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USING DISCRETE-EVENT SIMULATION FOR POTENTIAL ANALYSIS OF PREDICTIVE MAINTENANCE IN SEMICONDUCTOR MANUFACTURING

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ABSTRACT

Predictive Maintenance (PdM) offers one possibility to improve productivity in semiconductor manufacturing. Current research on PdM mainly focuses on its technical implementation. By applying discrete-event simulation, we provide results how maintenance strategies influence operational performance, and how PdM contributes to an overall improvement of productivity in wafer fabrication.

1 MOTIVATION

The semiconductor domain faces rising complexity of manufacturing processes and is characterized by high cost pressure due to increasing competition and customer requirements in terms of quality. Therefore, it is important to explore and establish technologies that increase productivity to remain competitive (Yugma et al. 2015). Driven by emerging Industry 4.0 technologies, Predictive Maintenance (PdM) offers one possibility to improve productivity. PdM describes an approach that continuously monitors and verifies an equipment's condition by analyzing data collected by sensors. The objective of PdM is to anticipate failure of machinery and initiate maintenance activities accordingly. PdM optimizes machine utilization, thus increasing overall productivity (Schroeder 2017). In terms of operational performance, machinery failure has been identified as the most significant risk. It induces cost-intensive downtime, which is in particular critical for the capital-intensive semiconductor manufacturing. Consequently, the demand for suitable maintenance strategies such as PdM grows. (Iskandar et al. 2015). Current research on PdM predominantly focusses on the technical implementation of PdM, thus lacking the investigation of its operational impact, which is yet a decisive factor prior to putting effort into implementation. We therefore apply discrete event simulation to study the operational impact of maintenance strategies in wafer fabrication.

2 METHODOLOGY

With the aim to investigate impacts of utilizing PdM in semiconductor manufacturing, a discrete-event simulation of a generic wafer fab is set up, based on the first MIMAC (Measurement and Improvement of Manufacturing Capacity) dataset, introduced by Fowler and Robinson (1995). This dataset incorporates real production data from the semiconductor domain and models two products (P1 and P2). Our simulation study follows the approach presented by Fowler et al. (2015): (1) model design, (2) model development, and (3) model deployment. We observe Overall Equipment Effectiveness (OEE), Mean-Time-To-Repair (MTTR), Mean-Time-Between-Failure (MTBF), and cycle time in order to assess the operational impacts.

PdM allows to optimize Time-To-Repair (TTR) and Time-Between-Failure (TBF). Improvements in TTR and TBF depend on numerous factors, hence we simulate three scenarios in this study, namely pessimistic, optimistic, and intermediate. The scenarios are developed based on a study presented by Deloitte (2017), referring to uptime increases of +10% to +20 %. We focus on the results in the pessimistic (+5%) and optimistic (+20%) settings due to limited space. The predominantly present Preventative Maintenance approach serves as reference for evaluation purposes, averaging in OEE of 80,1 %, MTTR of 8.27 hours, MTBF of 64.77 hours, and cycle times of 628.20 hours (P1) and 649.38 hours (P2).

3 APPLICATION AND RESULTS

The model is designed in *AnyLogic*, including two products, 83 tool groups, and 32 operator groups. Moreover, 48 units add up to one lot and each product passes more than 200 process steps. The re-entrant flow is considered deterministic, while the rework processing is modeled stochastically. Due to the procedural nature of the model, we decide to use discrete-event simulation to represent the system. We furthermore complement the model by adding the evaluation metrics introduced above as well as maintenance and scrap data. Scrap is implemented stochastically according to the MIMAC dataset with >15 scrap occurrences per product. We model maintenance as service blocks (>185 per product), following a Weibull distribution (Schoemig and Rose 2003) with 61 maintenance resource pools. After a 1-year warm up period to avoid an initialization bias, we simulate the PdM approach for five years.

The results show that in the pessimistic scenario, OEE increases by 1.2 pp. MTTR is reduced by 0.40 hours to 7.87 hours, while MTBF increases to 67.69 hours by 2.92 hours. The observed products are processed 4.67% (P1) and 5.87% (P2) faster, respectively. Moreover, the results of the optimistic scenario show that OEE is enhanced by 3.3 pp to 83.2%. MTTR decreases to 6.66 hours (-1.61 hours), and MTBF increases to 76.43 hours (+11.66 hours). Cycle times improve by 16.99% (P1) and 21.68% (P2).

For all three scenarios, the OEE improvement is justified by increased system availability, since PdM minimizes MTTR and maximizes MTBF. Considering the cycle time for the different PdM scenarios on an operating curve, PdM enables semiconductor manufacturers to produce closer to the theoretically possible processing time. Alternatively, fab utilization can be increased in order to maintain consistent cycle time.

4 CRITICIAL APPRAISAL AND OUTLOOK

This project exemplifies a concrete application for discrete-event simulation in semiconductor manufacturing by analyzing the potentials of applying PdM. The results of this study indicate that even modest improvements of TTR and TBF contribute to more efficient operational performance in fabrication and hence lead to improved productivity in the overall semiconductor fab.

Limitations of the presented approach include that the simulation model is based on a dataset that may contain outdated data and building blocks. Moreover, the model does not include all prevalent performance loss factors and dispatching rules. Since complexity of the simulation model is limited compared to reality, future work may complement the MIMAC model with additional and more current information, which in turn leads to more accurate results.

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