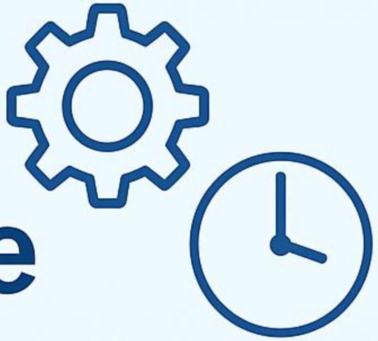
Optimization of Machine Downtime



Presented by Suneetha

Business problem-machine downtime optimization

Machines which manufacture the pumps. Unplanned machine downtime which is leading to loss of productivity.

Business Objectives

Minimize unplanned machine downtime

Business Constraints

- Minimize maintenance cost
- Maximize equipment efficiency

Business Success Criteria

Reduce unplanned downtime by at least **10%**

Economic Success Criteria

- Achieve a cost savings of at least $1M

Project Overview and Scope

Project Overview

•The project aims to optimize unplanned machine downtime in manufacturing units.
•By leveraging machine logs, sensor readings, and downtime history, the focus is on identifying major failure causes.
•The outcome will support data-driven maintenance planning, improved productivity, and reduced operational loss.

Project Scope

•**Data Collection & Analysis** → Study downtime patterns (spindle, torque, coolant, oil temperature, vibration).
•**KPI Development** → Track Downtime %, Mean Time Between Failures(MTBF), Mean Time To Repair(MTTR), and Overall Equipment Effectiveness(OEE).
•**Visualization** → Create Power BI dashboards for real-time monitoring.
•**Optimization Measures** → Recommend predictive & preventive maintenance strategies.
•**Business Impact** → Increase machine utilization, reduce cost of failures, and enhance production efficiency.

Data Dictionary

Column Name	Description	Data Type	Scale of Measure
Date	Date when the machine data was recorded	Date	DD-MM-YYYY
Machine_ID	Unique identifier for the machine (includes brand, line, unit, and year)	String	N/A
Assembly_Line_No	Identifier for the assembly line or shop floor location	String	N/A
Hydraulic_Pressure(bar)	Pressure in the hydraulic system	Float	bar
Coolant_Pressure(bar)	Pressure in the coolant system	Float	bar
Air_System_Pressure(bar)	Pressure in the pneumatic system	Float	bar
Coolant_Temperature	Temperature of coolant fluid	Float	°C
Hydraulic_Oil_Temperature(°C)	Temperature of hydraulic oil	Float	°C
Spindle_Bearing_Temperature(°C)	Temperature of spindle bearings	Float	°C
Spindle_Vibration(µm)	Vibration amplitude of the spindle	Float	µm
Tool_Vibration(µm)	Vibration amplitude of the tool	Float	µm
Spindle_Speed(RPM)	Rotational speed of the spindle	Integer	RPM
Voltage(volts)	Electrical supply voltage to the machine	Float	Volts
Torque(Nm)	Torque applied by the spindle during cutting	Float	Nm
Cutting(kN)	Cutting force exerted during machining	Float	kN
Downtime	Reason for machine downtime	Categorical	N/A

360 DigiTMG®
Digital Transformation | Management | Governance

Exploratory Data Analysis [EDA]

Statistical Insights

Average Downtime per machine: ~4.2 hrs/day
Downtime Distribution: Right-skewed (few machines contribute to majority of downtime)
Top 3 Failure Causes: Tool vibration failure (32%), Oil temperature failure (27%), Coolant pressure drop (18%)
Assembly Line Impact: Lines 2 & 4 record the highest downtime incidents
Shift Analysis: Night shifts show ~25% more downtime compared to day shifts
Machine Age Effect: Older machines (>5 years) have **40% higher failure rate**

Business Insights

Frequent machine downtime leads to **15–20% productivity loss**, directly impacting output
Assembly Line 2's repeated failures cause **delayed deliveries & customer dissatisfaction**
Tool vibration failures are the **highest cost driver** → strong case for predictive maintenance implementation
Oil temperature & coolant pressure failures reveal **need for improved IoT sensor monitoring**
Investing in preventive maintenance could save **₹12–15 lakhs/month** in losses
Data suggests **phasing out older machines** or retrofitting with advanced monitoring can reduce breakdowns

Data Preprocessing

- **Data Collection** →Machine downtime dataset (collected during internship at **Aispry**)
- **Data Cleaning** → Handle missing values, remove duplicates, and correct inconsistent entries.
- **Invalid Data Removal** → Filter out irrelevant or faulty sensor readings.
- **Feature Engineering** → Create new features (e.g., Downtime Duration, Failure Type, Machine Utilization).
- **Data Transformation** → Normalize/scale sensor data for consistency.
- **Categorical Encoding** → Convert categorical data (e.g., Failure Reason, Machine ID) into numerical form.
- **Outlier Detection** → Identify abnormal downtime or sensor spikes.
- **Final Dataset Preparation** → Split data into training, validation, and testing sets for modeling.

Data Visualization

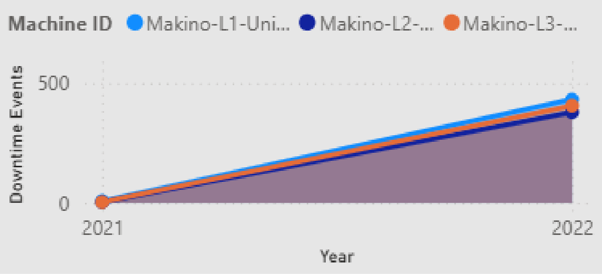
Filter By Machine Downtime

All

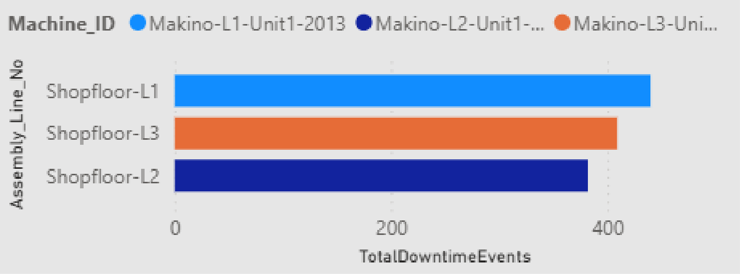
Machine Downtime & Maintenance KPI Dashboard

Down Time Events	Failure %	Spinlde Vibration Failure	Oil Temp Failure	Tool Vibration Failure	Torque Failure	Coolant Pressure Failure
1231	51.70	1.00	47.55	25.39	22.76	5.12

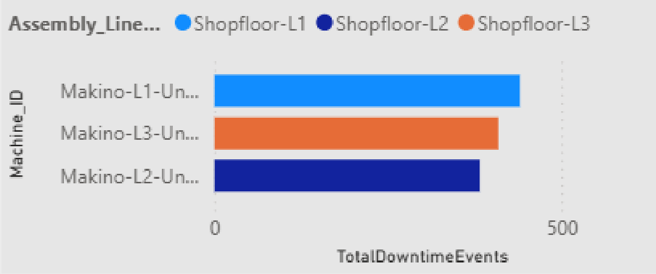
Machine Failures Over Time



Machine_ID vs TotalDowntimeEvents



Assembly_Line_No vs TotalDowntimeEvents



Downtime Record with Sensor Readings

Year	Machine_ID	Assembly_Line_No	Downtime	Hydraulic_Pressure	Coolant_Pressure	Air_System_Pressure	Coolant_Temperature	Hydraulic_Oil_Temperature	Spindle_Bearing_Tempe
2021	Makino-L1-Unit1-2013	Shopfloor-L1	Machine_Failure	635.00	46.81	49.95	201.00	389.00	
2021	Makino-L2-Unit1-2015	Shopfloor-L2	Machine_Failure	215.14	16.30	18.98	61.70	152.40	
2021	Makino-L3-Unit1-2015	Shopfloor-L3	Machine_Failure	247.92	20.26	19.48	24.50	127.00	
2022	Makino-L1-Unit1-2013	Shopfloor-L1	Machine_Failure	36,467.83	2,204.24	2,810.18	8,443.90	20,492.90	15,
2022	Makino-L2-Unit1-2015	Shopfloor-L2	Machine_Failure	32,736.29	1,948.12	2,467.74	7,680.20	18,014.90	13,
2022	Makino-L3-Unit1-2015	Shopfloor-L3	Machine_Failure	34,302.78	2,068.07	2,635.85	8,109.40	19,362.40	14,
2021	Makino-L1-Unit1-2013	Shopfloor-L1	No_Machine_Failure	229.92	8.31	12.79	33.60	95.00	


Thanks