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A Review on Semiconductor Manufacturing using AI Techniques

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ABSTRACT

The semiconductor manufacturing industry is facing a dynamically growing complexity in the management of production bottlenecks, efficiency of manufacturing equipment and product quality management. In order to maintain the competitiveness in both productivity and sustainable growth, manufacturing organizations are seeing huge opportunities in the application of Artificial Intelligence (AI) as a competitive advantage. To address this approach in a case study, this paper reviews the literature on the application of AI in the manufacturing industry and proposes several AI-based solutions in the subfields of machine learning and computer vision that can be applied to address the challenges faced by a back-end semiconductor manufacturing organization (Company-A). The primary KPI or Key Performance Indicator of this organization is the on-time delivery of manufactured Integrated Circuit (IC) products with high quality at minimized cost. The ideas presented show how Artificial Intelligence can be potentially used to solve problems in the semiconductor manufacturing operations.

Keywords. Artificial Intelligence, Back-End Semiconductor Manufacturing, Smart Manufacturing, Industry 4.0, Machine Learning, Computer Vision.

1. Introduction

Artificial Intelligence has received a major focus in both academia and the industry recently due to the competitive advantages that it can provide to manufacturing organizations in creating a more efficient and sustainable operation [1]. The manufacturing sector is going through a period of change (i.e. Industry 4.0 or Smart Manufacturing) with production and AI technology progress setting the pace of this transformation. At the same time, more and more new emerging AI technologies such as big data analytics, advanced robotics, expert systems for diagnosis, computer vision and pattern matching for outgoing product quality are creating an impact to the manufacturing industry in a major way. The introduction of cloud computing, real-time data processing, Internet of Things (IoT) solutions, prediction technologies and big data analytics has all led to the creation of smart manufacturing platforms that act as a conduit to further accelerate the application of AI solutions in the manufacturing industry.

2. Proposed AI Initiatives

2.1 Challenge #1: Supply Chain Bottleneck

The aim of the proposed solution is to solve the problems with production scheduling bottlenecks in the manufacturing line that are caused by the huge number of product mix changes and customers' orders that causes high machine setup change times that increases machine downtimes and reduce productivity. With a spike in the number of product mix changes and customer priorities, the machines experience more setup times for reconfiguration and a lot of manpower is spent in doing those changes. It is vital that the production scheduling has a further horizon of forecasted products such that any pre-orders or expected orders that have not yet happened from customers can be built ahead accurately. This not only minimizes the production bottleneck, but also reduces the product manufacturing cycle time.

Presently, within the production planning function of the organization, the supply chain planning execution systems are used for the scheduling of IC production materials for back-end assembly and testing processes based on the product type and quantity required by customers' purchase orders (PO) that continuously come in from day to day. The production materials are tracked in batches called "production lots". Although to some extent, the planning system has some automated algorithms to determine the best arrangements of machine-to-lot setup with regards to the input of production material and requirements into the systems, it is severely limited by the horizon that it can track and makes many assumptions on the planning instead of based on real-time data, as the planner only knows the product to be built once the PO comes in. Any urgent POs that come in at the last moment will disrupt the entire planned schedule as it is not on a real-time basis.

The proposed AI-solution is to utilize the combined historical input data from the ERP, MES and Testscape systems (such as Customer Name, Product ID, Incoming Wafer Quantity, Order Quantity, Urgency Status, Period, Historical Cycle Time, Historical Machine Performance, etc.) to implement a data acquisition, preparation and predictive analytics system that takes this information and train a machine learning model such as Deep Learning Neural Networks to predict the cycle time, equipment utilization and output quantity of products.

It is comprehensible to leverage the real-time data from the already existing datasets available in Company-A's digital systems and build a machine learning model as shown in the Figure 1. This provides the capability to the organization to obtain insights from real-data rather than using assumptions in the planning system, thereby improving the accuracy of predictions and the ability to respond faster by building ahead of customer demands and using the manufacturing capacity much more efficiently, and solving the problem of machine bottlenecks. It should be noted that in order to implement the solution, a suitable high performance computer is required in order to run the AI solution as it is expected to be computing power-intensive. As the data is gathered from already clean databases, the amount of data preparation is expected to be minimal.

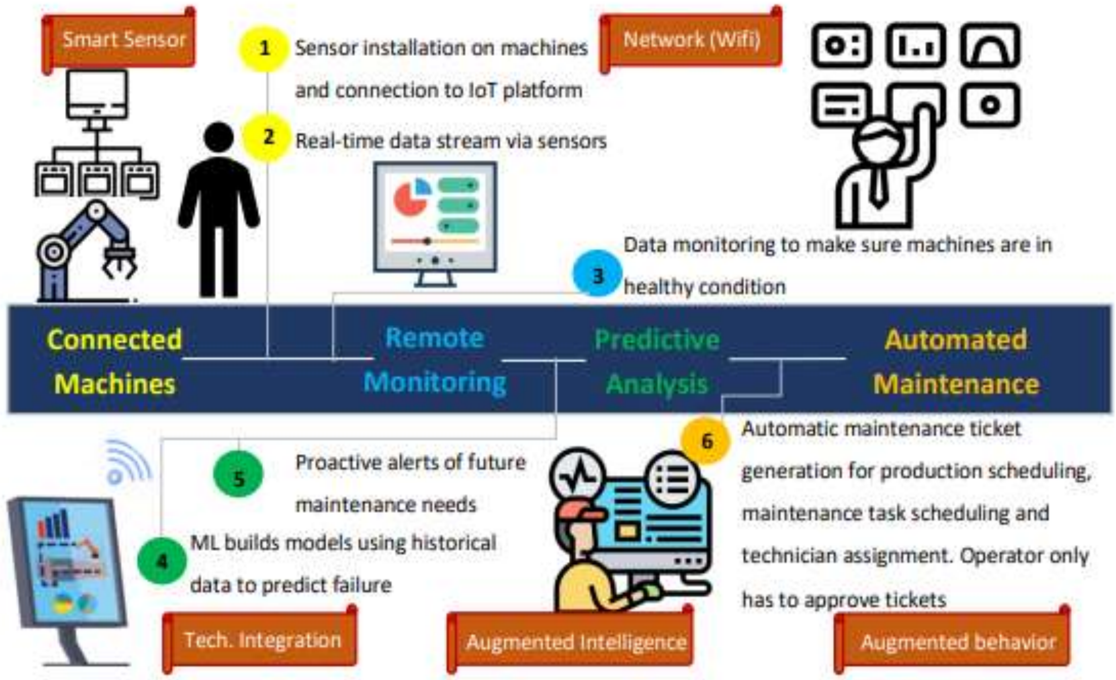

Figure 1: Process incorporated for automation in smart manufacturing and machine maintenance.

2.2 Challenge #2: Product Quality Issues

The aim of the proposed solution in this subsection is to use AI to solve the product quality problems that are related to gaps in the current test and physical visual inspection capabilities and processes. A high number of quality related incidents were reported by end customers in the recent years despite several measures put in place to provide extra inspections and testing. One of the main reasons is the solutions put in place are human-dependent, such as extra gates of manual visual inspections which not only causes a longer production cycle time, but increases the cost of manufacturing. Although Company-A's semiconductor inspection machines already have automatic optical inspection (AOI) capability as the first inspection gate prior to the manual inspection process, the reference image template matching is not very reliable to properly filter the defects that are too miniscule to be directly screened.

Over-adjusting the reference good image template (over-fitting) causes the good semiconductor ICs to be wrongly rejected, whereas under-adjusting it (under-fitting) causes defective semiconductor ICs to be wrongly accepted as good units that get wrongly shipped to customers. Due to this difficulty in balancing the adjustment of AOI templates manually, an AI-based solution that does not require a manual adjustment of the reference image template is required. The proposal is that the good/bad reference image should be based on historical good and bad semiconductor images trained on a machine learning algorithm (for example, CNN) in combination with image processing.

Currently Company-A is already using a network of industrial control systems (Testscape and AOI) to monitor its manufacturing equipment for the purpose of quality and yield control, and the data is uploaded to a central FTP server using a real-time test data acquisition platform called "e-Test" as shown in the Figure 2. The collective capability of each system is can be leveraged through the implementation of an integrated solution. The gap in the current system is that the reference images used for comparison is always static and set by the engineer manually and are not always accurate especially for minor defects. Therefore, the proposed AI-based solution is to the use the historical data sources from these systems so that they can be used to train a neural network machine learning model in combination with image processing algorithm to build a dynamic decision support tool for better product inspection accuracy which in effect, uses dynamic reference images for comparison.

Figure 2: Testscape and AOI equipment for Smart manufacturing

In the proposed AI-solution, the images from the AOI system that were uploaded to the FTP server will be fed to a series of image pre-processing techniques to enhance and restore, and feature extract using color segmentation so that any minor defects on the IC chips can be detected easily. From here, the pre-processed images are used to train a neural network machine learning model to predict whether an IC can be accepted or not. With labeled images of good and bad ICs being constantly fed to the machine learning model for training, we can obtain a very accurate and dynamic image recognition system that does not rely on a fixed reference image as a deciding factor.

To enhance the system further, the data from Testscape and e-Test associated with each image are tagged to the image database so that if there are any historical patterns of visual defects that could be related to the process variabilities, the machine learning model can help detect these hidden patterns and provide an alert to the engineer so that the upstream processes can be investigated for root cause analysis and troubleshooting. Thus, this AI solution is a 2-in-1 solution: to improve the accuracy of visual inspection by using a dynamic reference image template and to serve as an early failure detection tool for IC defects that might be cause by upstream manufacturing processes.

In this subsection, an innovative AI solution is proposed to solve the excessive cost of manufacturing that is largely related to the replacement of worn-out machine spare parts or test contactor pins either prematurely (i.e. replacing spare parts that are still in good condition) or overdue (i.e. not replacing worn-out spare parts on a timely manner causing excessive unscheduled machine downtimes). The machine spare parts of focus in this study are the test contactor pins widely used in semiconductor electrical test operation to make electrical connection to each IC unit during high voltage electrical testing that can get worn out as they get used many times. Fig. 7 shows how they get worn out .In recent years, Company-A spent increasingly on replacement of test contactor pins. Due to human eye judgment, these spare parts were typically replaced before their lifespan was reached and this was estimated based on the given standard rated number of "touchdowns" or "contact" instances made by the spare part with the IC unit. Not only were the replacement cost increasing due to frequent replacements, but inaccurate estimation of when the spares should be replaced is causing problems with unexpected machine downtimes. This was because Company-A uses a cyclic "Preventive Maintenance" system (e-PM) which tracked each machine to be down for maintenance on a fixed monthly basis rather than on a predictive basis..

The proposed AI-based solution is to implement Predictive Maintenance by using image processing to capture and pre-process the images of spare parts and using machine learning to train a classifier model to identify good and bad test contactor pins. This will lead to a very accurate judgment of whether a spare part is worn out or not. Presently, the only IT system related to equipment maintenance in use at Company-A is the e-PM (Preventive Maintenance System) which stores the machine information along with associated spare part change dates. The framework of this proposed solution as shown in the Figure 3. Table 1 summarizes the key factors associated between the Traditional and smart manufacturing.

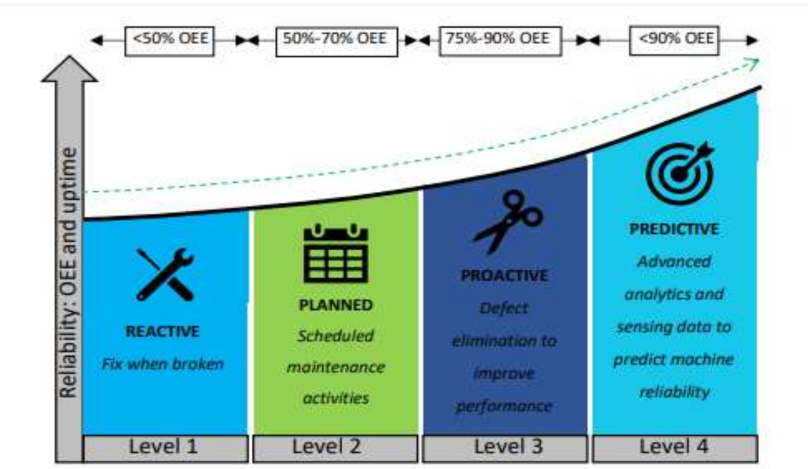

Figure 3: The Framework of proposed solution using AI technique

Table 1: Comparison between Traditional Manufacturing and Smart Manufacturing

Key	Traditional manufacturing	Smart manufacturing
Data	Not fully exploited, not total accessible	Real time data collection and visualization
Process and operations	Manual optimization	Automatically optimized, and full traceability
Downtime	unpredictable	Predictable
Maintenance	Preventive/Corrective	Preventive/Corrective/Predictive
Supply chain	Traditional	Smart and 100% transparency
Efficiency	Not fully exploited	Fully exploited
Product development	Time wasting and not flexible	Faster developed products even for complex products
Energy optimization	N/A	Yes
Quality	Manual inspection	Hight quality, less cost, automatic inspection
Flexibility	Not totally flexible	Totally flexible
Decision making	Poor data	Real time data, smart algorithm to prediction

Therefore, a more intelligent way of performing such maintenance is required to resolve both problems with high cost incurred with replacement of spare parts and excessive downtimes. Using this data as input in combination with images associated with the spare parts, the predicted outcome of whether to replace or not replace test contactor pins can be obtained at real-time, thus realizing the concept of predictive maintenance.

3. Conclusions

With this solution, the technicians no longer need to make a decision whether to replace a machine spare part or keep using it based on their own judgement and can leave this challenging decision to an AI system which learns from past historical data and can accurately decide it based on actual data rather than assumptions. To make this work, an additional camera and computer vision system needs to be installed for the purpose of capturing the images of the spare part and to monitor whether it is time to replace the spare part. Once the spare part reaches its actual worn-out condition, the AI system will intelligently send an alert to the technician to do the replacement. Thus, this serves as a decision making support tool. To further augment this system, a user-guided augmented reality system can be developed to help users without any idea of knowing if a spare part is worn-out or not; to be able to accurately replace the spare part at the correct time.

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