Data Analytics for Operations Management in a Selected Outsourced Semiconductor Assembly and Test (OSAT) Manufacturing Company

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Abstract: Encouraged by the increasing accessibility of data and recent advances in modern manufacturing and optimization methodologies, data analytics has been increasingly applied to operations management issues. If production processes become more complex and mechanized, the exploration of new operational insights must be automated. An OSAT manufacturing company's current methodology of assessing operational output is primarily performed in a manual and segmented scheme. These manual tasks are time-consuming, inefficient, costly, and affect certain planning and organizational decisions, mistakes, or misjudgments. In this paper, a project was initiated where a system was proposed and built using SDLC methodology to apply data analytics to operations management in three major areas – *Shipment*, *WIP*, and *Output management*. The project aims to automate and unify the aggregation and evaluation of manufacturing data collected during operations in an OSAT manufacturing company by a manufacturing execution system (MES) and computer integrated manufacturing (CIM) system and to develop a data analytics system to support the analysis of operations results. The results reported in this paper demonstrated a processing time improvement of 4X and 55X for the service and user activities, respectively. Moreover, the developed frameworks can be used as a basis for developing data analytics solutions for operations management.

Key Words: big data analytics; operations management; computer integrated manufacturing; software development life cycle; semiconductor manufacturing

1. INTRODUCTION

Operations management (OM) is commonly known as the discipline which employs scientifically sound analytical methods to help make optimal decisions for organizations. It is inherently related to the use of data (Choi et Al., 2018). Research in OM has traditionally focused on models for understanding, typically at the strategic level, how companies should operate. Prompted by the growing availability of data and recent advances in machine learning and optimization methodologies, there has been increasing application of DA to problems in OM (Mišić, and Perakis, 2020). This shift has been driven primarily by the increasing availability of data. In the semiconductor manufacturing domain, richer data are becoming more voluminous and more granular than ever before.

In manufacturing systems, large amounts of heterogeneous data are being generated, collected, and stored (Kozjek et al., 2018). These data, which, due to their characteristics, can be considered as big data, represent a great potential for discovering new specific knowledge and for developing new data analytic tools that can be used to improve further the performance of manufacturing systems (Esmaeilian et al., 2016). Manufacturing operations could be significantly enhanced by allowing decisions related to these systems to be combined across multiple distributed operating units and made closer to the factory floor with better contextualization of the connected networks (Sprock et al., 2019).

Nowadays, OSAT companies face the challenges and issues of dynamic and unpredictable business environments, the strong influence of globalization, demands for rapid development of new complex products, requests for changes during the development process, short delivery times, accurate due dates, etc. On the other side, they are facing incomplete information, lack of knowledge, unpredictable nature of resources, difficulties in supply chain, various disturbances, and many others. All these complexities must be well mastered to fulfill orders, obtain customer satisfaction, and stay competitive and relevant on the market. Within this setting, effective management of manufacturing shop floor operations and material flow is one of the critical factors in controlling the operational complexity of such highly dynamic environments, specifically in OSAT manufacturing.

Attempting to combine different information sources for diverse decision-support analysis models and varied execution mechanisms present a significant challenge in OM (Sprock et al., 2019). Currently, at the selected OSAT manufacturing company, the agents employed on combining operations data, running factory models across varying customer product attributes, analyzing various results, and generating reports are predominantly done in a manual scheme and segmented. As production systems become more complex and automated, assisting the discovery of complex operations insights need to be automated as well.

1.2 Background of the Project

The OSAT manufacturing company in this study is one of the world's largest providers of outsourced semiconductor packaging, design, and test services. As the original pioneers of the OSAT industry, the company in the case study has helped define and advance the technology manufacturing landscape. For the past five (5) decades, the company has delivered innovative packaging solutions with the service and capacity global customers rely on. The company's factories, particularly in the Philippines, provide a full range of assembly and test services, including key packages and technologies in various applications. The company has three (3) factories located in two (2) municipalities in the Philippines.

Data that are being consumed during these operations reviews are coming from factory MES and CIM data warehouses. MES data provides all transactional information in the shop floor, lot movement, and other quality assurance requirements. CIM data, on the other hand, provides equipment utilization information, and other process related transactions. The historical data, from these data warehouses, can then be reviewed to understand how the factory operations did in the last quarter, month, week, or day. This information is relevant to operations managers and key stakeholders since they can see operations performance metrics. Operational logics and formulas and other OM variables are manually embedded or adjusted on the excel software. The formulation of OM reports, data extraction and ingestion, and analysis of constraints are done separately and by factory level down to package line level. These activities and the conventional methodology are done in a manual fashion, which consumed significant time, employed high resources, displayed un-standardized multiple report formats, and creating siloed analysis. Due to this conventional method, operational decisions, and formulation of strategies account for some errors or misjudgments in dealing with operational deviations and on crafting tactical and operational plans.

1.3 Statement of the Problem (SOP)

The OSAT manufacturing company has over 100 customers and offering 100 different integrated chip (IC) packages producing about 6 to 8 billion IC units annually. There are over 6 thousand automated machines from over 500 types and have over 30 process stations. The nature of the manufacturing company is "high volume and mix" and has a very complex manufacturing operation. Given this manufacturing environment complexity, managing the daily operations proved to be difficult and cumbersome, especially utilizing manual methods in analyzing operations performance. The need for better methodology and a new modern system for faster and efficient operations analysis has given birth to the idea of applying DA in OM. Literature also suggests that the application of DA to OM in the OSAT industry have not been explored. The fruit of this project will not only address the business challenges outlined but also provide valuable information for future researchers in the same field.

The objective of this project was to develop and implement a data analytics system for operations management (OMDAS) in an OSAT manufacturing company. Specifically, the project aims to answer the following questions:

1. How will the DA system for operations management be developed to fit in the OSAT manufacturing company's existing manufacturing systems and environment?
2. How will the DA system for OM be implemented across the three factories?

2. METHODOLOGY

2.1 Methodology

A software development process, also known as a software development life cycle (SDLC), is a structure imposed on the development of a software product. There are numerous models for such developments, each describing approaches to a variety of activities that take place during the process (Sarker et Al., 2015). In this paper, the SDLC (Figure 1) method is utilized in the development of the OMDAS.

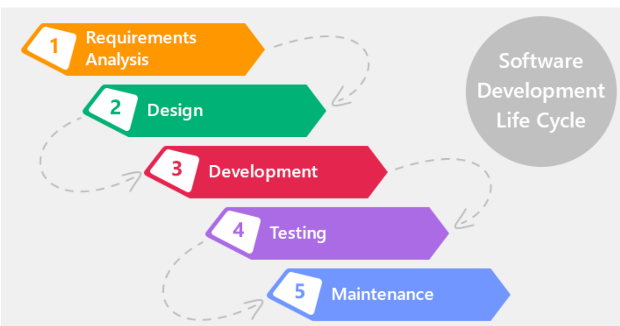

Fig. 1. The SDLC Waterfall Model (WM)

This paper followed the 6 stages of waterfall, namely, requirements analysis, design, coding, testing, and operations. The WM allows the development team for a more comprehensive scope and design due to the planning and documentation as to its initial stages. The project scope under each stage is evident that is why it is well suited for a milestone-driven development, and it is straightforward to draft a timeline, assigning start and end dates for each milestone (Powell-Morse, 2016).

The following are the phases involved in the development of the OMDAS:

2.1.1 *Requirement Analysis (RA)*

During this phase, the requirements of the application are analyzed and written down in a specification document that serves as the basis for the development of OMDAS. The requirements were collected using the OSAT manufacturing company's' standard RA template.

2.1.2 *System / Software Design (SD)*

The SD process determines to provide enough detailed data and information about the system and its system elements to enable the implementation consistent with architectural entities as defined in models and views of the system architecture. The operational *DA Architecture Framework* (DAAF) shown in Figure 2 was presented. An architecture framework provides principles and practices for creating and using the architecture description of a system. It structures architects' thinking by dividing it into domains, layers, or views, and offers models - typically matrices and diagrams - for documenting each view ("Enterprise architecture framework," n.d.). Figure 2 illustrates the operational DAAF of the planned system. *Data sources* X are collected by the software agents in workstations from multiple domain architectures of the OSAT manufacturing company. *ETL strategies Y* collect, clean, aggregate, and transform the data. The *ETL Strategies Y* handles the big data transformation of the *Data Sources X* to prevent bogged down of the OLTP servers in the manufacturing environment. The *ETL Strategies Y* results are sent to the *Transformed Data*. The *Analytics Strategies Z* pull the *Transformed Data* and load it into the server's memory as the *In-Memory Data*. The *Analytics Strategies Z* performs the aggregation, calculation, data relationship, and other

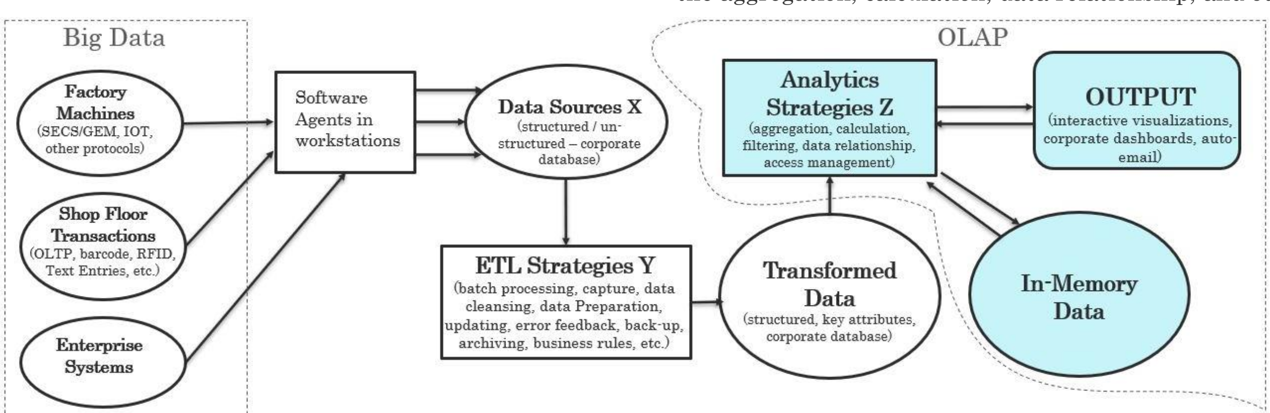

Fig. 2. The Data Analytics Architecture Framework

logical processes for the OM using the *In-Memory Data*. Moreover, the *Analytics Strategies Z* handles the data filtering and access management for the OLAP and responsible for creating the *Output*. The *Output* provides interactive visualization, corporate dashboards, or auto-email reports and is linked back to the *Analytics Strategies Z* for user interaction.

2.1.3 Coding/Development

In this phase, actual software development will be coded by the developer, implementing all models, business logic, and service integrations specified in the prior stages.

2.1.4 Testing

This phase intends to find out whether the software functions work according to the specification, evaluate whether the software performs all activities after integration with the existing operating environment, and measure up the reliability and quality of the software.

2.1.5 Operation and Maintenance

This phase guarantees the information system is fully operational and performs optimally until the system reaches its end of life. The operation and maintenance of the OMDAS will be managed through the OSAT company's standard IT service management system.

2.2 Implementation Approach Framework (IAF)

The IAF will be the operational guide to implement the system in production. The IAF (Figure 3) will be in sequence alongside the SDLC phases. The first stage is the *exploration* where it will coincide with the RA phase of SDLC, where all the requirements will be gathered. The second stage will the *Pre-Implementation,* and this is where the planning and analysis activities are performed. The third stage will be *Data Implementation,* where the ETL implementation activities will be completed. In this stage, all data preparations will be organized. The fourth stage will be the *Build and Implementation,* where the actual development, implementation of business rules, and user permission management will be achieved. The fifth stage will be the *Execution* where testing and deployment activities will be performed. This stage will complete all the necessary production release. The last stage will be the *Operationalize* phase, where the post-go-live activities of the new system will happen. At this stage, the system stabilization will be monitored.

2.3 Data Collection

2.3.1 OM Data

Data collection will be carried out through a script using SQL programming given a specific timeframe. The steps will be done in three parts:

1. Extract the report from the *existing* method and convert it into an excel format.
2. Extract the report from the *OMDAS* and convert it into an excel format.
3. Perform necessary data analysis.

2.3.2 Performance Comparison Data

A time study method will be performed to record the duration of each of the process steps for both methodologies to be used in the analysis of the performance data of the old and new methods.

2.4 Data Analysis

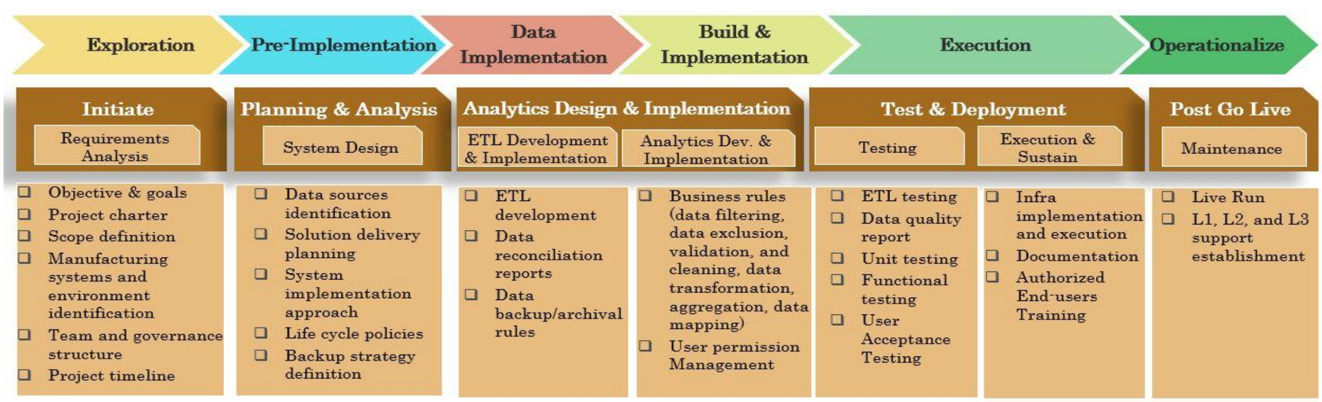

Fig. 3. OMDAS Implementation Approach Framework

2.4.1 OM Data Matching

The study will analyze data from the old methodology using the Excel sheet method vis-à-vis data processed using OMDAS. The analysis will be done on a Microsoft excel sheet using VLOOKUP and MATCH functions.

2.4.2 Performance Comparison

The performance comparison data of the new system will determine the difference between the conventional and automated methods of extracting, loading, and generating reports.

2.4.2.1 To calculate the '*percentage decrease* (% Decrease),' the following formula will be used:

$$\% \boldsymbol{Decrease} = \left(\left(Original\ Time - New\ Time\right) \div Original\ Time\right) \times 100$$

2.4.2.2 To calculate '*Increase by a factor of,'* the following formula will be used:

$$\boldsymbol{Increase\ by\ Factor\ of} = Original\ Time\ \div New\ Time$$

3. RESULTS AND DISCUSSION

The OMDAS was developed following the SDLC methodology and designed utilizing the DAAF. An IAF was presented to provide the overall implementation of the OMDAS to the three factories. The OMDAS was operationalized with a live run of the system. The data validation comparing the generated OM data between the old methodology and OMDAS was resulted in PASSED. Moreover, UAT results also resulted in PASSED (Table1).

Table 1. The Data validation (variance) and UAT results

Factory	Variance Result	UAT Result
Factory 1	< 1%	Passed
Factory 2	< 1%	Passed
Factory 3	< 1%	Passed

Finally, to validate the efficiency and performance of the OMDAS, a comparison of the old and new methodology in analyzing operations results was outlined in Table 2 and 3. Table 2 summarized the various steps to analyze factory results on the three major OM areas, namely, shipment, output, and WIP, and table 3 shows the streamlined activities using the new system. The duration was captured using a time study method. To identify the machine and human activities, the "owner" is added into the column headers represented by service (machine) and user (human). The old step recorded a duration time (DT) of 80 minutes for the service execution and 110 minutes for the user execution. The new step recorded a DT of 20 minutes and 2 minutes for the service and user's execution, respectively. The service activities recorded a 75% decrease of DT or improved by a factor of 4 (or 4X) against the old methodology. The service speed improvement is attributed to the practical design of the ETL. The user activities recorded a 98% decrease of DT or improved by a factor of 55 or (55X). The user speed improvement was credited to the automation and power capabilities of the analytics platform. The summary of the comparison of execution time between service and user executions is shown in Table 4.

Table 2. The duration time of the old methodology

OM AREAS	OWNER	DURATION (MINS)
SHIPMENT	Service	25
	User	35
OUTPUT	Service	30
	User	55
WIP	Service	25
	User	20
TOTAL		190

Table 3. The duration time of the new methodology

OM AREAS	OWNER	DURATION (MINS)
SHIPMENT, OUTPUT & WIP	Service	20
	User	2
TOTAL		22

Table 4. The comparison of execution time

Owner	Old Method	OMDAS	Decrease	Factor
Service	80	20	75%	4X
User	110	2	98%	55X

Based on the evidence of the results discussed above, the project objectives were met, and the SOP were answered. The improved performance using the OMDAS showed a significant enhancement from the traditional method. The new system is better as it includes an inclusive range of visual analytics to help discover patterns and uncover meaning in data. It responses the question of the operation quickly and simply with a minimal number of clicks, responds quickly and delivers appropriate answers without the need for complex programming or preparation. The new system provides fast, convenient access to operations insights on personal computers or laptops and integrates and analyzes data from multiple sources to make decisions and trigger operations actions in response to gaps or trends.

It is known that good big DA and applications are more than just the proper deployment of techniques and strategies (Choi et al., 2017). According to Chen and Zhang (2014), the complete big data architecture design is critical. In this paper, the OMDAS architecture, together with the implementation approach, was presented and validated using real manufacturing data from MES and CIM. The design of the OMDAS architecture constructed from this study can be used as a basis for developing DA solutions for OM in the OSAT industry. Moreover, Albergaria et al. (2020) and Kozjek et al. (2018) reinforced this project that the use of DA capabilities and manufacturing data help organizations make better and faster business decisions at the OM level.

4. CONCLUSIONS

A unified operational factory performance dashboard for OM was designed and implemented on the analytics platform providing shipment, output, and WIP visualizations for the three factories. The OMDAS provides automated DA reports, visualizations, and analysis and with access management controlled by the analytics platform. Authorized users can only access the system. Different standard visualizations based on the OSAT manufacturing company's structure were integrated into the OMDAS, providing multi-level factory OM insights capability and faster decision making.

From the results of the project and observations, it can be concluded that the implementation of OMDAS at the OSAT manufacturing company is successful and can be appropriately used in the production environment. With this DA system, it can make it easier for authorized users to manage the factory operations results. Management of factory operations becomes more effective and efficient because users no longer need to use manual and conventional methods. Moreover, operational gaps in *Shipment*, *WIP*, and *Output* performances will be understood and resolved more quickly and efficiently, and the processing times improved by a factor of 4 and 55 for the service and user activities, respectively. This significant improvement in the analysis execution would be beneficial to the end-users and key OM stakeholders.

As the proponent's recommendation, *predictive analytics* and OSAT *big data* can provide numerous opportunities to academia and management practitioners in the semiconductor industry. The proponents firmly believes that the use of *real-time* data can help to expand the boundary of OM research and that big DA has vast potential to revolutionize existing OM theories. Operational line behavior has become an integral part of OM. Thus, the ability to predict manufacturing operations line behavior has implications on production innovation, IC product manufacturing, logistics and distribution, and revenue optimization.

5. ACKNOWLEDGMENTS

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