FACILITY DRIFT DETECTION & PREDICTIVE MAINTENANCE

DEPARTMENT OF INDUSTRIAL SYSTEMS ENGINEERING AND MANAGEMENT (ISEM)
IE3100M SYSTEMS DESIGN PROJECT AY 2017/2018

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PROJECT OVERVIEW

Problem Description

To develop efficient and effective algorithms to closely monitor the sensor signals and flag out abnormalities observed or drift detected

SMOKE SENSOR — Drift or anomaly →

Serious drifts can lead to machine failure which may cause
1. Wafer scrap
2. Significant losses

Effective algorithms **prevent loss** due to machine failure

Project Background

Each sensor may measure different conditions such as

Temperature | Humidity | Water level

Some possible indicators that may signal potential drifts are
1. Unusual amplitude change
2. Sudden gradient change

Micron currently implements **Preventive Maintenance**
1. Failures are warded off
2. Perform unnecessary maintenances

Current Method by Micron

Shewhart Control Chart

- Specific limits are set for each sensor
- Alarm is triggered when any point is out of the control limits

Drawbacks

1. It is **not sensitive enough** to detect small shifts, which leads to delay in detection
2. It monitors individual sensors **independently without** the consideration of **correlations** between sensors

Key Objectives

1 Drift Detection

- Propose efficient statistical methods to detect drifts using multivariate variables with minimal delay
- Efficiently output the drifting sensors and drifting event time while keeping the false alarm level low

2 Predictive Maintenance (PdM)

- To determine the effectiveness of the usage of the results given by drift detection for predictive maintenance
- Future exploration and extension from drift detection

DATA PREPROCESSING

Step 1
Removing duplicated columns and columns with constant values

Step 2
Test for seasonality using Fourier Transformation

Step 3
Remove trend using differencing. Test for stationarity using Augmented Dickey–Fuller test and Kwiatkowski, Phillips, Schmidt, and Shin Test

Step 4
Standardizing using MinMax Scaler*

Step5
PCA to reduce the dimensionality of the data

*Step 4 and Step 5 are only applicable to Drift Detection Method 1

The purpose of data preprocessing is to process the raw data as to satisfy the data characteristics assumptions for the statistical methodologies implemented. This helps to guarantee the performance of the methodologies.

PROJECT METHODOLOGY

Drift Detection Method 1: Multivariate Exponential Weighted Moving Average (MEWMA) with Principle Component Analysis (PCA)

PCA

- Reduces the dimensionality of the data, data redundancy and computational complexity
- The Principle components obtained are able to explain at least 95% of the variance in data
- The Principle components are input into the MEWMA model

MEWMA

- MEWMA simultaneously monitors the change in process mean of multiple variables. The most recent data carries higher weightage in the calculation.

$$Z_i = \Lambda X_i + (1-\Lambda) Z_{i-1}$$

- Key Statistics:

Hotelling's T-Square

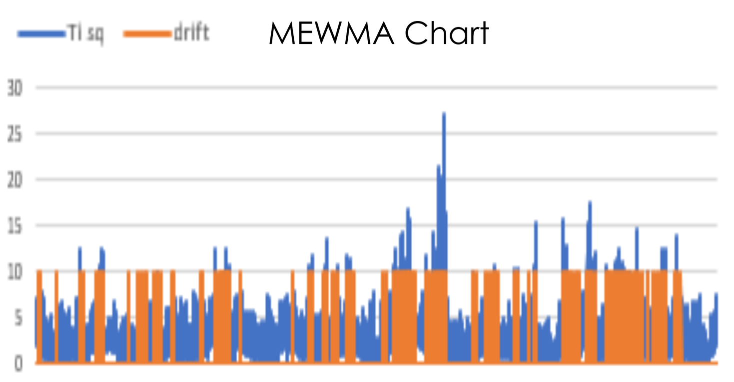
$$T_i^2 = Z_i' \sum\nolimits_{Z_i}^{-1} Z_i$$

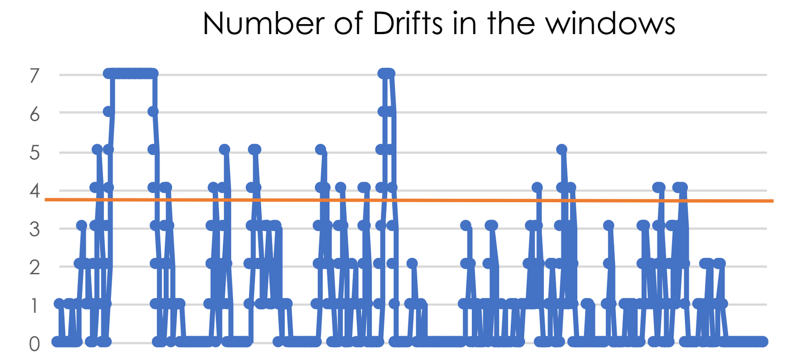
Covariance Matrix

$$\sum\nolimits_{Z_i} = \frac{\lambda}{2-\lambda} \sum$$

- **Strengths:**
1. Customised **sensitivity**
2. Taking in to the account of the **correlation** between the sensors
3. Detect **gradual change** in process mean

High False Alarm Rate (Type II Error)



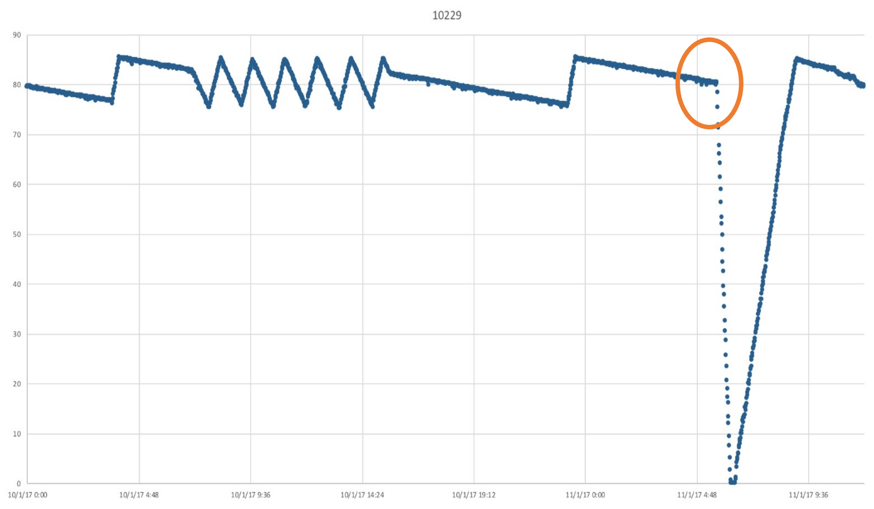


Moving window

- The window period is set as 7 data point and moves point by point
- PCA components and the key statistics are calculated every 24 hours
- Alarm is triggered when the percentage drift is more than 4 drifts are found in the window, the percentage drift is > 4/7

Strengths:
- **Real-time live** data monitoring
- **Reduce false alarm rate**

Drift Detection Method 2 : Gradient Change Detection



$$\text{Gradient} = \frac{\Delta x}{\Delta t} = (x_t - x_{t-1})/\Delta t$$

A sudden change in gradient may imply
- The abnormal status of the machine
- Start of the drift even though the sensor values are still in control

Strengths:
- **Faster** drift detection
- **More sensitive** than the Shewhart control chart

Does the gradient value exceed the most positive or most negative gradients (gradient limits) ?

Y

Does the value exceed gradient threshold ($Threshold = gradient\ limit \times mulitplier$)?

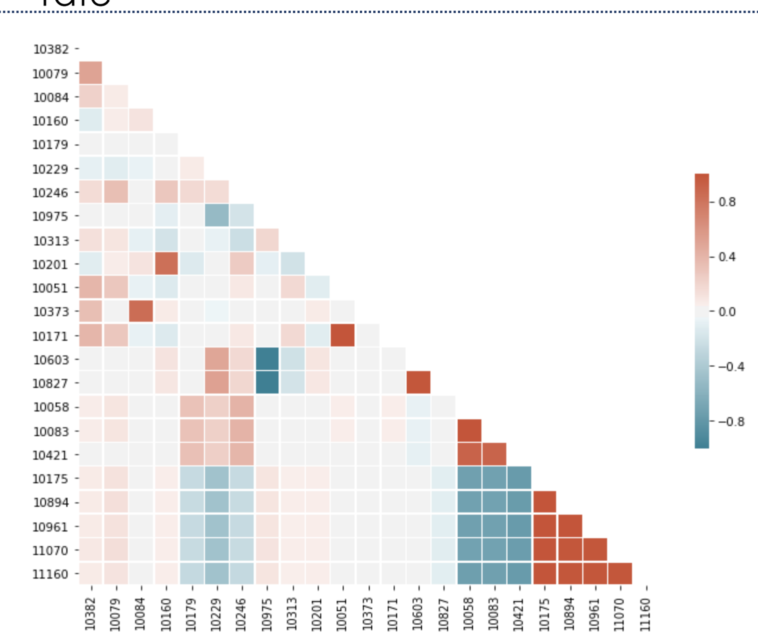
Y: Will it lead to machine failure?
- Y: Technicians to rectify the issues
- N: Update the gradient limits; Increase the multiplier for the current sensor and the highly correlated sensors

N

Check the next sensor

Correlation Heat Map

- The drifts in one sensor is likely to induce drifts in other correlated sensors
- Correlation analysis is necessary to understand how individual sensors are related in order to achieve earlier detection and reduction in false alarm rate



Predictive Maintenance Methodology

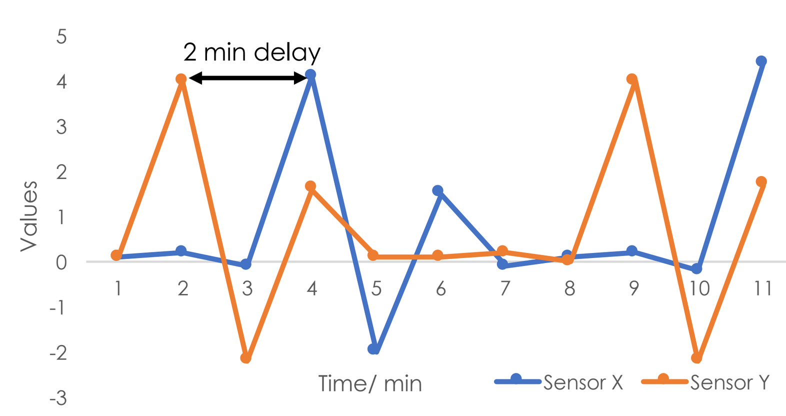
From the results of the drift detection, machine breakdowns can be predicted when the number of drifts detected shows an increase trend, suggesting the degradation of the machine system.

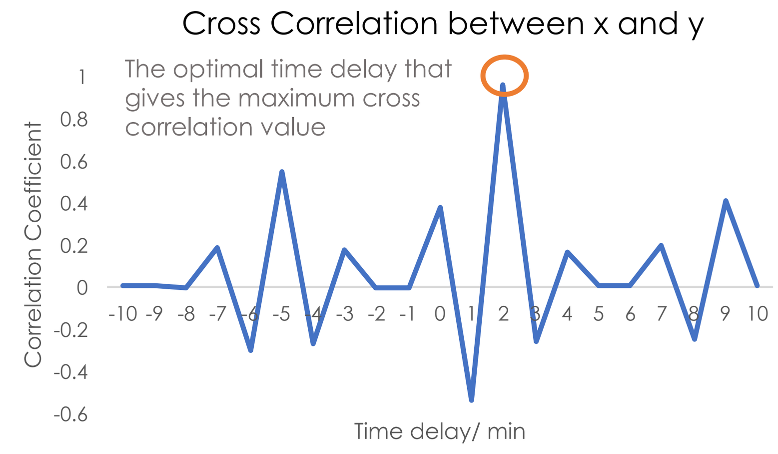
Limitation

- **No gradual increase** in the number of drifts detected leading to the facility event as the breakdown was sudden.
- **Not effective for predictive maintenance** with regards to this particular facility event and the data sets given.

Future Exploration: Cross Correlation

- Able to identify the correlation between the sensors with time delay.
- Theoretically, sensors drifted earlier are able to suggest potential drift events of the highly cross-correlated sensors after a particular time delay duration.





RESULTS AND ACHIEVEMENTS

Results

	MEWMA with PCA	Gradient Change Method	MEWMA ∩ Gradient	MEWMA ∪ Gradient	Micron
Specific Sensor Identification	No	Yes	Yes	Yes	Yes
Accounting for Correlation	Yes	Yes	Yes	Yes	No
Timing	5.43am	5.41am	5.41am	5.41am	5.47am
Non-attributable drifts detected	16	5	2	19	Undisclosed

Recommendations

Data Characteristics

- Approximately normally distributed signals
- Anomalous data exhibits gradual change in process mean

→ MEWMA

- Serially correlated signals
- Anomalous data shows abrupt change in value

→ Gradient Change

Different Objectives

- To achieve minimum detection of the non-attributable drifts → MEWMA ∩ Gradient
- To achieve maximum hit rate and earliest detection timing → MEWMA ∪ Gradient

Achievements

- Real-Time Data Analysis
- Groundwork for PdM
- 100% Hit Rate for Failure Detection**
- High Compatibility
- Cost Savings

** 100% Hit rate based on all test data given

Skillsets

1 Quality Engineering
- Control step of DMAIC process, using Statistical methods: EWMA, Control Chart, Multi-variate Analysis and Anomaly detection

2 Data Analytics
- Programming: Python, Matlab
- Big data mining and processing, data imputation, time series data monitoring and analyzing

3 Project Management
- Problem Solving, Time Management, Process Redesign, Frame Work Development