Chapter 18
Predictive Analytics for Equipment Maintenance Operations:
A Case Study From the Semiconductor Industry

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ABSTRACT

Predictive maintenance (PdM) is a key application of data analytics in semiconductor manufacturing. The optimization of equipment performance has been found to deliver significant revenue benefits, especially in the wafer fabrication process. This chapter addresses two main research objectives: first, to investigate the particular challenges and opportunities of implementing PdM for wafer fabrication equipment and, second, to identify the implications of PdM on key performance indicators in the wafer fabrication process. The research methodology is based on a detailed case study of a wafer fabrication facility and expert interviews. The findings indicate the potential benefits of PdM beyond improving equipment maintenance operations, and the chapter concludes that the quality of analytics models for PdM in wafer fabrication is critical, but this depends on challenging data preparation processes, per machine type. Without valid predictions, decision-making ability and benefits delivery will be limited.

INTRODUCTION

The semiconductor industry (SI) is one of the most capital-intensive industries, with significant capital investment in equipment, and optimization of equipment performance has thus received noteworthy attention. SI manufacturing processes generate large amounts of metrology data that can be used to analyse and understand failure patterns and to improve the yield of high quality products (Munirathinam & Ramadoss, 2016). Speaking at the January 2000 Industry Strategy Symposium, the former Intel Senior

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Vice President, Michael Splinter stated that one hour of downtime for a critical unit of process equipment could be translated into $100,000 of lost revenue. Hence, in a generic wafer fabrication facility, a downtime reduction of only 1% on the 50 most critical tools can lead to revenue opportunities and cost savings of around $100 million annually. By improving response times and repair times, and by predicting the point in time when problems may occur, a reduction of unscheduled downtimes can be achieved (Munirathinam & Ramadoss, 2014).

Rødseth & Schjølberg (2016), Chiu et al. (2017) and Motaghare et al. (2018) are amongst a number of authors who see predictive maintenance (PdM) as a data-driven approach to address these goals. At its core is the use of advanced analytics capabilities to support the development of maintenance strategies and activities. This chapter assesses the potential impacts of a PdM strategy on the equipment maintenance (EM) operations and manufacturing performance in the SI, and is based on primary research undertaken in the period 2016-2020 (Preis, 2021). Following this introduction, relevant background information is set out. The research methodology, based on a case study at a wafer fabrication facility is then explained, and in the following section the manufacturing process at the case study company is outlined. The findings from the case study are then set out and analysed. Finally, the research questions are addressed, the main themes emerging from the study are reviewed, and future areas for research in this field are discussed.

RELEVANT LITERATURE

Data analytics has become a critical capability for modern businesses. For instance, big data analytics have been utilized in the context of the financial stability of Asian banks (Zhu & Yang, 2021), and the performance of preventive medicine in the healthcare industry (Ivan & Velicanu, 2015). Gronwald (2015) classified data analytics into five categories: (1) descriptive analytics, (2) predictive analytics (PA), (3) prescriptive analytics, (4) sentiment analysis (SA) and (5) text mining. He defined each category with different orientations, techniques and goals, indicating the necessity of defining the goal before selecting an appropriate approach. For instance, prescriptive analytics focuses on the underlying causes as well as the predicted result, while PA focuses only on the predicted result. In addition, this classification provides a clear overview of the various capabilities of data analytics. Among others, important technologies that enable data analytics are NoSQL databases, knowledge discovery tools, in-memory data fabric, and data integration and data quality tools (Maruti Techlabs, 2017). According to the recent Gartner Magic Quadrant for Business Intelligence and Analytics tools, some of the most important tools in this area are Microsoft Power BI, Tableau and Qlik (King, 2021).

The yearly increase in the number of academic publications relating to PA indicates its growing significance in organisations, and the number of articles that focus on PA *in the context of manufacturing* has increased disproportionately. Between 1996 and 2000, less than 10% of all PA-related articles were concerned with manufacturing aspects. From then onwards, the attention on manufacturing aspects increased significantly. Between 2011 and 2015, 27% of all articles were related to manufacturing, and between 2016 and 2020 the percentage reached 54%. In some research publications, there is a significant overlap between PA and the concept of data mining (DM). Some authors try to demarcate PA from DM (Hair, 2007), whereas others tend to use both terms synonymously (Abbott, 2014; Gulati, 2015). However, some critics have suggested that neither contribute anything fundamental to science or economics but reuse existing methods from statistics and machine learning (ML) (Chahal et al., 2019; Ripley & Chen,

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