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A Systematic Literature Review of Automation's Contribution to the Growth of the Semiconductor Industry for development of VLSI Design Processes

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Abstract Technological improvements have greatly advanced the semiconductor sector, with automation playing a crucial part in driving these progressions. This study examines the substantial amount of research about the impact of automation on the expansion of the semiconductor industry, particularly in relation to VLSI (Very Large-Scale Industry) design procedures. The manufacturing of semiconductors is an intricate procedure that involves several subprocesses and a wide range of equipment. The scale of the semiconductors necessitates a large quantity of units to be manufactured, hence demanding substantial data for the purpose of managing and enhancing the semiconductor production process. Thus, this work conducts a systematic analysis by examining a subset of 137 published publications in the scientific community that focus on data mining applications in semiconductor manufacturing. The review synthesizes research on the enhanced productivity, efficiency advantages, and reductions in time-to-market attributable to automation, as well as the quality improvements obtained via these technological interventions. Subsequently, the findings are examined and inferences are made

Keywords Semiconductor; VLSI; Automations; Industry; Growth

1. Introduction

In recent decades, there has been a significant proliferation of goods and services related to electrical and electronic equipment. Additionally, electronic and electrical equipment has become prevalent in a wide range of products and services, with continual evolution (Biebl et al., 2020). In recent years, as semiconductor manufacturing techniques have decreased in size, the capacity to produce transistors on a single silicon wafer has increased to one billion units (Bui et al., 2020). Semiconductor production refers to the manufacturing process of integrated circuits, which include components including transistors, LEDs, and diodesThese components are frequently seen in electrical equipment and consumer electronics. The front-end process involves the fabrication of the crystalline silicon ingot and the subsequent cutting of the wafers. Subsequently, the electrical circuits are created by the utilisation of photolithography and additional chemical procedures. Ultimately, the circuits undergo electronic testing. During the back-end process, the wafer is divided into sections, connected using adhesive, enclosed, and subjected to testing

Semiconductor manufacturing facilities, also known as fabs, are highly capital-intensive and fully automated production systems. These facilities utilize similar processes and equipment to manufacture integrated circuits through a variety of extensive and complex processes. The manufacturing processes are tightly controlled, with reentering process flows, advanced and complex equipment, and strict deadlines to meet the constantly changing demands of an expanding product mix (Khakifirooz et al., 2018)

Industry 4.0 involves harnessing the power of artificial intelligence, data mining, big data, and deep learning to improve the existing industrial infrastructure and drive substantial progress. (Reis et al., 2017). The objective is to incorporate this paradigm, allowing for flexible decision-making and intelligent manufacturing systems, as envisioned by the Industry 4.0 concept. Therefore, the adoption of Industry 4.0 will be crucial in utilising the capabilities of the Internet of Things (IoT) and other developing technologies, which will have a significant impact (Lin et al., 2020). The proliferation of unmanned operations and heightened automation in semiconductor manufacturing systems, along with other production technologies, is progressively growing (Lee et al., 2019).

Traditionally, semiconductor production systems are renowned for their intricate and protracted manufacturing process. Usually, the production of semiconductor wafers involves several process stages, which may easily exceed a few hundred (Hsu et al., 2020). Semiconductor businesses are well acquainted with the constant need for integrated circuits that may provide superior performance at reduced prices. Wafer metrology instruments are used to meticulously monitor line widths, film characteristics, and potential faults in the fabrication of semiconductors, with the aim of enhancing the manufacturing process.

2. Methodology

This segment outlines the approach utilised for carrying out the Systematic Literature Review (SLR) in our investigation. The used data sources have been catalogued. Next, the procedures for doing the search along with selection are elucidated. A SLR effectively addresses the perceived limitations of a narrative review (Khemiri et al., 2018). A systematic literature review typically involves three separate stages: preparation, direction-finding, publication, and dissemination. Each stage of the review process may consist of many phases within a technique or system designed to accurately and objectively address the main topic that the review aims to answer. The study followed the research design used in previous studies (Correia et al., 2017).

2.1 Research Question Formulation:

Provide a clear and precise definition of the research topic or purpose of the literature review. For instance: "What is the influence of automation on the expansion of the semiconductor industry, specifically in relation to VLSI design processes?"

2.2 Search Strategy:

- Created an extensive search plan by using appropriate keywords and Boolean operators. Some keywords that were used as examples included "semiconductor industry," "automation, "VLSI design," and other similar topics.
- Determined and chose suitable databases, such as IEEE Xplore, ScienceDirect, and Springer.
- Record the search queries used for each database.

2.3 Inclusion and Exclusion Criteria:

- Established unambiguous inclusion and exclusion criteria that were directly derived from study topic. Took into account variables such as the date of publication, the methodology used in the research, and the pertinence to the subject matter.
- Recorded the specific standards that were used for evaluating during the screening procedure.

2.4 Study Selection:

- Evaluated the discovered articles using the specified criteria for inclusion and exclusion. Performed the screening process in many phases, which included “title screening, abstract screening, and full-text screening”
- Employed a methodical and clear-cut methodology to record justifications for eliminating publications.

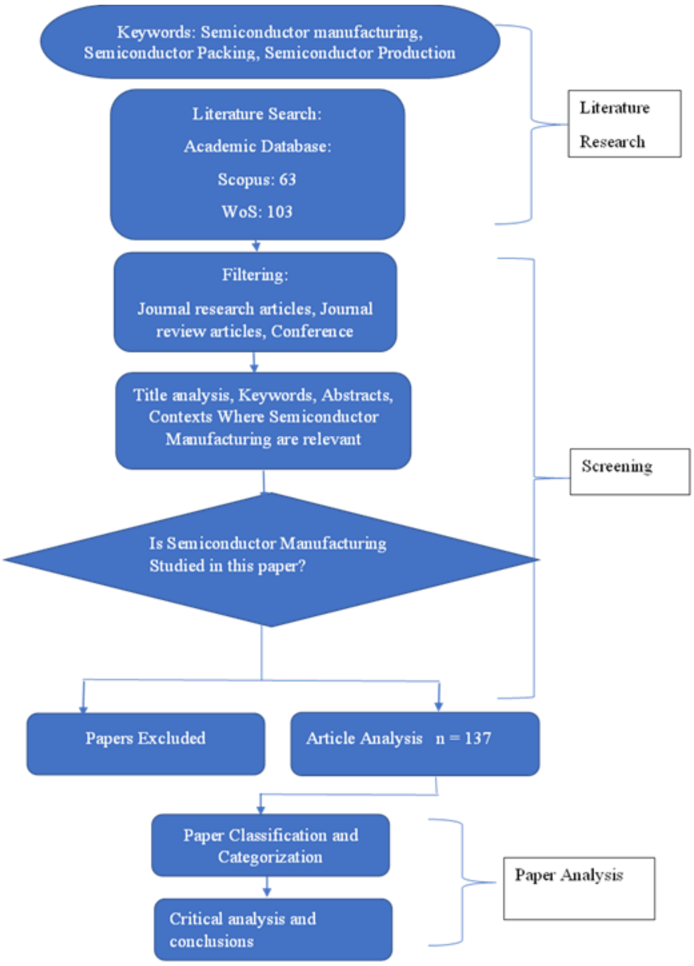

Figure 1: PRISMA flow diagram for the systematic literature

Figure 1 displays the flowchart illustrating the process of selecting papers. Ultimately, a total of 137 publications were used for the study of the article. This sample includes almost all of the publications that were discovered using the specified keywords.

2.5 Data Extraction:

- Create a data extraction form with the purpose of methodically extracting pertinent information from chosen research. Provide specific information such as the author's name, the year of publication, the research methods used, the main results, and any limitations of the study.
- Conduct a trial run of the data extraction form on a smaller group of studies to guarantee uniformity.

2.6 Quality Assessment:

- Evaluate the quality of chosen research by using recognized criteria such as study design and methodology.
- Thoroughly record the quality evaluation procedure and take into account any biases.

2.7 Data Synthesis:

- Provide a concise overview of the main discoveries from the chosen research papers. Analyse the literature to discern recurring patterns, trends, and prevalent themes.
- If relevant, it is advisable to use methodologies such as theme analysis or meta-analysis.

2.8 Quality Improvements:

The results highlighted the enhancements in product quality that arise from technology interventions, such as automation. These findings indicate that the use of automated procedures in semiconductor manufacturing has a beneficial impact on the overall quality of the final semiconductor products.

3. Results

The width of semiconductors has significantly decreased, transitioning from the micrometer scale to the nanoscale scale. Simultaneously, there has been a rise in processing capacity and memory. Integrated circuits, composed of a semiconductor material like silicon, play a crucial role in contemporary electronic gadgets throughout business and consumer sectors. These circuits must possess the capability to function as a transistor, which serves as an electrically controlled switch, in order to carry out fundamental arithmetic operations in a computer. In order to get this almost immediate switching capacity, the circuits must be constructed using a semiconductor material, which is a substance that has electrical resistance that falls between that of a conductor and an insulator.

Table1: Automation applications for quality control in distinct steps of semiconductor manufacturing.

Author and Year	Overall Proposal	Proposed Algorithm	Techniques
Li et al., 2020	An analysis of data mining applications for the purpose of quality control in semiconductor manufacturing	Mountain clustering algorithm Weighted Modified Hausdorff Distance (WMHD)	Clustering
Gallo and Capozzi, 2020	Accurately detecting genuine faulty patterns in Wafer Bin Maps (WBM) to facilitate the enhancement of production yield	A hybrid clustering approach is proposed, which combines cluster analysis with spatial statistics.	Clustering
Kim et al., 2019	The fault detection and diagnosis model is derived directly from the discovery of variable-length status variables (SVID) in the etch process.	Convolutional neural networks (CNNs)	Classification
Jin et al., 2019	A framework for detecting and classifying defect patterns in WBMs using clustering-based methods.	Density-based spatial clustering of applications with noise (DBSCAN)	Clustering
Choi et al., 2019	A Bayesian inference and Gibbs sampling approach is used to analyze complex semiconductor production data for the purpose of defect identification.	Bayesian inference, Gibbs sampling, high dimensional linear regression, multivariate adaptive regression spline (MARS), and Cohen's kappa statistics are all important concepts in statistical analysis.	Classification
Correia, 2017	Identification of process flaws and implementation of effective process enhancements.	Classification using decision trees Using C4.5 in KNIME	Association rules

Table 1 displays the classified papers based on automation claims for quality control at various stages of semiconductor manufacture. The stages, if available, are indicated and may be located in the summary proposal. The table is split into seven primary columns, some of which provide the year of publication, reference, and a short summary of the research. One of the remaining columns provides information on the data mining algorithm that is either proposed or utilized. This column is useful for rapidly identifying a particular method. The following columns indicate whether the sample data was obtained from an actual manufacturing site or whether it was artificially generated. whether the data is authentic, it is recognized, if feasible, by the firm and country of origin. Furthermore, the text emphasizes the need of conducting experimental validation investigations on site.

3.1 Technological Advancements and Automation Impact:

The assessment emphasized that advancements in technology, namely in the arena of automation, have played a substantial role in the development of the semiconductor industry.

3.2 Focus on VLSI Design Procedures:

The research focused on analyzing the effects of automation on VLSI design processes in the semiconductor industry. This emphasis indicates an acknowledgment of the crucial function performed by automation in the progress of VLSI procedures.

3.3 Productivity and Efficiency Advantages:

The synthesis study emphasized the increased productivity and efficiency benefits associated with automation in semiconductor production. These findings indicate that the use of automated methods has had a beneficial effect on the overall efficiency of VLSI design techniques.

3.4 Reductions in Time-to-Market:

The analysis revealed that automation in the semiconductor sector led to significant decreases in the time required to bring products to market. This suggests that the use of automated procedures helps to accelerate the development and manufacturing cycles, which might result in quicker product releases.

3.5 Automation Application for Maintainance in Semiconductor Manufacturing

In (Kinghorst et al., 2017), a data mining approach is suggested that may provide early warning by detecting tool excursion in real time. This technique is designed to enhance equipment management and reduce yield loss. Its effectiveness has been confirmed by actual implementations in the field. The last research focuses on enhancing the accuracy and detection of faulty and malfunctioning tools in semiconductor production at Advanced Micro Devices, Inc. (AMD) using spatial pattern recognition.

3.6 Data Mining Applications for VLSI Design Process

Data mining is essential in several phases of the VLSI design process in semiconductor manufacture. VLSI design encompasses the process of fabricating integrated circuits (ICs) that include an immense number of transistors, ranging from millions to billions, all on a solitary chip. Data mining solutions in this context facilitate the optimization of the design process, promote efficiency, and elevate the quality of the end result.

The imperative need to continuously pursue advancements in semiconductor production processes, aiming to enhance yield and reduce time-to-market for sophisticated designs and processes, necessitates the examination and verification of process tools and wafers using state-of-the-art measurement systems and equipment. This subject includes a total of 19 papers. The subjects discussed in this part include models that involve a specific way for controlling semiconductor photolithography processes, as well as virtual metrology that utilizes meaningful associations between focus measurement data obtained via data mining and tool data (Chen et al., 2020).

Virtual metrology is a frequently discussed subject that involves using sensor data and machine parameters to predict the properties of a wafer. This eliminates the need for costly physical measurements of the wafer properties (Yang, 2021; Yan, et al., 2020). Due to the higher frequency of sampling and immediate availability of machine data compared to metrology data, an accurate virtual metrology can significantly enhance process control & monitoring by providing a continuous supply of real-time forecasted metrology data. Several feature extraction techniques for virtual metrology using multisensory data are suggested in references (Galati and Bigliardi, 2019; Muñoz et al., 2020).

After analyzing all the studies collected in the sample, many discernible patterns start to emerge. Firstly, there is a notable scarcity of research on data mining applications in subprocesses such as Integrated Circuits (ICs) and mask design. Similar observations can be made about research on wafer cutting, cleaning, drying, and polishing. However, there is a lack of specific studies focused on the subprocess of edge rounding and lapping. It is evident that the bulk of research focus on 5-6 primary stages. Some studies lack specificity about the subprocesses in which data mining methods are used, and these subprocesses are not shown.

Another interesting observation made in the literature is the diverse range of data mining tools that were utilised. Data mining is utilised in semiconductor production in different ways, depending on the specific domains associated with the manufacturing procedures. However, most publications tend to prioritise topics such as quality control, maintenance, and manufacturing. In semiconductor literature, various methods are commonly employed to evaluate wafer quality, detect faults, or forecast cycle-time (Anaya et al., 2019). Various methods are employed in quality control to classify defects, failures in bin maps, or manufacturing lots. Various methods, including rule induction, decision trees, and association rules, are employed to analyse the causes of yield loss or diagnose failures (Mörzinger et al., 2019).

There are still several chances and areas for development. For instance, semiconductor businesses may use the internet of things and sensors to enable industrial units to analyze data and provide real-time analytics to an application that can offer insights and warnings to relevant parties (Chien et al., 2020). This will enable these gamers to accumulate a substantial quantity of data. Despite the ongoing development of VLSI design process in the semiconductor manufacturing sector, the usage of internet of things and data mining applications presents a significant potential for enterprises in this industry. It is crucial for these organizations to promptly embrace and explore this opportunity. However, the successful deployment and widespread adoption of the internet of things, along with the extensive use of data mining methods, may be contingent upon the ability of industry participants to promptly overcome certain obstacles (Ciacchella, et al., 2018).

4. Limitations

Despite the significant benefits shown by several research in this study, VLSI design approaches in this business nevertheless include certain inherent drawbacks, which are outlined below:

- VLSI systems have the potential to infringe upon individuals' privacy. The lack of safety and security may have severe negative consequences for users, resulting in misunderstanding among staff and giving rise to legitimate privacy issues.
- Security is a crucial aspect that applies to all data-focused technologies, including semiconductor production. Highly sensitive data is susceptible to malicious assaults (Dogan and Birant, 2021)
- Excessive and repetitive information gathering may be detrimental, since it poses a struggle to deal with unnecessary data.
- There is a potential for the abuse of information throughout the mining process. Data mining systems must adapt in order to reduce the abuse of the information ratio (Silva et al., 2019).
- Another constraint of data mining approaches is their lack of precision. Accuracy is a metric used to assess the performance of a data mining model in terms of how well it can accurately measure and predict outcomes. Various accuracy and error metrics are often used for regression and classification tasks.
- Data mining may provide many obstacles in terms of data integration and interoperability. The performance of an organization is influenced by the interoperability and integration of data. In order to tackle the issues of interoperability and integration, it is necessary to use a complete strategy (Da Silva et al., 2019).
- The presence of incomplete or disproportionate data is a significant difficulty in this particular business. Imbalanced data often leads to subpar performance in most classification methods. Given the importance of wafer yield improvement as a critical performance indicator in semiconductor wafer production, it is essential to carefully choose and control key process stages (Lee et al., 2019).
- The duration of data processing is a constraint that greatly affects the amount of time available, since data preparation often consumes over 50% of the time and resources allocated to the whole data analysis procedure (Misrudin and Foong, 2019).

The advancement of semiconductor production is strongly dependent on the proliferation of big data, which is crucial for addressing the aforementioned constraints and difficulties faced by the semiconductor industry. Supporting larger quantities and longer records of data has enabled several solutions to accurately represent the dynamics of systems, greatly simplify complex interactions between multiple variables, reduce disruptions, and address difficulties related to data quality. In order to take use of the parallel computing capabilities and processing power of high-capacity storage, data mining algorithms in these systems need to be reconfigured to efficiently analyze data within a shorter timeframe. Nevertheless, the abundance of data and the diverse array of data mining approaches do not always equate to increased predictive capabilities and insights (Moyne and Iskandar, 2017). Researchers and practitioners must modify data mining approaches to suit unique applications, taking into consideration factors such as data quality, available data, and objectives.

5. Conclusions

The manufacturing of semiconductors is an intricate procedure that involves several subprocesses and a wide range of equipment. The scale of the semiconductors necessitates a large quantity of units to be manufactured, hence demanding substantial volumes of data to effectively manage and enhance the semiconductor manufacturing process for VLSI design process. Hence, this work conducted a systematic analysis by examining a sample of 137 published publications in the scientific community that focus on data mining applications in semiconductor manufacturing. An extensive bibliometric study was conducted. The categorization of all data mining apps was based on their respective application domains. Five discrete domains were delineated: quality assurance, upkeep, manufacturing, decision support systems, and, as a collective, measurement, metrology, and instrumentation.

The findings indicated that quality was the predominant factor, with 47 articles, accounting for 34.3% of the total publications. There have been few studies conducted in the field of maintenance, which emphasizes the existing gap and the need for further research in this domain. The research conducted on data mining applications in semiconductor production has potential theoretical ramifications. An analysis and classification of many practical and effective instances will greatly enhance future research endeavors aimed at using a diverse set of methods to enhance the implementation and dissemination of data mining applications in semiconductor manufacturing.

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