Optimization of Photo Inter-workstation Capacity Balancing and Material Usage through Scheduling Logic Automation

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IE3100M Systems Design Project (Group 10)
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Project Overview

Problem Description

The photolithography process is highly complex and dynamic. Variables such as planned tool down and process holds are common sources of disruption. This inherent variability results in frequent deviation from the forecasted run rates, affecting the photoresist consumption as well. Consistent monitoring of photoresist inventory is needed to anticipate and resolve any excess or shortages.

Current Approach by Micron

The **Materials Team** is responsible for monitoring photoresist inventory levels and anticipating excess or shortage.

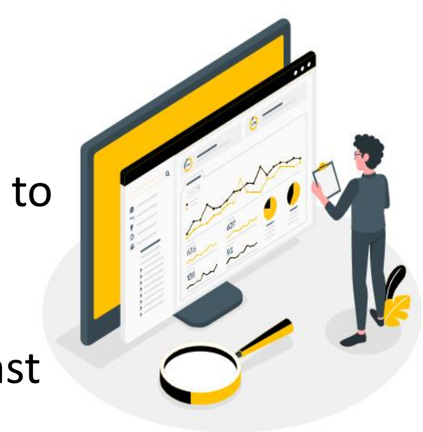
The **Photolithography Team** is responsible for adjusting planned run rates at the inter-workstation pairs based on feedback from the Materials Team to resolve inventory gaps.

Key Problems:

1. Inefficient communication between both departments
2. Periodic review process is performed with a review period of one month, leading to slow response times.

Key Objectives of Proposed Solution

- ✓ Improve response time and adaptability to disruptions
- ✓ Provide a common data platform to enhance collaboration
- ✓ Automate and standardize calculations to monitor photoresist inventory
- ✓ Recommend adjustments to the forecast to resolve anticipated inventory gaps



PART I: Historical Data Analysis

Tableau Dashboard allows the user to visualize deviations (actual – planned) in run rate of the Design ID for the respective Step, Workstation, Material Description and Work Week.

Tracking signal can help determine if forecast is bias – over forecasting or under forecasting.

PART II: Excess and Shortage

Calculations were automated using figures of the

1. Real time inventory levels to get the Quantity on Hand (QOH)
2. Batch expiry dates
3. Forecasted run rates

Anticipating Excess: Cumulative bottle consumption at any time within the future 13 Micron work weeks < Cumulative number of bottles reaching expiry by that time

Anticipating Shortage: Cumulative bottle consumption at any time within the next 13 weeks > the current QOH

Implementation of Solutions Approach

PART III: Linear Programming on Python

Theoretical LP Model

- Adjusts run rate across all workstation pairs to resolve anticipated excess or shortage of photoresist inventory.
- Able to consider all part types and associated step names simultaneously

Limitation

- Impractical due to the high dynamicity of manufacturing process

Objective Function:

For a particular photoresist, l experiencing a Shortage within the next 13 work weeks:

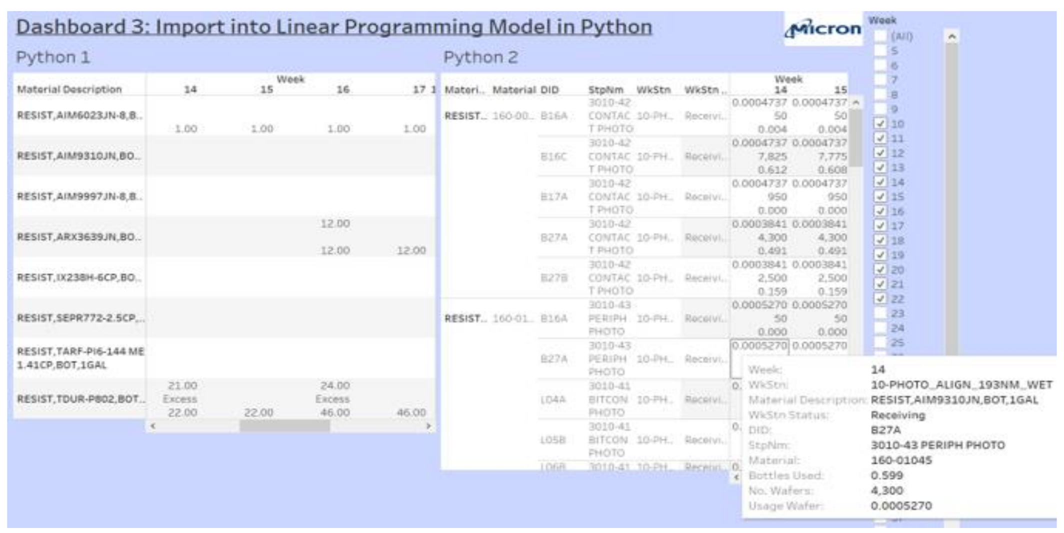
$$\text{MAX}\left(B_l - \sum_{i=1}^{11}\sum_{j=1}^{7}\sum_{k=1}^{4}\sum_{m=1}^{13} C_{ijklm} * T_{lm} * X_{ijklm}\right) \text{ for the relevant photoresist } l$$

For a particular photoresist, l experiencing an Excess in week m* when a particular batch of bottles reach expiry, E_{lm^*}:

$$\text{MIN}\left(E_{lm^*} - \sum_{i=1}^{11}\sum_{j=1}^{7}\sum_{k=1}^{4}\sum_{m=1}^{m^*} C_{ijklm} * T_{lm} * X_{ijklm}\right) \text{ for the relevant photoresist l, expiry week m*}$$

Proposed LP Model

- Simplified run rate optimization problem
- Adjust run rate only for a part type that has the largest expected photoresist consumption
- Built on Python for a more efficient generation of a run rate



Example of Final Output

```
Weeks Left: 3
Material Description: RESIST,TDUR-P802,BOT,1GAL
Part Type: B16C
Step Name: 3010-14 STAIRCASE PHOTO
Workstation: 10-PHOTO_ALIGN_248NM
Adj runrate: 100.0
Remaining Bottles: 8.308514450655217
```

Ideal Output

- Remaining Bottles = 0

(Photoresist's Quantity on Hand – Total Photoresist Consumption)

Recommended Forecasting Methods

Current Forecasting Method

Simple Moving Average (SMA) takes the average of the run rate of the last 5 weeks

Weakness:

Does not reflect the greater relevance of the more recent data by assigning them a higher weightage in the average

Proposed Methods:

1. Exponential Moving Average

$Y_t = \alpha X_{t-1} + (1 - \alpha)Y_{t-1}$, $0 < \alpha < 1$

Advantages:

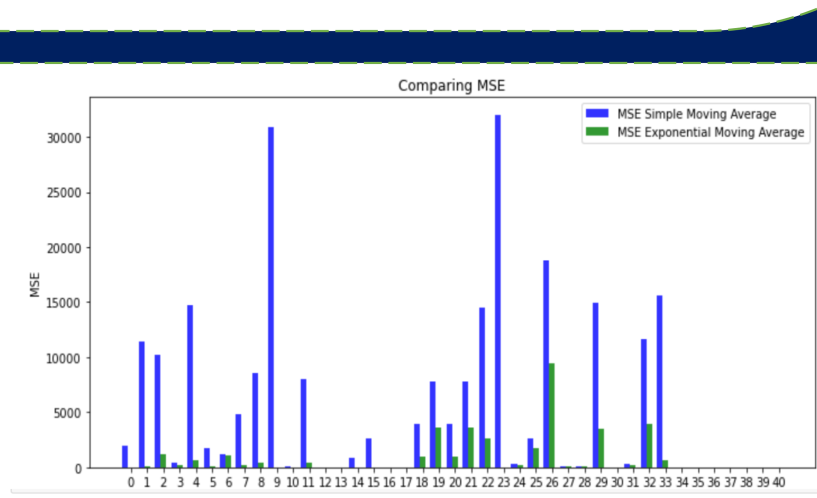
- Optimal α can be automatically determined using Python
- Only requires data of the week prior to forecast

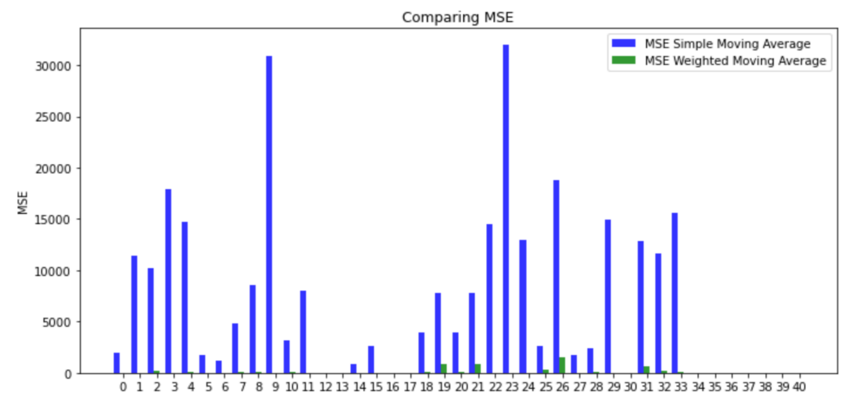
2. Weighted Moving Average

$Y_t = w_1X_{t-1} + w_2X_{t-2} + w_3X_{t-3} + w_4X_{t-4} + w_5X_{t-5}$, $w_1+w_2+w_3+w_4+w_5 = 1$

Advantages:

- Works with any number of data available
- Simple to implement





Further Improvements

- Integrate the python solution method into Tableau using Tabpy to minimize manual exporting and importing of data
- Tracking signal can be improved to flag out whether consistent bias in forecasting is an underlying issue with forecasting method or a capacity problem of the workstation

★★★ Key Skills Sets

- Data Visualization using Tableau
- Data Cleaning & Analysis using SQL, Python, Excel
- Statistical Learning
- Linear Programming
- Project Management

Conclusion

Reduced communication inefficiency:
Centralised data platform on Tableau
-> close down information gap

Increase the adaptability in workstation loading:
LP model on Python -> generates new loading percentage (run rate) in real time

What's Next:
Extend the proposed methodology to other fabrication plants