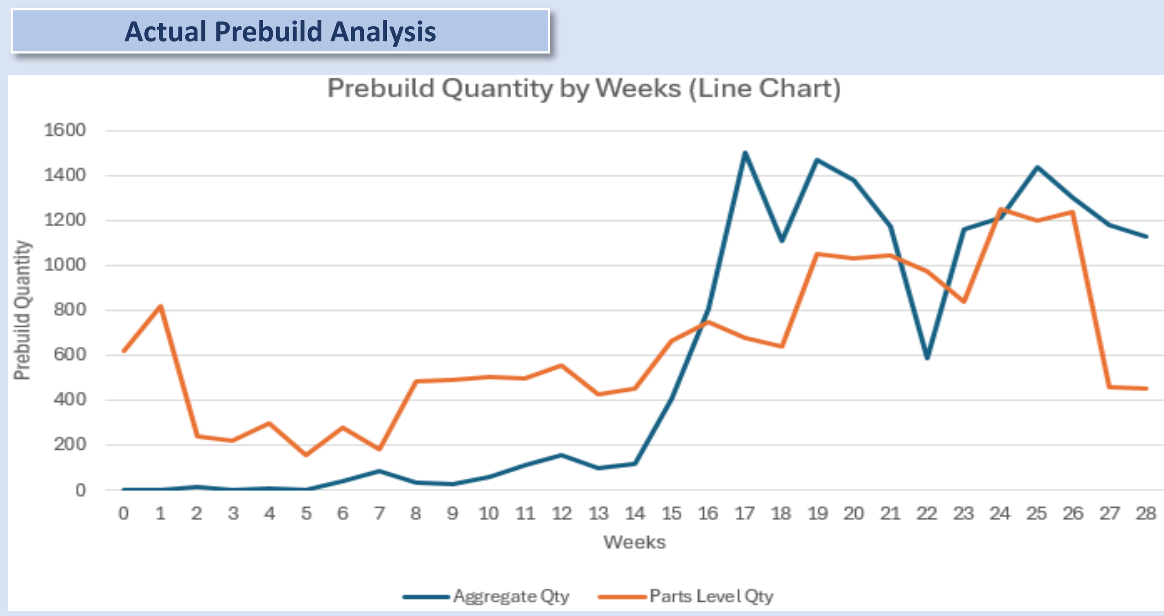
- The diagram shows whether the production planning has met the supply chain guidelines which the actual prebuild cannot exceed the allowance
- From the results obtained, both the aggregate level and parts level has met the prebuild allowance guideline

Shortage Analysis



- Shortages are represented as slack variables and defined as instances where there is not enough demand and prebuilds to satisfy the operating plan.
- From the results obtained, the shortage increases in the later parts of the weeks for part level as majority of the demand in these few weeks has been used for prebuild in the previous weeks

Actual Prebuild Analysis



- This analysis serves to support the shortages analysis outlined above.
- For week 23,27 & 28, prebuilds for part-level < prebuilds for aggregate level, validating the occurrence of shortages.

Key Takeaways

- The **digital transformation of manufacturing** through the adoption of AI, IoT, data analytics marks a significant milestone in the advancement of Industry 4.0, driving substantial improvements in **operational excellence**
- It is imperative for manufacturers to implement **scalable and flexible production systems** to stay competitive in an increasingly dynamic and customer-driven marketplace

Achievements

Streamlined the manual wafer loading planning process

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Generate the wafer loading plan **from days to within minutes with a click of a button**

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Improve **Accuracy, Reliability, Efficiency & Reduce wastage**

Recommendations

- Use **the optimization and machine learning models** for the wafer loading planning as our models enhance reliability and accuracy.
- Future exploration **in Deep Learning** is encouraged for problems with increasing complexities.

Limitations

- The duration required for running the models will **extend significantly** as the complexity of the problem increases thereby and the solution spaces expand.
- The mixed integer linear programming model results may be inaccurate if the model **cannot fully capture the specific constraints** in reality