Enabling Machine Learning For Improved Tool Matching And Greater Process Control

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COVID has not just impacted the world from a devastating health and economic perspective, it has fundamentally accelerated digitization and increased the use of electronic capabilities in both the professional and personal spaces. This increased demand for electronics has had a direct impact on the semiconductor industry with an increased demand for output and higher yield. The majority of semiconductor manufacturing exists on a foundation of decades of experience in achieving high output and high yield, but it is getting harder and harder to achieve the highest yield levels with advanced chip processing. Traditional methods are meeting their limits.

To keep production tools up and running, we can no longer depend only on conventional tool control methodologies such as Statistical Process Control (SPC) or Fault Detection and Classification (FDC) control, which both rely on having defined control limits for univariate signals coming from the tools. The signal to noise ratio of the problems to be solved are in the next realm – the multidimensional realm. This requires using multivariate analytics (MVA) techniques on large data sets – the world of Machine Learning (ML) and Big Data. Big Data techniques are based on statistics and there are many software tools available to enable this, but the critical missing ingredients are access to richer tool data and the application of knowledge of the process tools themselves – or Applications Engineering.

The approach from Lam Research is to ensure the right data is available in the right format as it is created (at the right time). As tool logs are essentially proprietary, even when recorded in ASCII text, the methodology is to convert these logs into JSON format, which is easily accessible to data engineers (it is an open format, and there are many readily available data loaders for JSON). This makes the tool data agnostic from the tool type or supplier and creates a source of data that is not only much richer, it has all the needed context information embedded – two characteristics missing in traditional data feeds (SECS/GEM or EDA2).

The second element of the Lam Research approach is the application of effective MVA approaches that solve actual tool challenges.

Discriminate analysis using PCA (principal component analysis) is a very effective way to uncover the relationships between observations and variables. The different Principal Components can be plotted against each other to create a visual representation. An example is shown in Figure 1 where each point in the plot represents a single wafer and each color represents a process chamber, using hundreds of tool sensor signals over a 90-day period. This allows an outlier chamber to be easily identified. This MVA approach also enables a drill-down (see Figure 2) in which sensors correlate with this deviation from the fleet to the sensor level (see Figure 3) which, when combined with tool knowledge, can dramatically accelerate the root cause and corrective action (RCCA). This approach has shown a >50% reduction in RCCA and >20% reduction is time to tool recovery. It should be noted that for the PCA plot shown in Figure 1, all the wafers were being run in production, which means that existing in-line process controls were "blind" to the chamber in the upper left being out of distribution or no longer matched.

As stated in this paper, the nature of tool issues being detected are at the outlier edges of tool performance and are not typically detectable using standard techniques. In-line process control often misreports the process tools as "in-control". Having access to the right data enables an MVA approach which enables an advanced early warning system or Predictive Maintenance. The detection is both a precursor and predictor before issues become catastrophic. The accuracy of these predictions can (and should) be tested using regression analytics and examples of which are shown in Figure 4.

Overall, with the use of multivariate machine learning, we can compare, analyze, predict, and control large fleets at a scale, speed, and sensitivity which has not been possible in the past. As such, we can improve the performance of manufacturing fab production in terms of revenue, yield, machine availability and productivity.

Figure 1: Using MVA PCA to identify an outlier chamber and bring it back to baseline

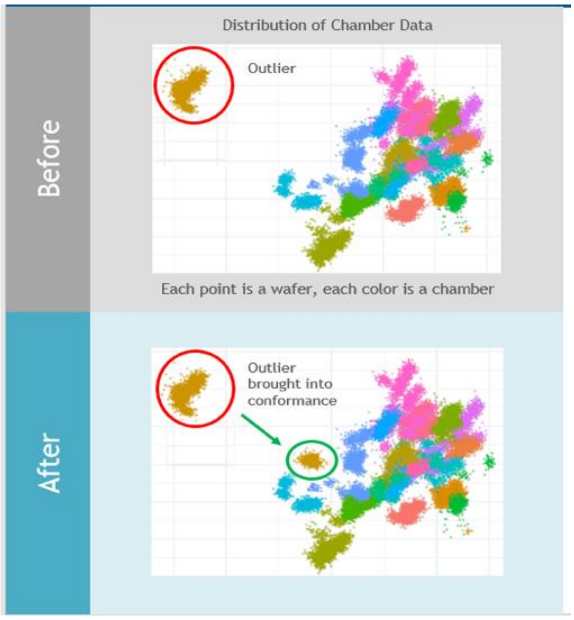

Figure 3: Drill down of individual sensor from feature ranking chart

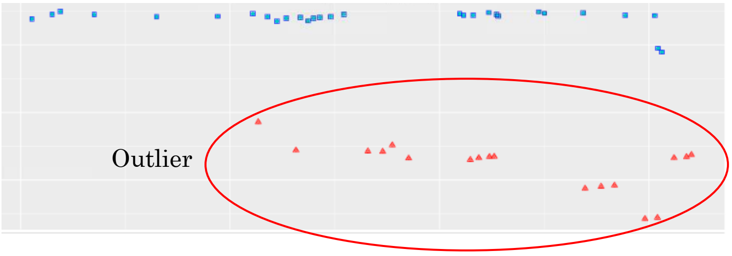

Figure 2: Identify root cause via top features ranking from highest to lowest contribution

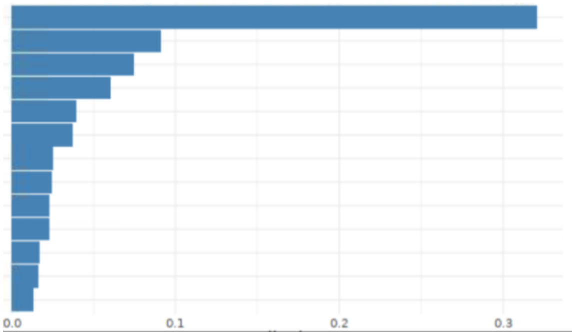

Figure 4: Regression Modelling (Stack Thickness)