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INTEGRATING DATA ANALYTICS AND SIMULATION FOR DEFECT MANAGEMENT IN MANUFACTURING ENVIRONMENTS

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ABSTRACT

Defect management in manufacturing environments requires effective identification of the defects and finding proper solutions to resolve them. Predicting and preventing the defects before they can occur is the focus of quality risk management. To effectively manage defects, companies need to analyze historical data to identify the causes and solutions for defects as well as study the impact the defect can have on the processes, priorities, and operations. This study integrates data analytics and simulation modeling to develop a system for defect management in manufacturing environments. Simulation is used to analyze the behavior of the system whereas data analytics is used to develop prediction models for defect resolution. A case study from high-end server manufacturing environment, which is characterized by extensive test processes to ensure high quality and reliability of servers, is provided. The proposed approach helps decision makers analyze and manage defects and develop proactive means to prevent them.

1 BACKGROUND

1.1 Introduction

Today manufacturing environments are characterized by continuously changing conditions driven by globalization and increased market competition. To adapt to these changing conditions, companies need to continuously evaluate their performance and make smart decisions based on quantitative data analysis. Different techniques for decision making have emerged in the last few decades. These techniques helped manufacturing environments make effective decisions to improve their performance. Simulation methods and analytics models are commonly used in manufacturing for decision support.

In most manufacturing companies, outsourcing of parts from suppliers is an important part of supply chain management. Outsourcing provides companies with many potential benefits including lowers costs, and shorter lead times. However, outsourcing can also present some risk factors to the company such as quality risks, material shortage risk, and transportation risks. If quality risks are not managed effectively, defects can transit through the supply chain and affect the different partners. Quality issues can increase the cost of quality and affect customer satisfaction. Usually, cost of quality consists of two components: (1)

quality risk loss cost, and (2) quality risk management cost. Reactive strategies are related to the quality risk loss cost whereas preventive strategies are related to the quality risk management cost.

In high-end server manufacturing, defects can cause major disruptions to the operations and may result in loss of millions of dollars. Defective parts can be disposed, repaired, or returned to the supplier depending on the type of defect. Removal of defective parts is necessary to protect the company's product, image and reputation, and customer satisfaction. Product quality is ensured through test processes, manufacturing, and design. Because servers are very expensive and they should have high quality, server components are tested multiple times by both suppliers and manufacturers. Major quality risk events can disrupt the smooth flow of products and operations in the supply chain. Quality management is responsible for stopping the flow of defective materials to the customers.

1.2 Related Literature

Defect analytics and quality risk management have been studied by many researchers. Previous studies have discussed the management of defects in different areas including construction (Park et al. 2013; Kwon et al. 2014), home appliances (Law et al. 2017), garment industry (Lee et al. 2013), manufacturing (Aqlan et al. 2015), software (Yadav and Yadav 2015).

The study of defects focuses on developing management systems and solutions approaches for the defects to predict and prevent them. For example, Park et al. (2013) proposed an approach for defect management in construction industry by integrating ontology, augmented reality and building information modeling. The proposed system can reduce defects that may occur during the construction process as well as improves the management of the defects. In a similar study, Kwon et al. (2014) integrated building information modeling, image-matching, and augmented reality for defect management of reinforced concrete work . An automated defect discovery for dishwasher appliances was developed in Law et al. (2017). The authors used a text analytics framework to detect defects from online consumer reviews. Defect management in garment industry was discussed in Lee et al. (2013). The study used rule mining to extract defect patterns to develop a prediction approach for defects and identify their root causes. Defect prediction in software using a fuzzy logic approach was presented in Yadav and Yadav (2015). The authors proposed a phase-wise prediction model using the top most reliability relevant metrics.

Simulation modeling has been widely used to study manufacturing systems. Simulation techniques, especially discrete-event simulation (DES), can effectively be used to capture and analyze the behavior and interactions of complex systems with less effort when compared to analytical models. Simulation can effectively be used to make accurate and sound decisions to identify the best alternative among several candidates (Aqlan et al. 2014). Jeddi et al. (2012) developed a DES model to study an automotive manufacturing system in an after-sale service shop. The goal of the study was to increase service rate while reducing the amount of waiting times which results in more customer satisfaction.

Data analytics techniques can be used to study and predict defects in manufacturing environments. Studies have discussed the use of analytics techniques to analyze defects. For example, Slimani et al. (2015) developed an analytical method to calculate defect tolerance of logic circuits using probabilistic defect propagation. The study provided a case of single defect model to validate the proposed approach. Aqlan et al. (2014) discussed defect analytics in a server manufacturing environment utilizing structured and unstructured data analytics techniques.

Integrating simulation models with data analytics provides an effective approach for managing defects by considering both current and future states of the system as well as performing scenario analysis and prediction. According to Kibira et al. (2015), such integration of data analytics and simulation methods can account for the multiple parameters and variables that affect system performance and allows for analyzing large volume and variety of streaming data.

In this study, we propose an approach based on data analytics and simulation for defect management in manufacturing environments. This topic is of great importance because defects, if not managed properly, can cost companies millions of dollars. Furthermore, the availability of big data sets allow for utilizing analytics models to predict and resolve the defects. The proposed approach is applied in a high-end sever manufacturing environment in which no single defect is allowed to pass to customer. To achieve this "Zero Defect" goal, multiple test processes are performed to ensure high quality and reliability of the servers.

2 PROPOSED METHODOLOGY

Shown in Figure 1, the proposed research methodology consists of two main parts: simulation and data analytics. Simulation is used to study the dynamics of the system and the impact of defects and defect management on the system performance. Analytics models are used to provide inputs to the simulation model based on utilizing historical data to identify defect patterns and predict appropriate resolutions for defects. The data analytics step consists of multiple steps. First, defect data is obtained from different resources including databases, Excel sheets, and manual records. The collected data is then pre-processed and cleaned to remove outliers and prepare the data for predictive models. Outputs from the developed models are used as inputs to the simulation models to determine the processing steps of parts.

Simulation model development consists of the following steps: 1) a conceptual model is developed for a selected part or product to identify process steps and decisions, 2) data is collected and analyzed to be used in the simulation model, 3) the developed simulation model is integrated with the outputs from the analytics model and the results are analyzed to study defects and their impact on the system.

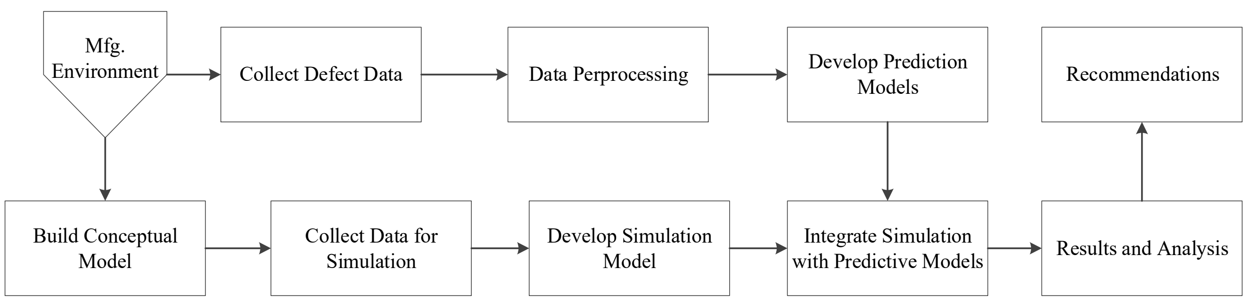


Figure 1: Proposed research methodology.

3 CASE STUDY

The system discussed in this study represents a high-end server manufacturing environment. The company produces high-end servers that are built with leading edge technology. High-end server manufacturing environment is characterized by aggressive introduction cycles of new products (i.e., every two years), extreme demand skews, significant engineering changes, and high inventory holding cost. An overview of the high-end server manufacturing system architecture is illustrated in Figure 2. The manufacturing environment is based on configure-to-order processes which is a combination of build-to-plan and make-to-order processes. This strategy, also known as fabrication-fulfillment model, provides the advantages of responding to customer orders rapidly and minimizing inventory holding costs. In the fabrication process, components or subassemblies are produced, tested, and assembled based on a projected production plan and are kept in stock until an actual order is received from a customer. In the fulfillment process, final products are assembled according to actual customer orders, such that no finished good inventory is kept.

According to Aqlan et al. (2014), the fabrication-fulfillment model provides the company with the flexibility of mass customization and the speed and efficiency of mass production. However, the randomness (i.e., random yields, system configuration, stochastic lead times, etc.) inherent to this model makes the inventory management and production planning a challenging problem. This can result in high inventory holding costs and missing opportunity costs. The high-end server manufacturing environment is characterized by skewed demand pattern where most of the customer orders arrive during the last month of the quarter. For any given quarter of the year, the arrival of customer orders is distributed as follows: 10%

of the orders arrive in the first month, 20% arrive in the second month, and 70% arrive in the third month. For the third month, 29% of the orders arrive in the first two weeks and 71% arrive in the last two weeks. For the last two weeks, 40% of the orders arrive in the first week and 60% arrive in the second week. Customer order starts a *potential order* and then a *reserve order*. The order is then moved to the next step, *firm order exception*, and then *firm order*. The order then gets processed and shipped to customer. If the order is cancelled by the customer, it is considered a *cancelled order*. If it cannot be shipped on time and customer is not willing to receive it late, it is considered a *backorder*. Otherwise, it is considered a *missed order*. Figure 3 shows the different stages of customer order in a high-end server manufacturing environment. Most of the orders get confirmed mainly in the last 2 weeks of the quarter. Furthermore, 85% of the total received orders get confirmed.

To deal with the uncertainty in customer demand, some of the key strategies that were implemented include 1) inventory sharing between different plants when there is a shortage of parts and components; 2) localized warehouse for suppliers at manufacturing sites; 3) flexible production planning for internal orders; 4) order fulfillment dashboard; and 5) information technology. These strategies are also important for defect management. For example, if part shortage occurred as a result of defects, tested parts can be obtained from another plant. The use of order fulfillment dashboard makes it easy to track defects and failures in real time.

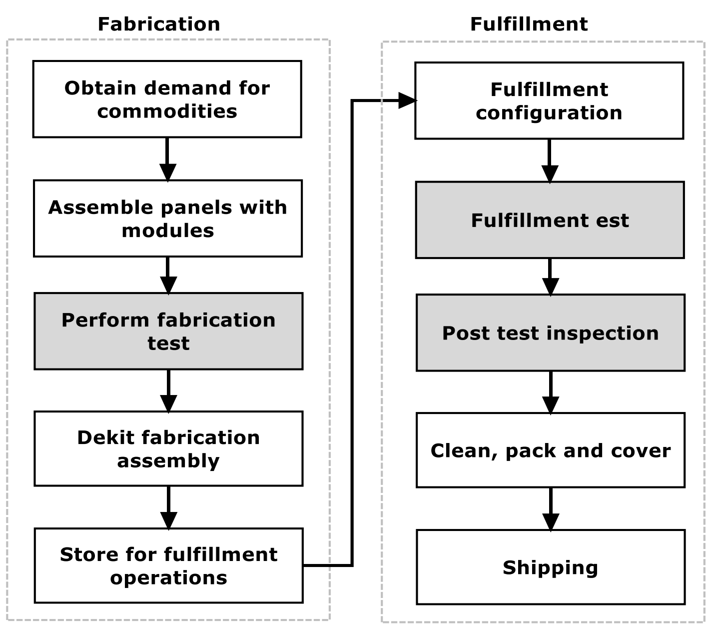


Figure 2: Process flow of high-end server manufacturing.

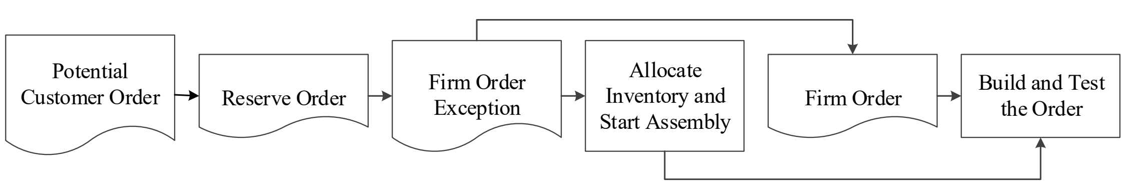


Figure 3: Different stages of customer order in a high-end server manufacturing.

The management of defects in manufacturing environments requires effective identification of the defects, finding proper solutions for these defects, and providing the required resources and tools to resolve the defects. Predicting and preventing the defects and quality issues before they can occur is the focus of quality risk management. Several tools are used for analyzing the defects including Risk Ranking and

Filtering (RRF), Failure Mode and Effect Analysis (FMEA), Hazard and Operability Analysis (HAZOP), and Fault Tree Analysis (FTA). Furthermore, automated systems have been proposed to identify defects and retrieve related solutions from the database. However, these systems do not consider the required skills and resources to solve the problem.

Defect identification and validation of high end servers in a manufacturing environment requires extended hours of troubleshooting sessions from groups of diverse and high skilled individuals in multiple disciplines. The difficulty is in the defect resolution response time of each sector. Many factors such as the complexity of the configuration of the entity being tested and the quantity and frequency of failures currently being captured generate massive amounts of data. The use of learner produced data to develop a predictive model to discover information for predicting and advising engineers and technicians learning throughout the different sectors in a manufacturing environment is discussed in this study.

One of the main parts of the server that fails frequently is the 'Memory Card' which is also known as known as Dual In-line Memory Module (DIMM), see Figure 4. DIMM is one of the three main components of the server node. This study will focus on studying the DIMM defects that can occur at any stage of the server production and test.

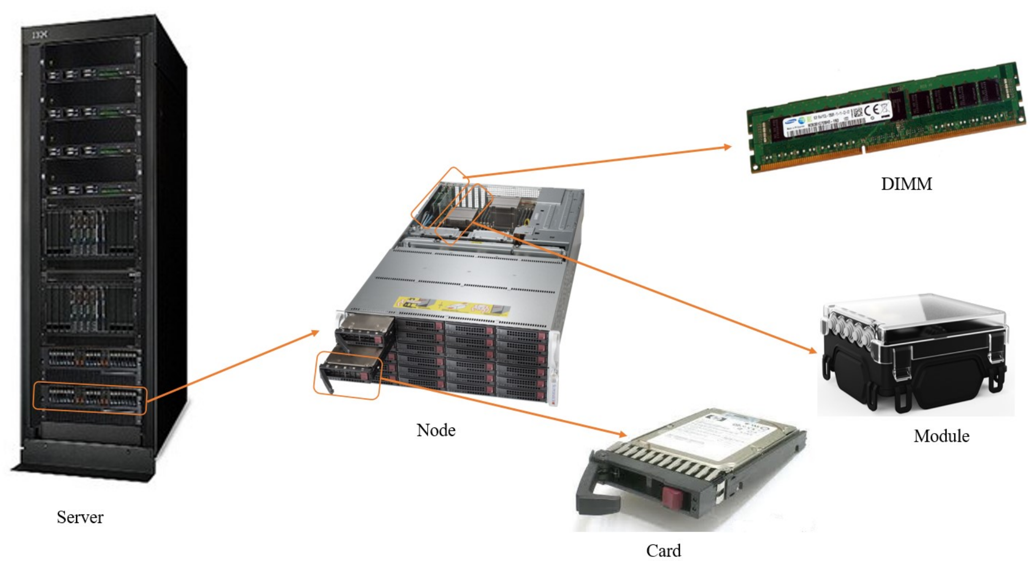


Figure 4: Main components of high-end server node.

3.1 Simulation Model

The simulation model is developed to study the behavior of the system and analyze the defects and their resolutions. The first step of conducting the simulation study is to create a conceptual model that shows the different entities of the system and their interactions. Figure 5 shows the conceptual model for the simulation study discussed in this paper. As mentioned earlier, this study focuses on one of the main components of the server, which is DIMM. The flow chart in Figure 5 represents a high level illustration of the fab-fulfillment process of DIMMs. The process starts with forecasting the demand for DIMMS. The forecasts are used as basis for creating the fabbing plan. Arrival of actual customer order drives the fulfillment process in which tested DIMMs are pulled from the crib and assembled into the customer order.

Data input for the simulation model was collected for three months (one quarter). The collected data includes cycle times, repair times, order arrivals, and defect rates. Based historical data and time studies were considered. Table 1 shows the statistical distributions of the simulation input parameters. For some attributes, historical data was collected and fitted into appropriate statistical distributions. For other attributes, historical data was either not available or not accurate. In this case, we either conducted time studies or asked experts for the minimum, maximum, and most likely process times. The manufacturing site sends 34% of the tested DIMMs to the sister sites and the rest 66% are used to fulfill customer orders in the same site. Defect rates, root causes, and resolutions are determined by the analytics models. The simulation model was developed using Arena software (www.arenasimulation.com). Figure 6 shows historical data for the number of orders (both forecasted and actual) arrived each week for one quarter. Forecasting is performed by the Central Planning Engine (CPE) of the company. It can be seen that almost 35% of the orders arrive in the last two weeks of the quarter. Table 2 shows the characteristics of the simulation model. The main characteristics of the simulation model are shown in Table 2.

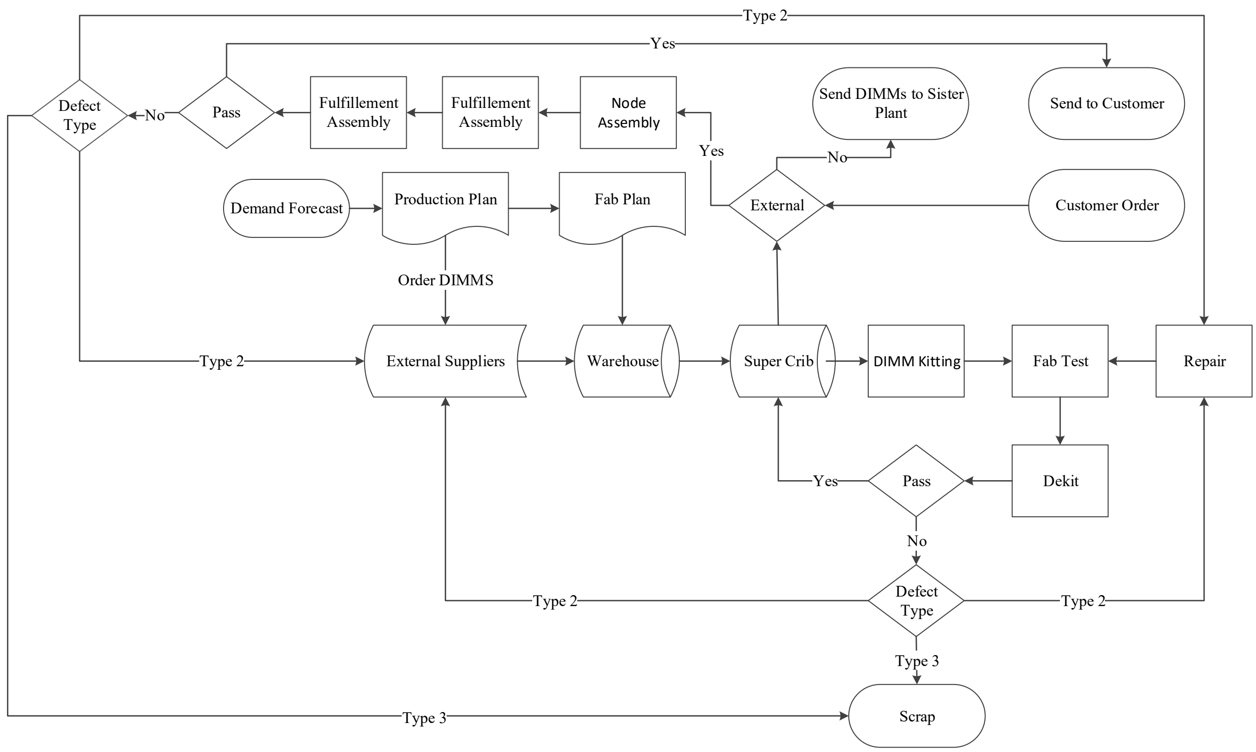


Figure 5: Fab-fulfillment process for DIMMs.

Table 1: Input data for the simulation model.

Simulation Input	Distribution	Data Source
Order Arrival	Time between arrivals (days): 0.999 + Expo(0.544) Orders per arrival: DISC (0.102,1, 0.328, 4, 0.607, 5, 0.820, 8, 1, 9)	Historical Data
DIMM Size Distribution	DISC(0.001, 1, 0.003, 2, 0.18, 4, 0.47, 8,0.81, 16, 0.98, 32, 1, 64) GB	Historical Data
Fab Inspection Time	TRIA(10.1, 11.4, 12.0) minutes	Time Study
Fab Test Time	TRIA(3.01,3.45,3.74) days	Historical Data
Node Assembly	TRIA(10.02,11.12,12.21) hours	Time Study
Dekitting Time	TRIA(15.3, 17.4, 19) minutes	Experts
Fab Repair Time	0.25*TRIA(3.01,3.45,3.74) days	Experts
Ful Assembly Time	0.52 + WEIB(1.63,3.84) days	Historical Data
Fulfilment Test Time	1.41 + 1.18 * BETA(1.5,1.76) days	Historical Data
Fab Inspection Time	TRIA (50, 60, 70) minutes	Experts
Ful Repair Time	0.25*[1.41 + 1.18 * BETA(1.5,1.76)] days	Time Study
Clean, Pack, and Ship	TRIA(0.5, 0.65, 1) days	Historical Data

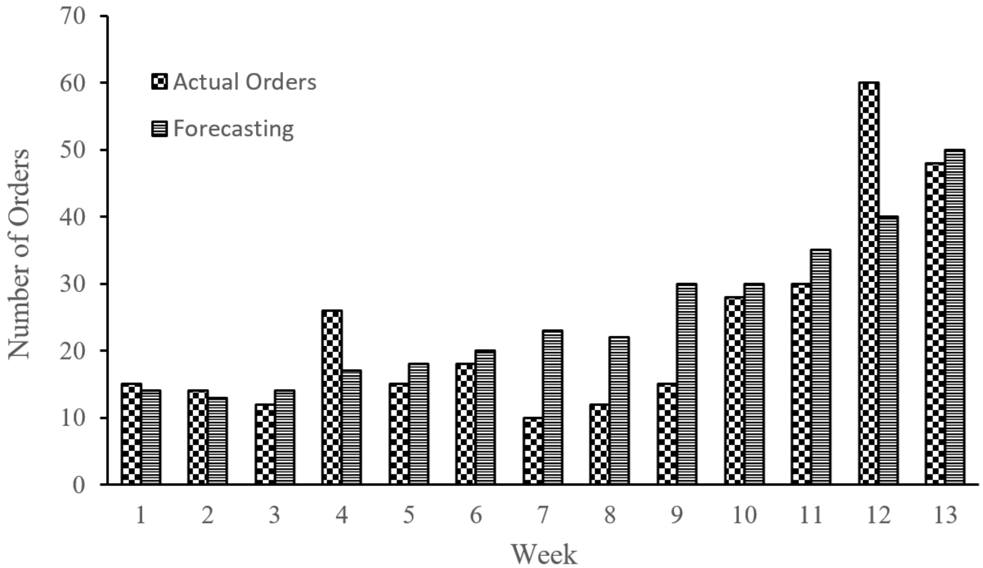


Figure 6: Actual and forecasted orders for one quarter.

Table 2: Simulation model characteristics.

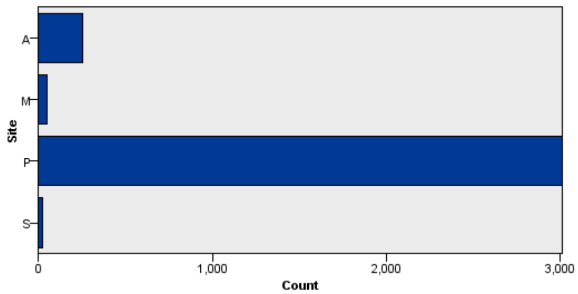
Characteristic	Entities	Resources	Inputs	Output	Number of Replications	Simulation Time
Description	• Customer Orders • Servers • Nodes • DIMMS	• Assembly Stations • Test stations • Repair Stations	• Arrival rates • Number of workstations • Cycle times • Failure rates • Repair times	• Throughput • Work-in-process • Inventory levels	30	90 days

3.2 Analytics Models

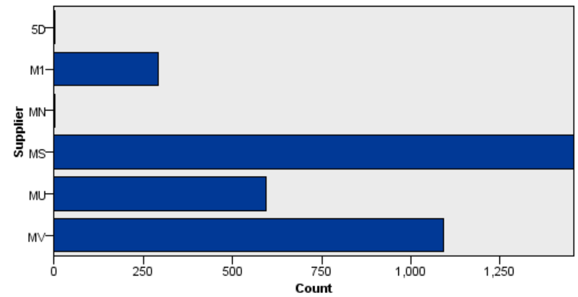
We use data analytics to identify the defect rates in each production stage based on historical data and determine the defect resolutions by developing predictive models. Data was collected from four manufacturing sites: P, M, A, and S. There are 5173 defect instances for two main product types. This study focuses on site P as it accounts for 90.39% of the defects. Moreover, four suppliers (MV, MU, MS, and M1) will be considered because they account for 99.93% of the defects. Figure 7 shows the defect distribution for the sites, suppliers, memory size, and memory type. The collected data represents three years (or twelve quarters).

In order to identify the percentage of DIMM defects for each production stage, we use the equation below where D_{ij} represents the DIMM defect rate for product i in stage j. Table 3 shows the DIMM defect rate for the different production stages for the two main product types, where D_{1j} represented the defect rate for product 1 and D_{2j} represents the defect rate for product 2. DIMM defects can also occur in other production stages such as packaging, transportation, and picking. However, only the main stages which have high defect rates are considered in this study.

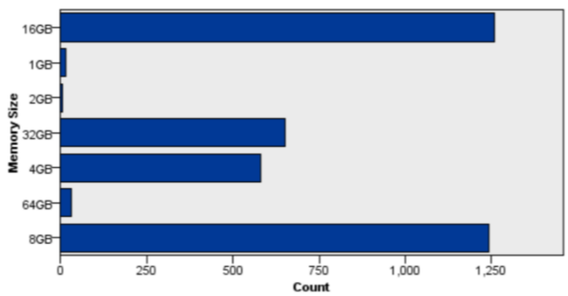
$$D_{ij} = \frac{Number\ of\ defects\ for\ product\ i\ in\ stage\ j}{Average\ number\ of\ DIMMs\ consumed\ in\ product\ i}$$



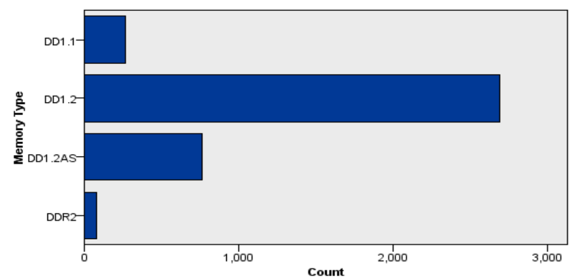
a. Defect distribution per site



b. Defect distribution per supplier



c. Defect distribution per memory size



d. Defect distribution per memory type

Figure 7:Distribution of defects based on historical data.

Table 3: DIMM defect percentages for per product type and stage.

Process	Stage (*j*)	D_{1j} (%)	D_{2j} (%)
Fabrication	FAB0.5	0.00	1.00
	FAB1	0.56	1.70
	FAB2	0.82	1.40
Fulfillment	Fulfillment Assembly	0.03	0.04
	Fulfillment Test	1.20	0.08
Node/Kitting	Node Assembly and Test	0.00	0.52
	Kitting	0.06	0.10
	Dekitting	0.12	0.24
Other	Other	0.17	0.04

Based on the data analysis, the main root causes of the defects were identified as shown in Table 4. The table also provides the percentage, based on historical data, of each defect root cause category as well as explanation of the root cause. We also included Failure Analysis (FA) experts opinions about the most common solution for each defect root cause category (see Table 4, last column). The data analytics model for defects was developed in IBM SPSS Modeler software (www.ibm.com). To predict the defect solutions, we used Neural Networks (NN) model. NN models have been proven to be an efficient approach in many areas, such as aerospace, automotive, mathematics, engineering, medicine, economics, meteorology, psychology, neurology, and many others. There are many learning algorithms used for ANNs. The most popular algorithm is Backpropagation (BP) neural network, which was used in this study. BP neural network is also called Multi-Layer Perceptrons (MLPs) and is based on gradient descent optimization approach in which the total squared error of the output signals is minimized. Figure 8 shows the model structure and the Neural Network nodes used to predict defect solutions. In Figure 9, Neural Network model and prediction results are presented. Eight input parameters were used to predict the defect solutions. The overall model accuracy is 87.1%. The highest accuracy, 95.52%, is obtained when a defect that should be "returned to supplier" is predicted as "Return to Vendor". The lowest accuracy is obtained when a defect that should be "repaired" is predicted as "Repair". For this case, there is a 42% chance that the defect is predicted as "Return to Vendor" and this is not a big issue because the repair of the defect can also be performed by the supplier.

Table 4: Main DIMM defect types and their description.

Defect Code	Percentage	Meaning and Explanation	Possible Causes	Common Solutions (Based on Experts)
DRAM CE	33.52	DRAM Correctable Error (single bit) Cannot read from single bit	Internal failure	Cannot be fixed onsite (on customer site, it can be fixed) DIMM returned to supplier
DRAM UE	10.81	DRAM Uncorrectable Error (multiple bits). Cannot read from multiple bits	Internal Failure	Cannot be fixed onsite DIMM returned to supplier
CRC	12.84	Cyclic Redundancy Check. MCM doesn't get same readings	Poor connections	Poor connection may be caused by contamination and/or scratch
LN SPARE	14.55	Lane Sparing. DIMM fails when spare lane are used	Poor connections	Poor connection caused by contamination and/or scratch on the lanes
VPD	2.10	Vital Product Data Cannot read product data	Contamination/ scratches. Supplier did not include data	VPD pins are located in the very end corners of the DIMM
MEM BUS UE	5.72	Memory Bus Uncorrectable Error	Poor connections	Swapping cards to ensure the failure is caused by the lanes
DMI	4.03	Device Maintenance Interrupt	Poor connections	Contamination and/or scratch
POISSON	1.90	POISSON Lane failure	Poor connections	Contamination and/or scratch
OVER TEMP	2.74	Overheating of DIMM	Poor cooling	Scrap
MECH	6.87	Mechanical failure	Damage	Scrap
OTHER	4.94	Other types of defects	Perform failure analysis	Depends on cause

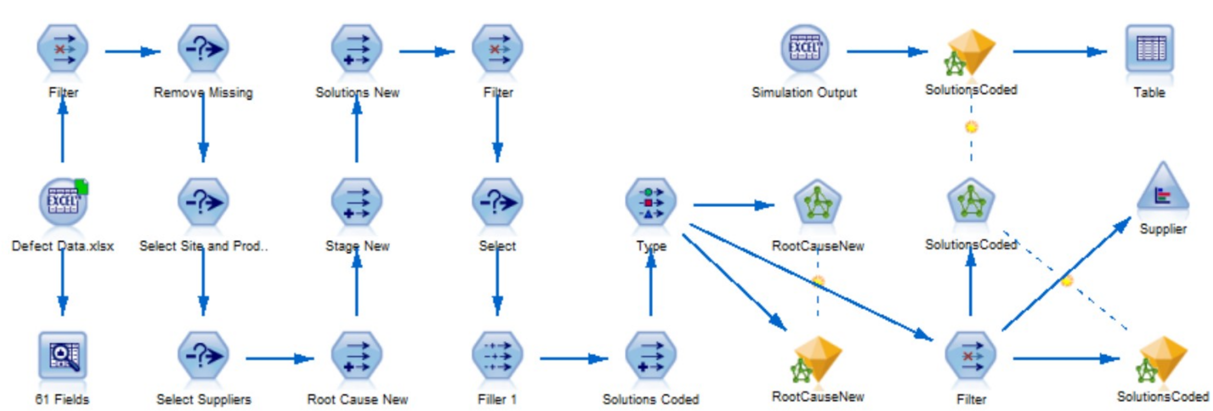
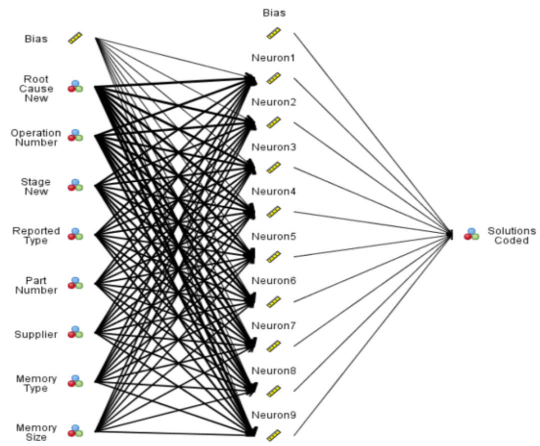


Figure 8: Data analytics model in SPSS Modeler.



Observed	Predicted		
	Repair	Return to Vendor	Scrap
Repair	55.7%	42.0%	2.4%
Return to Vendor	4.5%	95.2%	0.4%
Scrap	3.1%	9.4%	87.5%

The overall accuracy, which is represented by the overall percent correct, of the neural Network model is 87.1%.

Figure 9: Neural Network model (left) and results (right) for predicting defect solutions.

3.3 Integrating Simulation and Data Analytics

The simulation model was developed in Arena software. The model was run for 90 days (or one quarter) and the results obtained include cycle time, throughout, and defects. The simulation model was verified and validated by comparing the simulation results to the real system output. The measures used for this purpose are throughput, for both servers and DIMMs (see Figure 10). Confidence level, α, value of 0.05 was used. The p-values are greater than 0.05 which indicates that the simulation results are not statistically different from the real system data.

Server Throughput

```
Test of mu = 266 vs not = 266

Variable  N    Mean  StDev  SE Mean         95% CI            T      P
Orders   30  266.300  1.685    0.308  (265.671, 266.929)  0.98  0.337
```

DIMM Throughput

```
Test of mu = 13020 vs not = 13020

Variable  N     Mean  StDev  SE Mean          95% CI             T      P
DIMMs    30  13031.0   34.9      6.4  (13017.9, 13044.0)  1.72  0.096
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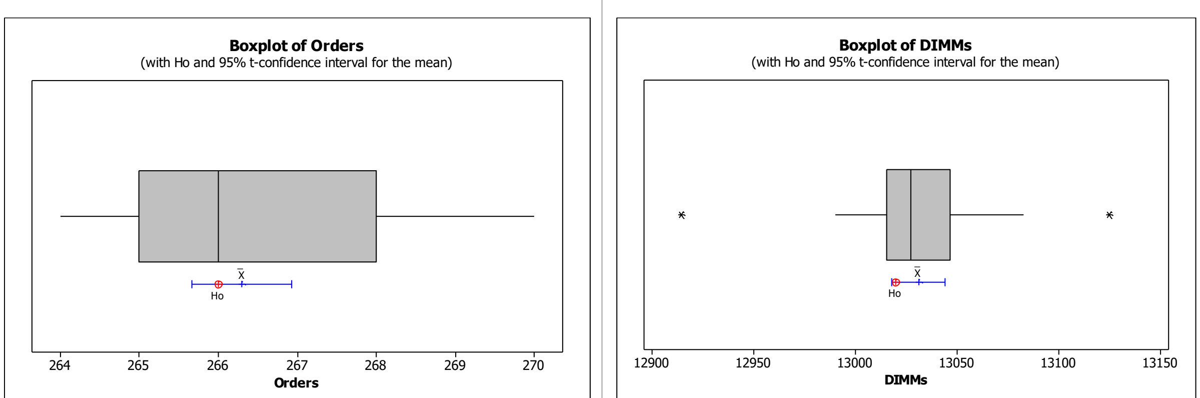

Figure 10: Statistical results for simulation model validation.

Simulation results for DIMM defects were used as inputs to the analytics model. The defect parameters obtained from simulation include: process, stage, DIMM type and size, supplier, part number, product model and types, operation, and root cause for the defect. Based on these parameters, the Neural Network model predicts the defect solution as shown in Figure 11. The Figure shows sample data for ten defects obtained from simulation. The last two columns include the prediction and corresponding confidence values obtained by the Neural Networks model. The prediction of the defect solutions is used to determine whether the DIMM should be scrapped, repaired, or returned to supplier.

	Defect Number	Part Number	Supplier	Reported Type	Operation Number	Memory Size	Memory Type	Root Cause New	Stage New	$N-Solutions Coded	$NC-Solutions Coded
1	Defect 1		MV		2004	32GB	DD1.2	LN SPARE	FULL	Repair	0.715
2	Defect 2		M1		0416	8GB	DD1.2	DRAM UE	FAB2	Repair	0.759
3	Defect 3		M1		0459	16GB	DD1.2	DRAM UE	FAB2	Repair	0.641
4	Defect 4		MV		0399	16GB	DD1.2AS	VPD	FAB1	Scrap	0.750
5	Defect 5		MS		0399	16GB	DD1.2	VPD	FAB1	Repair	0.731
6	Defect 6		MS		2001	16GB	DD1.2AS	VPD	FULL	Repair	0.799
7	Defect 7		MS		2001	16GB	DD1.2AS	VPD	FULL	Repair	0.799
8	Defect 8		MS		1225	4GB	DD1.2AS	VPD	FAB1	Return to Vendor	0.627
9	Defect 9		MS		0399	16GB	DD1.2	VPD	FAB1	Repair	0.731
10	Defect 10		M1		0602	4GB	DD1.2	MECH	FAB1	Return to Vendor	0.986

Figure 11: Simulation results for DIMM defects and associated analytics predictions.

4 CONCLUSIONS

This paper presented a framework for integrating simulation and analytics models to study and analyze defects in manufacturing environments. Simulation models were effectively used to study and analyze the behavior of the manufacturing system taking into consideration the uncertainty and randomness. For defect prediction, analytics models were utilized. Both simulation and data analytics were combined to provide an integrated approach for defect management and resolution. A case study from a high-end server manufacturing was provided. Results from the case study showed that both simulation and data analytics can be effectively integrated for managing defects in manufacturing.

Future work will focus on automating the integration process by developing an interface that connects simulation and data analytics models. Furthermore, the system will be designed to run in real time in order to provide decision support for the failure analysis workers.

REFERENCES

Aqlan, F., S. S. Lam, and S. Ramakrishnan. 2014. "An Integrated Simulation–Optimization Study for Consolidating Production Lines in a Configure-to-Order Production Environment". *International Journal of Production Economics* 148: 51–61.

Aqlan, F., C. Saha, and S. Ramakrishnan. 2015. "Defect analytics in a high-end server manufacturing environment". In *Proceedings of Industrial and Systems Engineering Research Conference*, edited by S. Cetinkaya and J. Ryan, 892–900. Peachtree Corners, Georgia: Institute of Industrial and Systems Engineers.

Jeddi, A. R., N. G. Renani, A. Malek, and A. Khademi. 2012. "A Discrete Event Simulation in an Automotive Service Context". *International Journal of Computer Science Issues* 9 (6): 142–147.

Kibira, D., Q. Hatim, S. Kumara, and G. Shao. 2015. "Integrating Data Analytics and Simulation Methods to Support Manufacturing Decision Making." In *Proceedings of Winter Simulation Conference*, edited by L. Yilmaz, W. K V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, 2100–2111. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Kwon, O.S., Park, C.S., and Lim, C.R. 2014. "A Defect Management System for Reinforced Concrete Work Utilizing BIM, Image-Matching and Augmented Reality". *Automation and Construction* 46: 74–81.

Law, D., R. Gruss, and A. S. Abrahams. 2017. "Automated Defect Discovery for Dishwasher Appliances from Online Consumer Reviews". *Expert Systems with Applications* 67: 84–94.

Lee, C. K. H., K. L. Choy, G. T. S. Ho, K. S. Chin, K. M. Y. Law, and Y. K. Tse. 2013. "A Hybrid OLAP-Association Rule Mining Based Quality Management System for Extracting Defect Patterns in the Garment Industry". *Expert Systems with Applications* 40: 2435–2446.

Park, C.S., D. Y. Lee, O. S. Kwon, and X. Wang. 2013. "A Framework for Proactive Construction Defect Management Using BIM, Augmented Reality and Ontology-Based Data Collection Template". *Automation in Construction* 33: 61–71.

Slimani, M., A. B. Dhia, and L. Naviner. 2015. "A Novel Analytical Method for Defect Tolerance Assessment". *Microelectronics Reliability* 52: 1285–1289.

Yadav, H. B., and D. K. Yadav. 2015. "A Fuzzy Logic Based Approach for Phase-Wise Software Defects Prediction Using Software Metrics". *Information and Software Technology* 63: 44–57.

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