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THRESHOLD VOLTAGE DISTRIBUTION NARROWING BY MACHINE LEARNING FOR TRENCH MOSFETS

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ABSTRACT

A narrow threshold voltage distribution is essential to ensure uniform performance among parallel-connected power MOSFETs. This work analyzes threshold voltage variation in trench MOSFETs using real data and proposes the use of machine learning models to improve manufacturing uniformity.

1 INTRODUCTION

Power MOSFETs play a critical role in high-performance electronic systems, particularly in automotive applications that require reliable parallel operation. A narrow threshold voltage distribution among parallel devices ensures uniform switching, thermal stability, and efficiency. However, deviations in semiconductor process parameters introduce a threshold voltage variation. This work identifies such influencing factors and applies machine learning techniques to model and mitigate these deviations, ultimately aiming to improve the uniformity of the threshold voltage across wafers.

2 METHODOLOGY

2.1 Data Collection and Analysis

The dataset was collected using Infineon's internal tools and databases, focusing on a specific field plate trench II MOSFET technology. Threshold voltage measurements, gate oxide thickness, source width, and implant machine type were collected from different databases. The final dataset was constructed at the wafer level by aggregating the mean values of the chip-level measurements.
In order to avoid data skew from production outliers, early manufactured wafers with anomalous behavior were excluded during preprocessing. Based on the conclusions, a set of parameters was selected as the features of the machine learning model.

2.2 Machine Learning

The task was formulated as a regression problem, with the selected parameters after data analysis as features and the threshold voltage as the target variable. Three regression algorithms were selected: Linear Regression, Random Forest Regression, and K-Nearest Neighbors (KNN). To ensure fair evaluation and prevent data leakage, the models were validated using two strategies: Leave-One-Out Cross-Validation (LOOCV) and Stratified 75:25 Train-Test Split. Random Forest and KNN models were further optimized through grid search-based hyperparameter tuning, while Linear Regression was used with default settings due to its simplicity and robustness for linear relationships.

3 RESULTS

The dataset consisted of 2215 wafers with varying availability of inline measurements. Four key parameters were initially considered: two measurements of gate oxide thickness, source width, and implant machine type. To explore their relationship with threshold voltage, scatter plots were generated and visualized. Notably, a distinct positive linear trend was observed between the second gate oxide thickness measurement and the threshold voltage, whereas the other parameters showed weak or no apparent correlation. Based on this insight and the supporting correlation matrix, the second gate oxide measurement was selected as the sole feature for modeling.

Among the models, Linear Regression produced the lowest mean squared error (MSE = 0.0188), outperforming even the tuned versions of Random Forest and KNN. Also using LOOCV as the validation method, linear regression showed the lowest error (MSE = 0.0198). The results further validate the assumption of a predominantly linear relationship between the oxide thickness and the threshold voltage.

4 CONCLUSION

4.1 Optimization Approach

A theoretical optimization strategy was proposed using the Linear Regression model to adjust implant doses during fabrication. Threshold voltage predictions based on the measured gate oxide thickness are compared against predefined upper and lower bounds (e.g., 9.6 V and 9.8 V). Wafers with predicted values outside this range would receive a slightly modified implant dose, either increasing or decreasing the dose to compensate. The simulation of this strategy showed a visible narrowing of the threshold voltage distribution.

4.2 Summary and Outlook

This study presents a data-driven methodology for reducing threshold voltage variability in trench MOSFETs. Using minimal data and lightweight ML models, a strong and actionable correlation was identified, with Linear Regression proving most effective. Future work could integrate additional features, automate implant dose adjustment, and implement feedback loops directly in production tools for real-time optimization. Future work could utilize data models and business processes for effective benchmarking, as it enables a standardized framework for data collection and analysis for this use case, facilitating more accurate and meaningful comparisons across different departments involved in the improvement of yield.

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