SYSTEMATIC APPROACH TO COMMONALITY ANALYSIS FOR SEMICONDUCTOR MANUFACTURING

IE3100R SYSTEMS DESIGN PROJECT AY2022/2023

DEPARTMENT OF INDUSTRIAL SYSTEMS ENGINEERING AND MANAGEMENT

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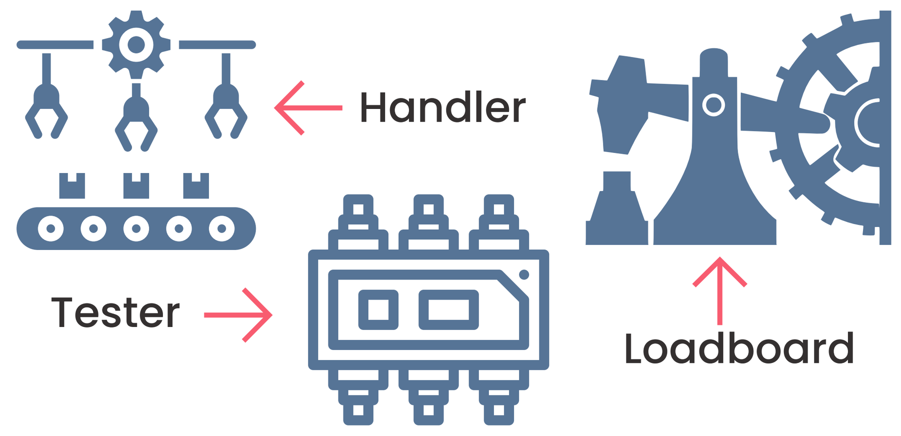
01 Problem Description

False failure identification in semiconductor chip testing process leads to re-test inefficiencies and monetary loss. Data driven, automated methods are needed to identify false positives caused by machine set up/performance error.

The machines involved are:



02 Current Methods

Statistics-based heuristics

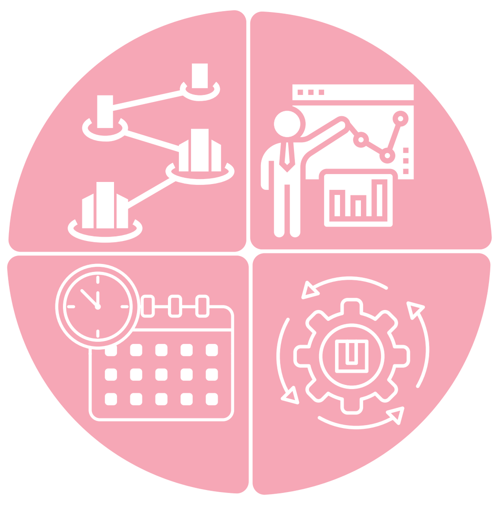
Automated-Lots-on-Hold-Assistant platform and manual inspection

The company currently identifies and fixes problematic machines through a combination of these two methods. However, they are time consuming and purely descriptive. Identification of machines are done manually.

03 Methodology

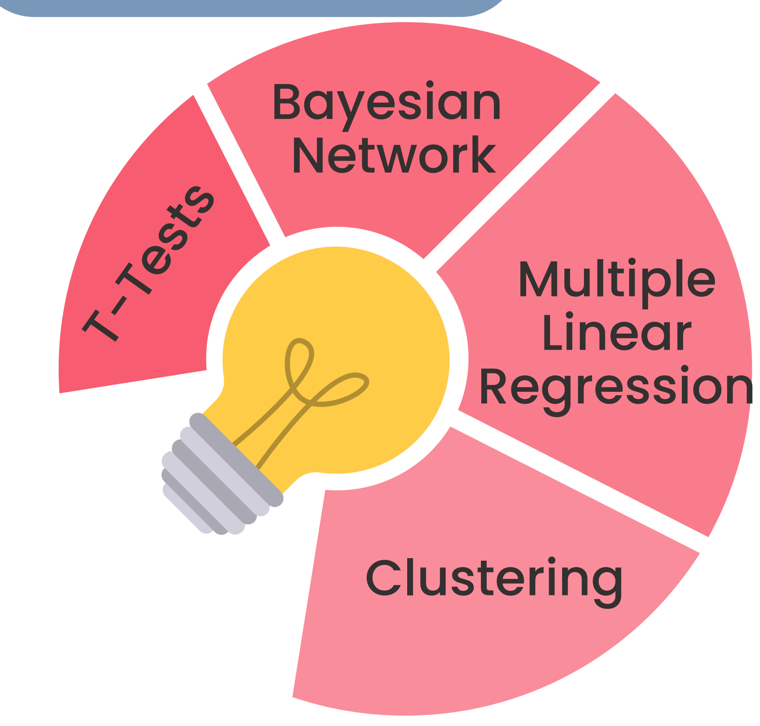
Conceptualisation

Ideas were generated using cutting-edge data analytics frameworks to achieve the goals of reliable and efficient automated problematic machines identification



Potential solutions were evaluated based on their Scalability, Interpretability, Period-Consideration and Robustness

Preliminary Design



The team generated 4 approaches and evaluated their potential before choosing Multiple Linear Regression as the base solution, with the complementation of Clustering

Final Solution

Formulation for Multiple Linear Regression

$$Y = C_{11}H_1 + ... + C_{1j}H_j + C_{21}L_1 + ... + C_{2k}L_k + C_{31}T_1 + ... + C_{3l}T_l + C_{41}P_1 + ... + C_{4m}P_m + C_{51}Tp_1 + ... + C_{5n}Tp_n + ...$$

where **Y** = loss contribution of the set of machines, C_{ij} = loss contribution learned of machine type i of variant j, H_i, L_i **and** T_i are binary variables representing the handler, loadboard and testers used, and P_i **and** Tp_i are binary variables representing the test package and program used.

Recommendations are sorted according to: $LCONT * \sqrt{COUNT}$

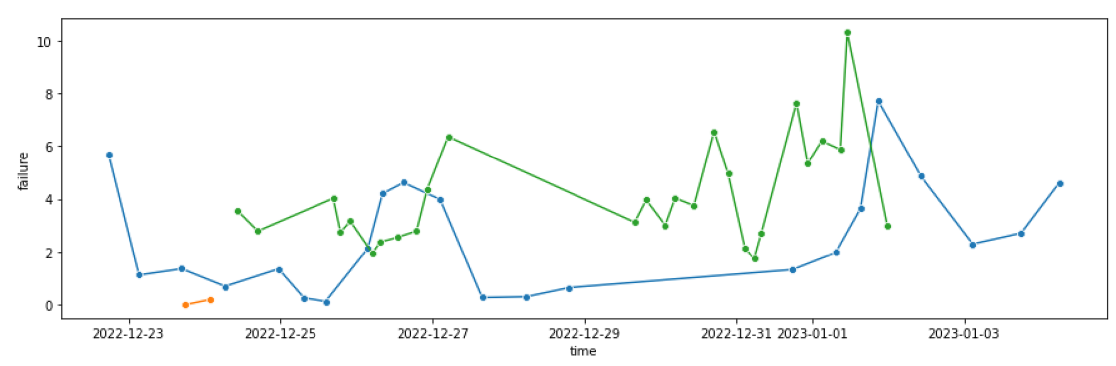
Implementation

1) Iterate through different handler names
2) Apply HDBSCAN for every unique handler
3) Append cluster number to the handler's name and add to dataset
4) Repeat steps 1 to 3 for different loadboards and different testers
5) Fit predictors handler_cluster, loadboard_cluster, tester_cluster into MLR model
6) Get problematic machines with contributions significantly greater than average
7) Output the recommendations

04 Results Analysis

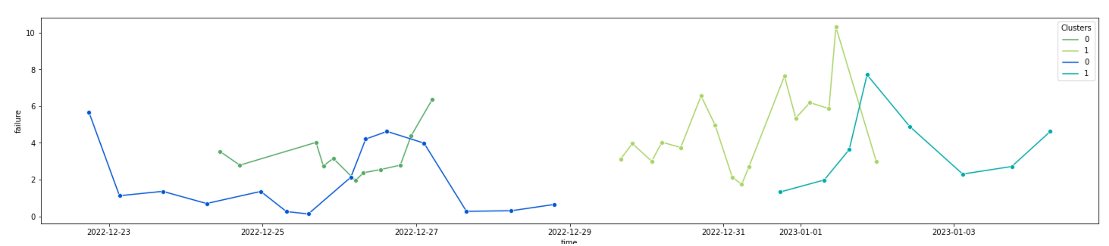
Effective Integrated Solution

Overview of test case #1



It is difficult to judge which is performing better than the other. Hence, time clustering is done on each setup. In this case, the focus can be drawn to the green and blue setups.

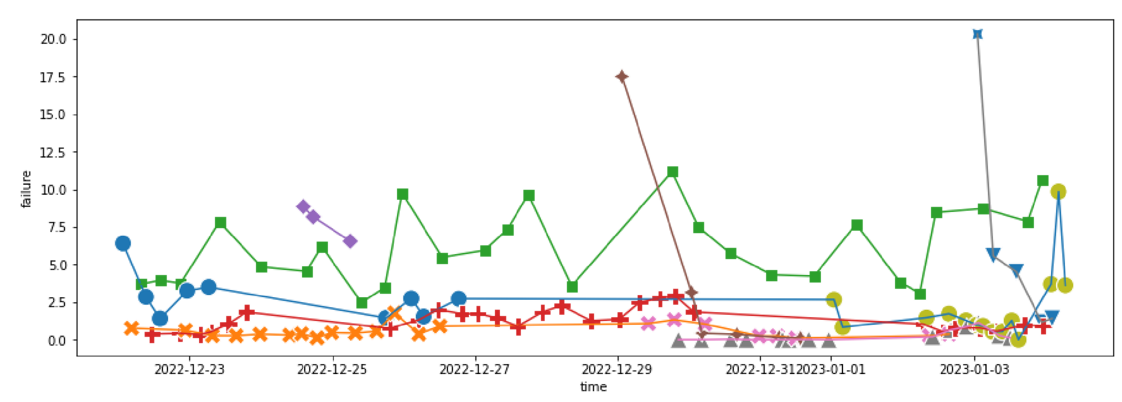
Time clustering



Fitting this clustered test case into the MLR model recommends that the light green and light blue clusters are likely to be problematic, with the light green being ranked higher than the light blue. This is the desirable result.

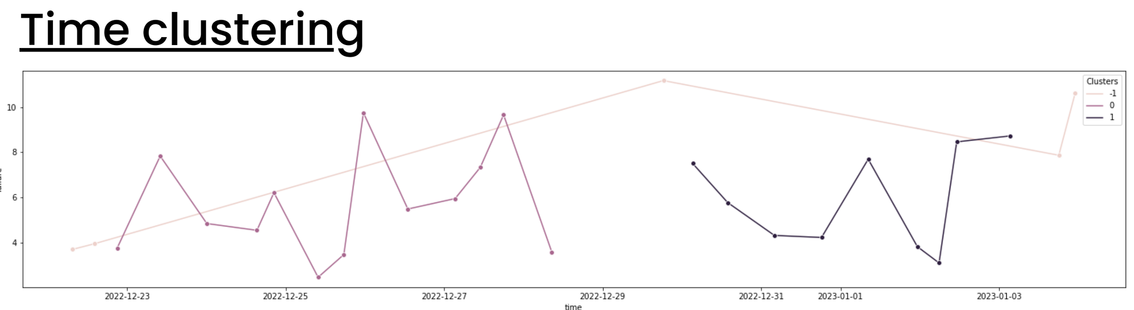
Analysis of Time Clustering

Overview of test case #2



The green set-up consists of the machines that should be highlighted as it has consistently higher failure rates than most other data points.

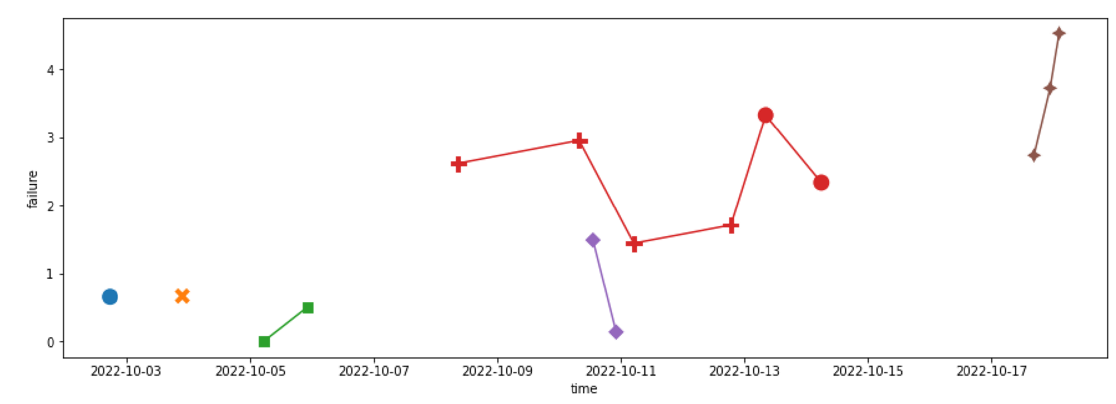
Time clustering



Clustering on this test case provided little improvement as it ranked all 3 different clusters for the green set-up at the top. The same recommendations could have been made even without clustering.

Applicable to Small Test Cases

Overview of test case #3



When time clustering was done on this test case, there were no meaningful clusters that were observed due to its small size.

The algorithm recommends the red set-up as problematic first, before the brown set-up. The solution flags out machines that are performing worse consistently, rather than those with worse performance for very few data points.

Overall, the effectiveness of the MLR coupled with time clustering was highlighted for both large and small test cases. The shortcoming of time clustering is addressed by allowing users to have the option of having clusters or no clusters.

05 Conclusion

Project Achievements

The team developed a model based on Multiple Linear Regression and supplemented it with Time Clustering to arrive at a comprehensive solution to the problem faced by Infineon. The solution has been proven to correctly identify problematic machines and optimised efficiency of the department. It will be deployed to engineers shortly after project conclusion.

Future Direction

Extensions to the applicability of the group's model can be done by pre-processing data using normalisation. By learning historical baselines of failure percentages, a standard can be established for normalisation. This allows for comparisons across multiple products simultaneously in our model and further improves efficiency.