euspen's 24th International Conference & Exhibition, Dublin, IE, June 2024
www.euspen.eu

Root cause analysis in Float-Zone crystal growth production using fishbone diagram and association rule mining

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Abstract

Float-Zone (FZ) crystal growth process is a critical process for producing ultra-pure silicon crystal with extremely low impurities, particularly low oxygen level. However, the occasional oxide problem on polysilicon surface acts as a impediment to the process efficiency. Hence, this study aims to address this problem by conducting root cause analysis. Specifically, association rule mining is applied on a dataset with the input identified by a fishbone diagram from different aspects. The results showed that a high moisture level from the early phase could potentially be a critical contributor to the oxide problem, thereby indicating the next step of research – exploring the underlying reasons for the high moisture level.

Float-zone crystal growth; root cause analysis; association rule mining

1. Introduction

It is undisputed that silicon wafers have become crucial to our modern life and the world's commercial and military applications. The demand for silicon wafers has witnessed a substantial surge in recent years, necessitating a substantial increase in productivity. In order to meet these growing demands and enhance the competitiveness of businesses, single crystal growth process as the key process for the fabrication of silicon wafers, has been driven to increase good-for-order single-crystal silicon yield while keeping costs low. Float-Zone (FZ) crystal growth process is a critical process in the production of high-quality single crystals used in various applications, including solar cells, insulated gate bipolar transistors (IGBTs) [1], etc, where there purity of the silicon crystal is essential. The FZ process can allow for producing a higher purity silicon crystal with much lower concentrations of impurities, particularly lower content of oxygen (below $5 \times 10^{15}\ \mathrm{atom}/cm^3$ [2]) due to the absence of crucible. However, the high production costs of FZ crystals have been a hindrance for its wider applications, due to the high costs for the feedstock material, polysilicon feed rod [3]. The contribution of the feed rod to the Cost of Ownership (CoO) of the growth process is far more than 50% [3]. Therefore, crystal yield is of great significance for the FZ process. However, the FZ process occasionally suffers from the oxygen contamination, which may disrupting the process efficiency, thus affecting crystal yield. The oxygen contamination can be visually observed in the images captured by the FZ vision system, as seen in Figure 1. To enhance the crystal yield and thus enhance the competiveness of the FZ process, it is essential to optimize the FZ process and achieve consistent quality by mitigating the oxide problem. Therefore, it is desired to discover the root causes of the oxide problem, which motivates this study.

Root cause analysis is a process through which we can understand the fundamental triggers of a problem, thus leading to more effective solutions. Knowledge-driven approaches are widely used in conventional root cause analysis involving domain-specific expertise, and human intuition to identify the underlying causes of issues. Typical examples are fishbone diagram, 5 Why, and FMEA. However, these knowledge-driven approaches are time consuming and inefficient, which becomes particularly evident in the era of big data [5]. The rise in data accessibility, coupled with the increased availability of computational resources, has prompted researchers and practitioners to utilize data-driven approaches such as data mining and machine learning techniques to enhance the efficiency of the root cause analysis process [5].

Hence, this paper aims to improve the FZ process, by conducting root cause analysis for the oxide problem in the FZ process. To this end, association rule mining [6], a data-driven approach would be leveraged for the root cause analysis.

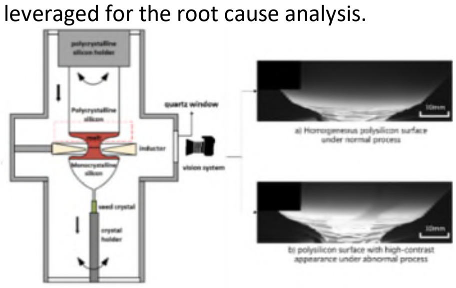

Figure 1. The comparison of normal process and abnormal process with oxygen contamination.

2. Root cause analysis with association rule mining

Association Rule Mining (ARM) [6] is a data-driven approach that can provide quantitative evidence of relationships between variables, allowing for discovering hidden relationships within the data that might have been overlooked. The frequent patterns extracted by ARM are in the form of $X \rightarrow Y$ The frequent patterns are then examined by a minimum threshold of statistical measures, such as support and confidence and lift. The larger these measures, the more robust the rule is. One only needs to look into the strong rules extracted from ARM, and examine if they are related to the source of the problem using expert knowledge.

However, it should be noted that ARM can only handle binary or categorical attributes, which is not common in manufacturing data. Therefore, if ARM is applied, the manufacturing data should be processed and converted into binary or categorical data. Besides, since the number of rules is highly dependent on support (frequency), some interesting rules might have been filtered due to the rarity. Hence, to assign equal importance to each variety of the oxide, ARM would be applied on each subdataset categorized by the varieties of the oxide.

3. Experiments

Before applying ARM, the relevant data associated with the oxide problem was first identified by a fishbone diagram from 5 aspects: Machine, Process, Ambition, Human, Material, as seen in Figure 2. Several potential factors were identified that may contribute to oxide (see Figure 2).

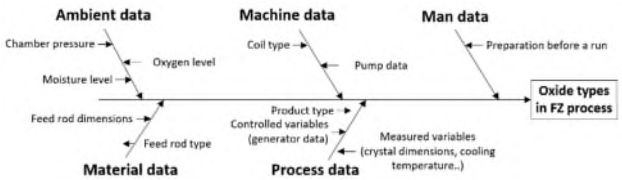

Figure 2. Fishbone diagram for identify potential factors that contribute to the oxide problem.

Subsequently, a total of 387 observations of these potential factors along with FZ images were collected from 387 production runs. These observations were cleaned and transformed to categorical data types. After data-preprocessing, the dataset consists of 387 samples and 135 features along with three oxide types: normal, spot and shadow. Next, FP-Growth from rCBA package in R was applied with a minimum class-wise support threshold of 30% and a maximum length of the itemsets of 3 which is equivalent to considering at most two features. The generated rules were pruned with the absolute confidence threshold of 50% and the absolute lift threshold of 1.2, followed by removing redundant rules that have no positive improvement on confidence and lift measures. Finally, a total of 68 rules were identified, with lift values ranging from 1.2 to 11.88.
The scatter plot for visualizing all rules can be see in Figure 3. As seen, the rules with the highest lift values are concentrated in the bottom left corner of the plot, indicating low support and confidence. In fact, the majority of these rules are linked to the normal type. While these rules may not be very actionable in practice, they offer valuable insights into the optimal conditions for a normal process. Another cluster stands in the upper-right corner of the plot with both a high level of support and confidence, making them particularly interesting. These rules are associated with spot and shadow oxide types. The network graph for the classes of normal, spot and shadow can be seen in Figure 4, 5, and 6, respectively. The highlighted itemsets of each graph are the most commonly occurring itemsets, indicating their great significance. As seen, the spot and shadow are associated with the moisture level from the early while the normal case is associated with high preparation time and low oxygen level. As mentioned in the scatter plot, the priority would be put on the rules of spot and shadow types rather than the the normal. Hence, the subsequent research would be to discover the root cause of high moisture level.

4. Conclusions

In order to identify the fundamental triggers of the oxide problem to improve the FZ process, association rule mining was leveraged for root cause analysis. The results showed that high moisture level from the early phase could potentially contribute to the spot and shadow types. Therefore, the next step of research would be focus on the root cause analysis of high moisture level.

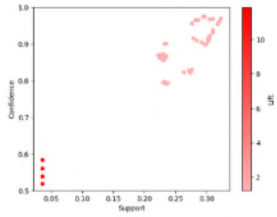

Figure 3. The scatter plot of rules.

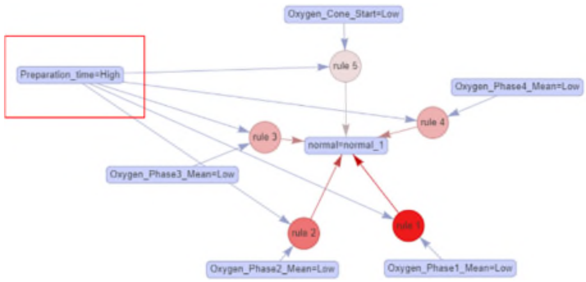

Figure 4. The network graph for normal case.

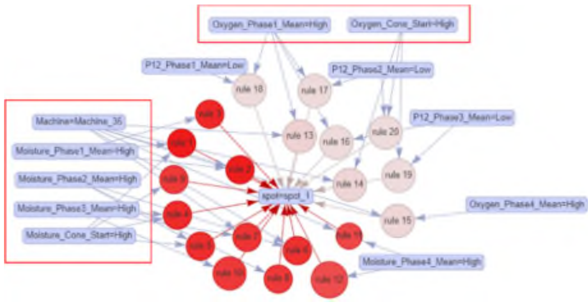

Figure 5. The network graph for spot case.

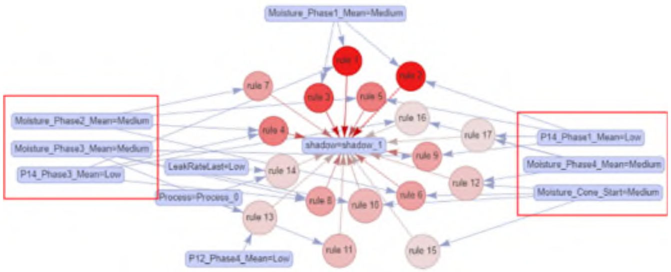

Figure 6. The network graph for shadow case.

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