Design and Implementation of an Intelligent Manufacturing Execution System for Semiconductor Manufacturing Industry

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Abstract-**This paper proposed an intelligent MES by integrating manufacturing execution system, data warehouse, online analytical processing and data mining system. The data warehouse for this system is provided by the massive amounts of data gathered from a MES. Through some process of integrating MES with data warehouses, data warehouses with decision analysis, and decision analysis with data mining systems. A three-tiered web-based systematic framework has been established. The result of this study is the integration of the MES and data mining system. According to experimental analysis, the product yield and the manufacturing cycle time all have been improved for manufacturing industry.**

Keywords: **Data warehouse; Data mining; Decision tree; Manufacturing execution system (MES)**

I. INTRODUCTION

In the 1960's, enterprises began using computer to manage information relating to daily business transactions, thus, saving valuable manpower and increasing the accuracy of information. According to Nonaka et al. [9], to gain a competitive advantage, knowledge must first be grasped. In an era of knowledge economy, knowledge will replace the traditional factors of production and become the most important of resources. To achieve success, enterprises must constantly create new forms of knowledge, infuse new types of knowledge into existing organizational systems, rapidly absorb new types of technology and replace outdated technology with new products. As more enterprises implement MES, they accumulate massive amounts of data. This research will explore some fundamental problems to be faced by enterprises in the future. The goal of this research is to make MES wiser. Through the integration of some major subject areas (MES, data warehouse, online analytical processing, data mining system) the massive amounts of data assets accumulated by MES may be used to obtain information valuable to enterprises in making important decisions. As part of this research, the framework for a data mining system has been designed. This framework allows for the integration of MES and data mining tasks. Moreover, in accordance, an appropriate information system is practically planned out and established.

II. LITERATURE REVIEW

A. Intelligent Management Decision System

Intelligent management decision systems are the combination of information technology and artificial intelligence. Such systems allow organizational networks to work toward the computerization of management systems, which are made up of particular regulations and tasks. Moreover, by putting to use such computerized systems, assisting systems may carry out data management, information analysis and anticipatory system monitoring in a convenient manner. Consequently, by performing all types of responses and management and decision-making, the computerized systems may carry out their assigned tasks.

B. Data Warehouse

Inmon [11] believes that a data warehouse is an integrated, subject oriented, time variant and nonvolatile collection of data in support of management's decisions.

Berson et al. [4] believes that data mart is a data store that is a subsidiary of a data warehouse of integrated data. The data mart is directed at a partition of data that is created for the use of a dedicated group of users. A data mart might, in fact, be a set of denormalized, summarized, or aggregated data. Online analytical processing gathers together, sorts through and analyzes the data stored in data warehouses, creating substantial data. Various modes of data are presented for users to access. This allows users to view data using various perspectives and subjects. Through complex search processes and the comparison of data, data reporting may facilitate many different levels of analysis.

C. Data Mining

Groth [10] points out that data mining is the process of finding trends and patterns in data. The objective of this process is to sort through large quantities of data and discover new information. The benefit of data mining is to turn this newfound knowledge into actionable results, such as increasing a customer's likelihood to buy, or decreasing the number of fraudulent claims. Berry and Linoff [7,8] point out that data mining is the exploration and analysis, by automatic or semiautomatic means, of large quantities of data in order to discover meaningful patterns and rules.

Chen [12] points out that the work process of data mining is composed of eight primary tasks. The eight primary tasks are task relevant data, background knowledge, problem statement, kinds of knowledge to be mined, data mining algorithm, models or knowledge patterns mined, interestingness, and user. The goal of data mining is to extract valuable and new information from existing data. Data mining is the process of discovering interesting patterns in databases that are useful in decision making [2]. Generally speaking, data mining includes the following major functions: classification, clustering, estimation, prediction, affinity grouping, description, etc.

III. MES AND PROBLEM DEFINITION

A. The MES

A semiconductor manufacturing entity includes integration of the processing equipment with all of the supporting systems for product and process specification, production planning and scheduling, and material handling and tracking. IC fabrication is a very complex and capital-intensive manufacturing process.

Presently, high productivity and a quick response to customers are essential for most producers. Reducing the processing time and inventories are objectives in managing production systems [3]. Customers today are more demanding: they want to buy high quality, low cost, high performance products configured with just the required features. Semiconductor companies are being forced to move from high volume production of commodity parts to low volume, flexible and leaner production of application-specific parts. The IC manufacturers' goals are to reduce costs, cut production time, improve quality, increase asset utilization and guarantee on-time delivery. An available tool to assist semiconductor manufacturers in achieving these objectives is a Manufacturing Execution System. Advanced Manufacturing Research (AMR) organization has defined MES as "an integrated architecture for plant wide information management that groups applications and functions around a central common database used to share product and process data among the applications" [14].

The MESA International definition of MES is: "MES delivers information that enables the optimization of production activities from order launch to finished goods. Using current and accurate data, MES guides, initiates, responds to, and reports on plant activities as they occur. The resulting rapid response to changing conditions, coupled with a focus on reducing non value-added activities, drives effective plant operations and processes. MES improves the return on operational assets as well as on-time delivery, inventory turns, gross margin, and cash flow performance. MES provides mission-critical information about production activities across the enterprise and supply chain via bi-directional communications." The functional model of MES is illustrated in Figure 1. [13]

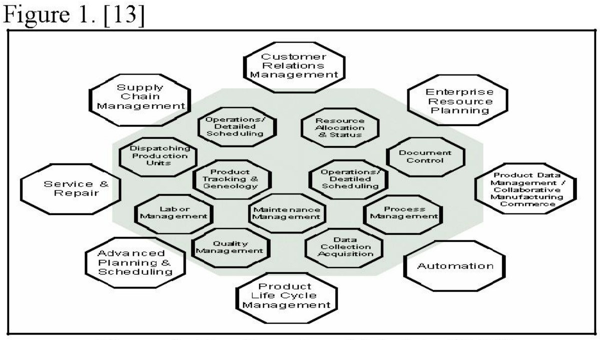

Figure 1. The Functional Model of MES

B. Problems of MES

The advancement of automation technologies has eased the operations of manufacturing and material handling. For example, an automated manufacturing cell may consist a computer numerical control for part processing, an articulate robot for loading and unloading, two conveyors for transporting arrival and departure parts, and several sensors for signal capture. Those automated equipments are then harmonized by a centralized controller, usually a programmable logic controller.

Unlike traditional production activity control or shop floor control systems which try to stabilize the production activities on the shop floor and focus largely on the scheduling and/or dispatching functions, MES focuses mainly on monitoring and summarizing the status of operational systems (i.e., the status of product quality, equipment, materials, and manpower on the shop floor). A MES is defined as an on-line integrated computerized system that is the accumulation of the methods and tools used to accomplish production [15].

However a single MES is not enough. The manufacturing execution system should be conducted to integrate physical operational systems, so a fully automated and integrated manufacturing management environment can be developed. And it is necessary to develop intelligent MES to integrate the information of distributed operational systems and discover the newfound knowledge. MES is unable to carry out a complete process of analysis, allowing massive amounts of data stored within the system to become more meaningful. Moreover, MES is unable to satisfy the needs of high-level management personnel in policy-making decisions, to speed up the creation of new strategy.

IV. DESIGN AN INTELLIGENT MES

A. The Overall Description of Proposed Framework for Intelligent MES

Based upon the data mining system, the design primarily focuses upon the following problems: the integration of MES and data warehouses, the integration of data warehouses and decision-making analysis, the integration of decision-making analysis and data mining systems, and the set up of a data mining engine.

B. The Framework for Integrating MES and data warehouses

With advancements in data warehouse technology, six distinct models have been developed in the establishment of data warehouses. This research utilizes the top to bottom model to design a data warehouse system. The database of MES serves as the origin of data, by extracting and transforming data, an integral and unified data warehouse system may be designed. Data marts and data warehouses have an one sided relationship, in which data from a data warehouse flows into a data mart.

When integrating a MES and a data warehouse, it is common to encounter the problem of inconsistent, incomplete and duplicate data. Therefore, the integration of MES and data warehouses involves the collection of different types of data from their original sources. This data is placed in a data staging area where it undergoes such processes as the cleaning, pruning, combination and removal of duplicates. Next, the data is stored within a presentation server. At this point, users can carry out search tasks.

Even if a data warehouse with all the potentially relevant data is available, it will often be necessary to pre-process the data before they can be analyzed [1]. The procedures for integrating MES and data warehouses include eight distinct steps. These steps are explained below:

(1)Collection: After gathering primary data, needed data is copied into a data staging area for further processing.
(2)Transformation: This includes revising of data accuracy and the removal from storage of unneeded data.
(3)Loading an indexing: Transformed data is saved in a data mart and indexed.
(4)Quality control check: Assuring the quality of data.
(5)Announcement or publication: The preparatory work for the official on-line installation of the system.
(6)Renovation: The continuous revision of out of date and inaccurate data.
(7)Search: Data search services are provided.
(8)Checks and preparations: Assuring the safety of the data warehouse to avoid potential damages.

C. The Framework for Integrating Data Warehouses and Decision-Making Analysis

There are some steps to build the framework for integrating data warehouses and decision-making analysis.

(1) Designing a schema for data warehouse: When designing a data warehouse system, the following schemas can be utilized: star schema, snowflake schema, and fact constellation schema. This research utilizes the star schema in designing the schema for data warehouse. This schema is based upon the manufacturing fact table, a time dimension table, an area dimension table, a product dimension table, and a quality dimension table. This is illustrated in Figure 3.

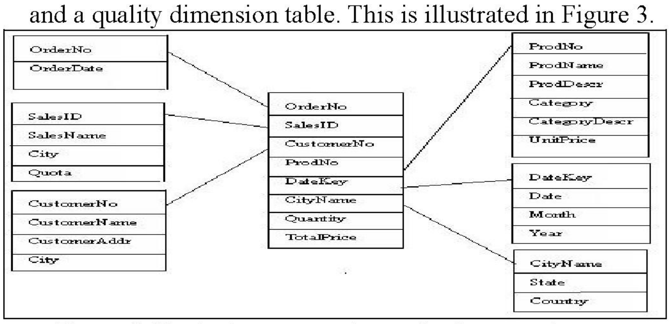

Figure 3. Designing a star schema for data warehouse

(2) Designing a fact table: The real data that we need is placed in the fact table. The data in this table cannot be altered; we may only add new information. Moreover, this table includes an index key related to a dimension table. When designing a fact table, several factors must be taken into consideration.

(3)Designing the dimension table: Data of dimension table is used as a reference to fact table data. When necessary, complex descriptions can be divided into several small parts.

(4)Designing a multidimensional data model: When analyzing data, multiple dimensions are brought together as one point of consideration. This process is called a multidimensional data model [6]. Data warehouse systems may include many data cubes. Each data cube may be the product of different dimension and fact tables. The OLAP operations in data cubes include rollup, drilldown, slice, dice, and pivot. A data cube may be an N-dimensional data model [16]. In order to provide an even wider range of search capabilities, this research uses the four dimensions of time, area, product and quality to construct a four-dimensional data cube model.

D. The Framework for Integrating Decision-making Analysis and Data Mining System

After completing the construction of a data cube, it is possible to integrate decision-making analysis and the data mining system (as shown in Figure 4) [12]. The goals of integration are to allow OLAP analysis results to supply the knowledge base within the data mining system, thus providing analysis information to the data mining system and creating a point of reference for data mining tasks. OLAP technology is able to blend together people's observations and intelligence within the data mining system, thus improving the speed and depth at which data is excavated. Furthermore, the intelligence discovered by the data mining system acts as a guide in OLAP analysis tasks, increasing the depth of analysis. As a result, information left unearthed by the OLAP, is extremely complex and delicate in nature.

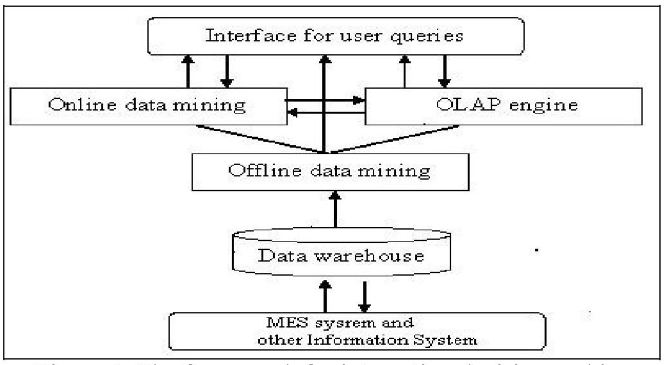

Figure 4. The framework for integrating decision-making analysis and data mining system

E. Designing a Data Mining System

Data mining technology can be divided between traditional and refined technologies. Statistical analysis is the representative characteristic of traditional technology. As for refined data mining technologies, all types of artificial intelligence are put to use. More commonly used types include: decision tree, neural network, genetic algorithm, fuzzy logic, rules induction, etc. Decision tree induction is one of the widely used tools for data mining [5]. This paper's algorithm used decision tree method for data classification and prediction. The algorithm acts as the nucleus of the data mining engine in classifying data hidden within the database and in anticipating information. The operational process and knowledge rules excavated by data mining can be displayed through visual figure. This allows users to operate data mining more easily and to understand the meaning represented by excavated data.

V. PRACTICAL IMPLEMENTATION AND OPERATION OF INTELLIGENT MES

A. The Information Infrastructure of the Intelligent MES

With the systematic information infrastructure provided by the worldwide web, users may use the Internet to interact in more convenient manner. This three-tier information infrastructure of the intelligent MES is illustrated in Figure 5.

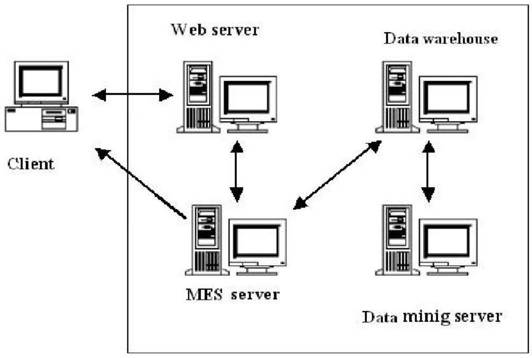

Figure 5. The information infrastructure of the intelligent MES

B. Operational Procedures of the Intelligent MES

The operational procedures of the intelligent MES are shown in Figure 6. The detailed explanations of the procedures are as follows:

(1)User entry system: Users operate related procedures of the data mining system through the Intranet or Internet.

(2)Loading the data of the MES into the data warehouse system: Based on the requirements of the manufacturing subject of the data warehouse, the manufacturing data tables, quality data tables, product data tables of the MES will be considered data source of the entries. Afterwards, through the clearing, collation, and transformation of the data, they are then entered into the data warehouse system.

(3)Establish schema of data warehouse: The data warehouse system is built according to the manufacturing subject, and the star schema is established. The manufacturing fact table is at its center, with the related quality dimension table and the product dimension table.

(4)Establish OLAP decision-making analysis: According to the manufacturing fact table, quality dimension table, and product dimension table, the operation of multidimensional data cube is simulated using ROLAP method.

(5)Select source of data and attribute for data mining: The data in the data warehouse system and the results of OLAP operations can be sources of data for data mining. The mission model editor of the data mining engine can be used to help user select the source of data and attribute.

(6)Select algorithm and functions of data mining: The data mining algorithm provided by the calculation database include decision tree, neural network, genetic algorithm, and market basket analysis; data mining functions include classification, clustering, prediction, and affinity grouping. This system uses decision tree as the algorithm, and it uses classification and prediction as the function.

(7)Executing data mining system: Mission processor is the core of the data mining. It uses a target-oriented processing system to execute data mining and acquire the wanted results.

(8)Interpretation, evaluation, and exhibition of results: The results acquired from data mining system are usually some abstract data. Consequently, the system uses the rule based knowledge presentation method of the expert system and complements it with a web-based framework to express and interpret data mining results to help user understand the results gained.

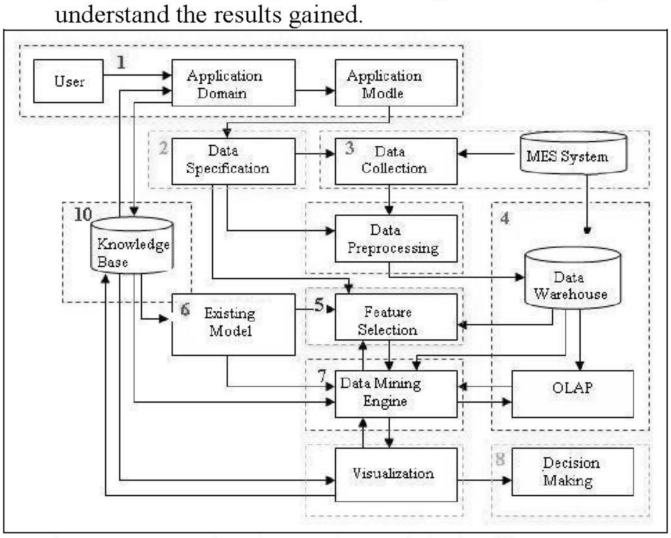

Figure 6. Operational procedures of the intelligent MES.

C. Practical Operation of the Data Mining

High quality data from the electronics industry database is used by this research to analyze categories of quality factors in the manufacturing process.

Table 1. Training data from the quality database.

No.	Heat_Up (°C/sec)	Cool_Down (°C/sec)	Tranmission_Speed cm/min	Drying_time sec	Quality_Information
1	>3	<=-3	70	80	NG
2	>3	>-3	70	80	OK
3	>3	>-3	90	100	OK
4	<2	<=-3	90	100	NG
5	<2	>-3	90	120	NG
6	>3	>-3	70	100	OK
7	2~3	<=-3	70	80	OK
8	<2	>-3	90	80	OK
9	2~3	>-3	90	120	OK
10	2~3	>-3	70	120	OK
11	<2	<=-3	90	120	NG
12	<2	>-3	70	100	OK
13	<2	>-3	90	100	NG
14	<2	<=-3	70	80	OK
15	<2	<=-3	70	100	OK
16	2~3	>-3	70	80	NG
17	2~3	<=-3	90	100	OK
18	>3	<=-3	70	80	NG
19	<2	>-3	70	80	OK
20	>3	<=-3	90	100	NG
21	>3	<=-3	90	100	NG
⋮	⋮	⋮	⋮	⋮	⋮
1000	>3	>-3	90	120	OK

In this research, we randomly select 1000 records from MES in 2004 as the training data. Prepare previously classified training data, as shown in Table 1.

After calculated by decision tree algorithm, training data will be partitioned in accordance with the selected test attribute. The completed decision tree is illustrated in Figure 7.

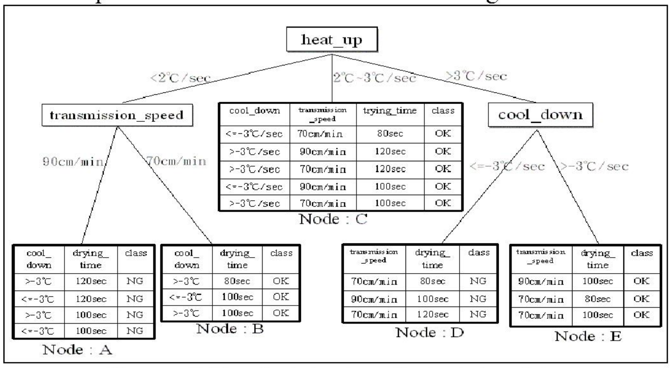

Figure. 7 The decision tree for training data

D. Analysis of Data Mining Practical Operation

The decision tree makes knowledge rules easy to understand, thus, the decision tree, selected as algorithm, serves as the nucleus of the data mining. Any specific information, which has already been classified, can be easily traced along the path from the root node to the leaf node by using the decision tree model. In this way, knowledge rules for classification may be established. When the goal of data mining is to classify or anticipate the results of data and create easy to comprehend rules, the decision tree algorithm is best suited to act as the nucleus of the data mining [8].

The knowledge rules possessed by the decision tree described above allow for the convenient gathering of information, by tracing this information along the path from root node to leaf node. In this research, knowledge rules are expressed through the rule based knowledge presentation method of the expert system, thus, revealing the knowledge rules possessed by the decision tree.

Whether or not a decision tree can successfully classify a new set of data can be evaluated through the data mining error rate. Test data can be used to evaluate the leaf node error rate. The evaluation of decision tree error rate can be divided into the following two steps [7]:

(1)Evaluate the error rate of each node: Calculation formula is " the leaf node error rate= the amount of incorrectly classified data within the leaf node/ the total amount of data in the leaf node". The leaf node error rate is as follows: A=0.2, B=0, C=0.2, D=0, E=0

(2) Evaluate the total error rate of the decision tree: The total error rate of the decision tree is the weighted total amount, calculated as shown below: The total error rate of the decision tree = 0.091

E. Benefit Analysis

This research uses the data mining system, with the vast amount of quality data from the manufacturing process as basis, to produce accurate quality information and knowledge rules. Moreover, based on the acquired knowledge rules, is able to understand the characteristics and attributes of the important causes of quality, allowing it to stay on top of the quality issue. By strengthening the training of quality assurance personnel, adding extra heaters for the increase of temperature, installing adjustable fans for the decrease of temperature, and controlling the speed of conveyors, these methods improve product quality, lower manufacturing costs, and turn raise the overall business performance. The benefits analysis of this improvement is as follows:

(1)Using the intelligent MES to dig up similar category quality information. Consequently, the average improvement rate on the product yield is 5.87%., as shown in Figure 8.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
Unimproved yield rate(%)	92.8	94.3	94.7	93.6	93.1	94.3	92.1	95.2	93.1	93.6	94.5	94.5	93.82
Improved yield rate(%)	99.5	98.9	99.2	99.1	99.1	99.8	99.2	99.7	99.1	99.3	99.4	99.6	99.33
Improving rate(%)	7.22	4.88	4.75	5.88	6.44	5.83	7.71	4.73	6.44	6.09	5.19	5.40	5.87

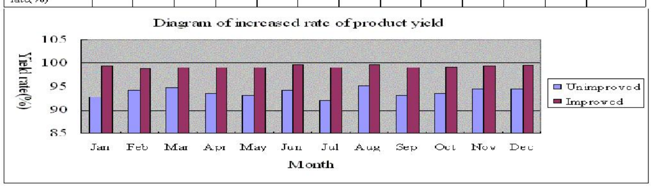

Figure. 8. Diagram of increased rate of product yield

(2)Using intelligent MES to reduce the rate of manufacturing cycle time to 23.49%, as shown in Figure 9.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
Unimproved cycle time (days)	6.8	7.2	6.8	6.9	5.8	6.6	6.7	6.8	7.1	6.6	7.2	7.5	6.83
Improved cycle time (days)	5.1	5.4	4.5	5.1	5.2	4.8	5.1	4.9	5.5	5.7	5.4	5.9	5.22
Improving rate(%)	25.00	25.00	33.82	26.09	10.34	27.27	23.88	27.94	22.54	13.64	25.00	21.33	23.49

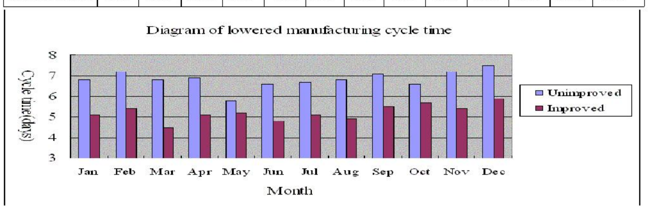

Figure 9. Diagram of lowered manufacturing cycle time.

VI. CONCLUSION

Through the actual establishment of data mining and intelligent MES, and the use of these systems on the manufacturing processes of the electronics industry for quality improvement, the experience has verified the following results:

- The basic framework of establishing intelligent MES will allow corporate computerized applications, which will not be limited to the level of data processing, but it can also aggressively work towards an information-based, knowledge-based, and intelligent form of management information system.
- Using the intelligent MES to dig up similar category quality information. Consequently, the average improvement rate on the product yield is 5.87%.
- Using intelligent MES to reduce the rate of manufacturing cycle time to 23.49%.

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