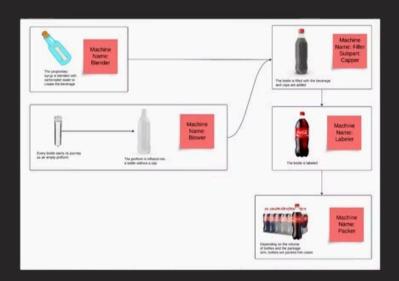
# Predictive Maintenance Analysis for Swire Coca-Cola

**Group 2** 

Richard Lim, Ketki Kulkarni, Anusha Vivekanand, Vedika Garg



## Background



Our capstone project focuses on identify and analyze breakdown patterns in machine downtime, and find major factors influencing breakdowns using IWC dataset across the 6 plants in worldwide.

The goal is to understand the breakdown frequency, timing, and locations, as well as the root causes and possible resolutions.

# **Objective**



#### **Analytical Goal**

Develop a predictive model to forecast machine downtime frequency and duration.



#### **Business Goal**

Provide actionable items for proactive maintenance, cost reduction, and efficiency improvement.

# **Assumptions**

#### **Predictable Pattern**

Machine failure patterns are consistent and predictable across equipment types and plant location.

#### **Preventive repair**

Equipment parts causing downtime can be pre-stocked for timely repairs.

## Limitations

#### **Unrecorded IWC Tracking**

Only significant breakdowns are recorded, potentially missing patterns from less severe issues.

#### **Large Missing Data**

Some work orders have over 70% missing data, impacting analysis accuracy.

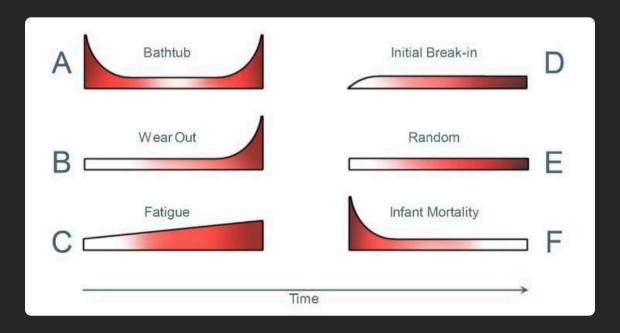
#### **Unidentified Machine Age**

Machine age and usage patterns may not be suitable for model development, affecting prediction accuracy.



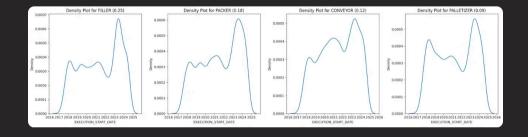
## **Dataset Overview**

The dataset contains 1,427,264 rows and 27 columns. Each row represents a work order recorded by IWC.



### **EDA**

#### **Top 4 Unplanned Equipments Breakdown [FUNCTIONAL\_AREA\_NODE\_4\_MODIFIED]**



It Consists of 64% of total unplanned breakdowns [FILLER] [PACKER] [CONVEYOR][PALLETIZER]

#### **Takeaways**

There are certain breakdown patterns per plant location in that we are collecting **unplanned equipment breakdown data only.** ([FILLER] [PACKER] [CONVEYOR][PALLETIZER]). For example, SILVERSTONE shows the consistent pattern as a (A) bathhub, which requires improving quality control to reduce early-life failures and designing for durability to extend the useful life.

# **Analysis Metrics**

50.0

32.0

36%

**Unplanned** 

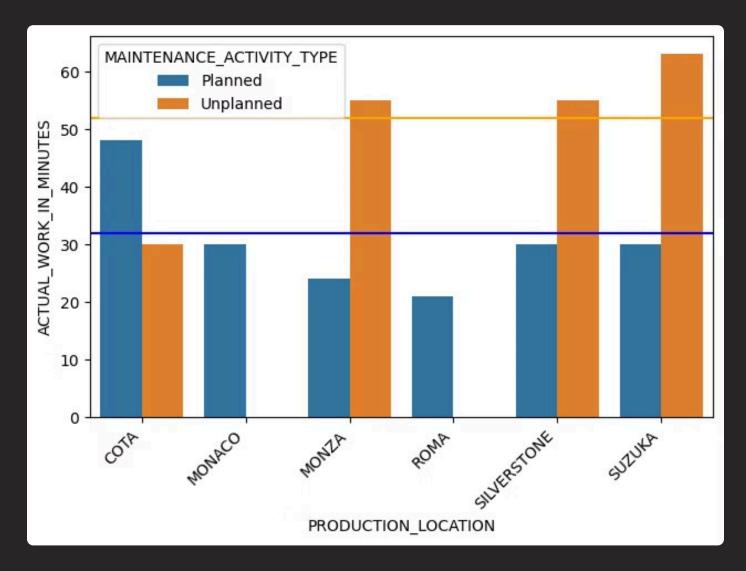
Minutes (Median)

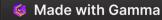
**Planned** 

Minutes (Median)

Reduction

Potential for improvement





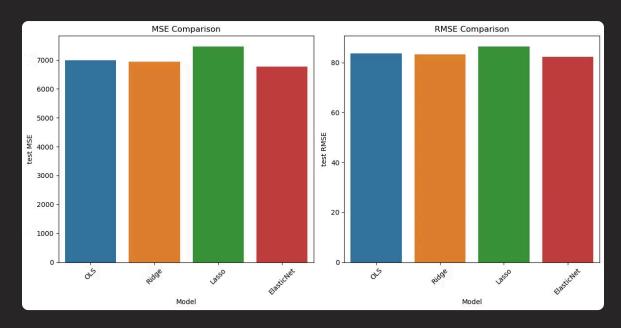
# **Modeling & Evaluation**

## **Regression Model**

#### **Data preprocessing**

• Group by given data with [df['PLANT\_ID'] + '-' + df['LINE\_ID'] + '-' + df['SUBPROCESS\_ID'] and predict when is the next breakdown duration based on historical data.

The model comparison provides valuable insights into performance across different regression approaches.



Model	RMSE	MSE	R-squared		
OLS	83.6577	6998.6032	0.6086		
Ridge	83.2756	6934.8299	0.6122		
Lasso	86.3950	7464.0931	0.5826		
Elastic-Net	82.2674	6767.9204	0.6215		

#### **Takeaways**

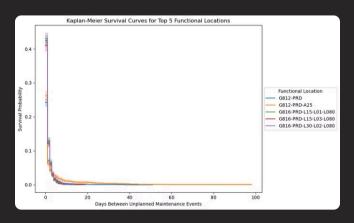
The ElasticNet model stands out, achieving the lowest test RMSE (82.27) and MSE (6767.92), suggesting it strikes the best balance between bias and variance, making it highly suitable for predicting maintenance outcomes.

# **Modeling & Evaluation**

## **Survival Analysis**

The **equipment threshold production capacity** defines how much equipment can be maintained until the machine is working at full capacity before needing maintenance.

• Analyze time between equipment failures across functional locations [FUNCTIONAL\_LOC]



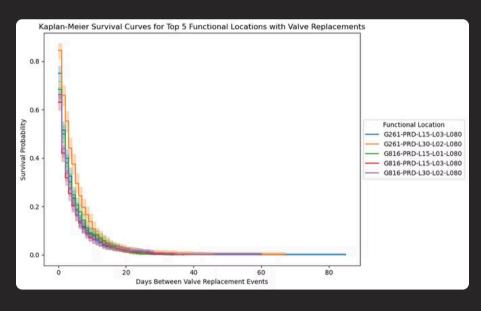
Survival Summary Stati	stics for Top 10	Functional	Locati	ons	(Sorte	ed by	Mean	Time	Between	Replacements):
	count mear	n std	min :	25%	50%	75%	max			
FUNCTIONAL_LOC										
G812-PRD	5406.0 0.473918	1.617539	0.0	0.0	0.0	0.0	51.0			
G816-PRD-L15-L03-L080	3800.0 0.656579	1.149846	0.0	0.0	0.0	1.0	19.0			
G816-PRD-L15-L01-L080	3639.0 0.685078	1.167064	0.0	0.0	0.0	1.0	17.0			
G812-PRD-A25	3641.0 0.702005	3.541655	0.0	0.0	0.0	1.0	98.0			
G816-PRD-L30-L02-L080	3554.0 0.702026	1.204813	0.0	0.0	0.0	1.0	14.0			
G816-PRD-L30-L02-L100	2474.0 1.006063	1.776300	0.0	0.0	0.0	1.0	18.0			
G816-PRD-L15-L01-L120	2353.0 1.061198	1.899605	0.0	0.0	0.0	1.0	19.0			
G816-PRD-L15-L03-L120	2190.0 1.131050	2.102381	0.0	0.0	0.0	1.0	34.0			
G816-PRD-L30-L02-L030	2028.0 1.228797	1.853521	0.0	0.0	1.0	2.0	27.0			
G221-PRD-L30-L02-L080	2144.0 1.248134	2.200411	0.0	0.0	1.0	1.0	27.0			

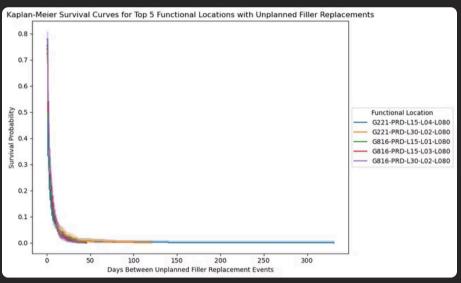
#### **Takeaways**

An equipment in Plant Location: Roma (G812) would fail on average at 0.47 days, Cota (G816) in 0.65 days and Suzuka (G221) at 1.24 days.

## **Survival Analysis**

Survival Summary Statistics for Top 5 Functional Locations





```
Survival Summary Statistics for Top 5 Functional Locations (Sorted by Mean Time Between Valve Replacements):

count mean std min 25% 50% 75% max

FUNCTIONAL_LOC

G816-PRD-L15-L03-L080 867.0 2.877739 4.764796 0.0 0.0 1.0 4.0 37.0

G816-PRD-L30-L02-L080 812.0 3.061576 5.263573 0.0 0.0 1.0 4.0 60.0

G816-PRD-L15-L01-L080 735.0 3.390476 4.861142 0.0 0.0 2.0 4.0 34.0

G261-PRD-L15-L03-L080 727.0 3.519945 6.027652 0.0 0.5 2.0 4.0 85.0

G261-PRD-L30-L02-L080 541.0 4.713494 6.066391 0.0 1.0 3.0 6.0 67.0
```

Survival Summary Statistics for Top 10 Functional Locations (Sorted by Mean Time Between Unplanned Replacements):

count mean std min 25% 56% 75% max

FUNCTIONAL\_LOC

(8316-PRD-L15-L03-L080 75.6.0 3.253264 5.551057 0.0 0.0 1.0 4.0 46.0

(8316-PRD-L15-L03-L080 715.0 3.4883112 5.158639 0.0 0.0 1.0 4.0 45.0

(8316-PRD-L30-L02-L080 682.0 3.645161 4.977206 0.0 1.0 2.0 5.0 42.0

(221-PRD-L13-L04-L080 722.0 3.6831440 14.785603 0.0 1.0 1.0 3.0 331.0

(221-PRD-L35-L04-L080 671.0 3.94426 9.199313 0.0 0.0 1.0 1.0 4.0 121.0

(221-PRD-L30-L02-L080 495.0 5.284848 6.963008 0.0 1.0 4.0 7.0 69.0

(221-PRD-L30-L01-L080 408.0 6.659314 8.128218 0.0 2.0 5.0 8.0 92.0

(8312-PRD-L15-L01-L080 277.0 9.227437 11.959877 0.0 1.0 4.0 12.0 78.0

(221-PRD-L30-L01-L080 259.0 9.691120 33.550107 0.0 1.0 2.0 6.0 422.0

(261-PRD-L30-L01-L080 258.0 9.755814 10.988076 0.0 1.0 6.0 14.0 56.0



## **Analytical Interpretation**

**Survival Analysis** 

Survival probabilities drop sharply within the first few days after maintenance in key locations like Suzuka, Sliverstone and Monza.

**2** Component-Level Insights

Our analysis shows that fillers, packers, conveyers and palletizers were the most parts identified with frequent breakdowns.

**3** Regression Models

Regression models provides the stability of modeling for predicting the last breakdown duration with 0.6 R-squared correlation across multiple models such as OLS, ridge, lasso and elastic-net.

**A** Risk Prioritization

The analysis helps rank functional locations by their maintenance needs, allowing for precise allocation of resources.



## **Business Interpretation**

Operational Efficiency

Proactive maintenance reduces downtime, ensuring smooth production cycles and safeguarding revenue.

**Cost Reduction** 

Predictive maintenance minimizes repairs and replacements, cut the labour cost leading to cost savings in maintenance budgets.

**3** Strategic Resource Allocation

Prioritizing high-risk locations optimizes resource allocation, ensuring critical parts are readily available.

Lean Inventory Management

Insights into high-demand parts enable better inventory planning, reducing overstocking and minimizing repair delays.

## **Call to Action**

Pilot Program

We recommend piloting this strategy at high-risk locations to quantify its impact.

2 Scalability Measurement

Once validated, the strategy can be scaled across Swire's operations.

3 Operational Roadmap

This is not a one-time solution, but a roadmap to establish operational excellence.



## **Questions & Answers**