Lean Manufacturing Waste Prediction and Reduction Model

B.B.S Makhanya, J. H.C. Pretorius and H. Nel
Postgraduate School of Engineering Management
Faculty of Engineering and Built Environment
University of Johannesburg
Johannesburg, Gauteng, South Africa
Bsm3174@yahoo.com, jhcpretorius@uj.ac.za, hnel@tennelli.com

Abstract

It seems impossible to increase efficiencies in a manufacturing setting without first pinpointing the causes of waste. The goals of this research were to use the quality management data collected to determine which aspects were significantly correlated with manufacturing waste, and then to use machine learning techniques to create a model that could predict manufacturing waste. The case study research was used for this analysis. The data range from 2019 to 2021 and includes 215924 rows and 13 features. Five predictors and eight terminal nodes were used to create the final CART model, which achieved an R^2 of 0.389 and an accuracy of 97.31%. Inventory management, customer wait times, meetings, and unscheduled breaks all contributed to 80% of the time that was wasted. High levels of inventory management problems occurred in months 6-11. The waiting times caused by customers averaged 2.97 hours per month between months 7 and 11. Meetings that started at 8:00 lasted, on average, 7.5 hours. The majority of the time spent waiting is caused by customer complaints that come in between the hours of midnight and 5 a.m. At 7:00, with a 4.3-hour lag, most reports of inventory problems were made. Only quantitative secondary data were used in this analysis. Qualitative approaches should be prioritized for future studies. Models for predicting waste in the future could benefit from using random forests and TreeNet.

Keywords
CART Analysis, Manufacturing Waste, Six Sigma, Supervised Learning, Waste

1. Introduction
In the manufacturing environment, it appears impossible to improve efficiencies without first understanding the sources of waste (Rasi et al. 2015; Yuphin and Ruanchoengchum 2020). Rehman et al. (2018), maintain that companies all over the world are constantly looking for ways to cut waste and reduce non-value-adding activities in their manufacturing systems or services. The term waste is commonly used to describe business activities that do not provide value to customers or increase productivity (Foster 2013; Mostafa and Dumrak 2015; Gupta et al. 2020). In the past, the focus has been on the adoption of Lean Manufacturing, Six Sigma, and Lean Six Sigma as strategies to deal with waste and variations in business processes (Pepper and Spedding 2010; Shokri and Li 2020; Sodhi et al. 2020). Rasi et al. (2015), on the other hand, argue that not all companies that implemented the aforementioned strategies benefited from them. To better understand the sources of inefficiencies, researchers are now looking for ways to leverage the tools that come with Industry 4.0, such as the study of Yuphin and Ruanchoengchum (2020), which integrated machine learning and lean manufacturing tools in Thailand's sprocket manufacturing. The integration resulted in a 74 percent increase in manufacturing process efficiency and a 10 percent reduction in turn-around time.

The global push to eliminate waste and improve business efficiencies has compelled South African manufacturers to adopt global best practices (Naicker 2017). As a result, the South African company in charge of manufacturing components, distribution, and maintenance of spare parts for rolling stock operators has implemented Lean Manufacturing and Total Quality Management to reduce waste. It has also implemented tools such as the Qliksense quality management system, which tracks hours spent on non-value-adding activities like defect repairs, waiting, transportation and overproduction, quality cost, and other business key performance indicators. Although the company implemented Lean Manufacturing and Total Quality Management in 2018, the study (Masemola et al. 2021) revealed that the majority of the business processes were not subjected to statistical process control. There was significant variation in waste across different manufacturing processes, as well as a misunderstanding of some lean manufacturing concepts.

The first objective of this study was to investigate the data that was collected on quality management and identify the aspects that had a significant correlation with the amount of waste that was produced during the manufacturing processes. The second objective was to develop a model that could forecast the amount of waste produced by the manufacturing section by making use of tools for machine learning. The study relied on secondary data that was supplied by the company identified for the case study.

2. Literature Review

In a lean production environment, there are three types of waste, according to the literature (Koskela et al. 2013; Roushdy 2019). The 3Ms, which stand for Muda, Muri, and Mura, are the Japanese words for waste in the Toyota Production System (Mostafa and Dumrak 2015b). Waste or Muda is anything that goes beyond what is needed. This could be equipment, material, employees, money, or the time it takes an employee to deliver goods or services. Taiichi Ohno says that there are several Muda wastes, one of which is waiting (Khalil El-Namrouty 2013). Waiting between processes is another type of Muda waste. Lean says that products should move in a smooth, steady stream. Waiting has also been found to cause long lead times, unhappy customers, and makes a company less competitive. Waste of transportation, which results from activities that move machines, parts, or products between operations but do not add value, can be called "waste." Waste from over-processing results from processing that goes beyond what the customer wants, and over-processing can waste time, money, materials, and labor. Waste from having too much stock is waste caused by keeping stock that is not needed. In the manufacturing industry, this kind of waste can slow down the flow of work, take up more space in the storage room, which can slow down the time it takes to serve a customer and make it harder to find things when they are needed. This can lead to extra costs for inventory, storage, and maintenance. Waste of motion comes from moving people from one station to another when they do not need to. Waste also results from defects or rework. A process must be able to control how many defects it makes. Defects show that the goods produced are of low quality, which makes customers unhappy and costs the business money.

Muri, which means "overburden," refers to the situation in which employees are given an excessive amount of work, to the point where they become too exhausted to perform their duties as effectively as they should (Vilumsone-Nemes et al. 2020). This may result in poor workmanship. Mura, meaning "unevenness," is a difference in the production process, where the same steps do not always lead to the same quality and quantity. In lean production, getting rid of waste can be accomplished with the help of a wide variety of tools, such as 5s, Just-in-Time, PDCA, and many others. These tools are utilized by various organizations, each in accordance with how well they fit their respective structures (Arunagiri and Gnanavelbabu 2014; Manzouri et al. 2014; Sodhi et al. 2020; Yuphin and Ruanchoengchum 2020). In other words, the selection of tools is dependent on the type of problem at hand as well as the goals of the company.

2.1 Prediction model

In the context of the manufacturing industry, waste can result in losses of several million dollars and hold up production (Myeza 2017; Sodhi et al. 2020; Vilumsone-Nemes et al. 2020). Manufacturers can monitor the conditions of the production line and take preventative measures if a failure is imminent thanks to the utilization of predictive models (Yuphin and Ruanchoengchum 2020). Through the use of data, mathematical algorithms, and methods of machine learning, predictive analytics attempts to forecast future events based on existing observations (Khadka 2019). Validation is an important part of the machine learning process because it helps to ensure that unreliable models are not built. The model is built with the help of the training data, while the performance of the model is evaluated with the help of the test data.

There are typically three distinct types of validation processes, each of which has different requirements depending on the volume of the data. Cross-validation methods such as leave-one-out cross-validation, K-fold cross-validation, and test set validation are used, respectively, when working with small sample sizes, and medium and large sample sizes. When the model is evaluated with the same data that was used to fit it, a phenomenon known as "overfitting" occurs. Validation procedures are developed to prevent data from being overfitting. All of these methodologies for validating data are included within Minitab, the statistical software tool that was utilized for this investigation. Learning under supervision, learning without supervision, and learning through reinforcement are the three primary categories of approaches to problems in machine learning and predictive analytics, respectively. The utilization of supervised models constitutes the primary distinction that can be made between supervised learning and unsupervised learning. In contrast to the unsupervised model, supervised models are defined by a predetermined set of independent variables and dependent variables. This research does not go into detail regarding the different algorithms that are utilized in supervised and unsupervised learning. This study made use of supervised learning techniques such as multiple regression and Classification and Regression Tree (CART) models.

A tree-based algorithm like the CART model makes predictions from one or more "decision trees" using a set of "if-then" rules. Multiple regression models have been utilized for decades, but tree-based models are simpler to comprehend and more accurate. CART models provide additional information on the model and are not constrained by parametric assumptions. They can map nonlinear relationships and complex interactions, manage massive data sets, and are insensitive to missing values and outliers.

3. Methods

This study is part of a larger initiative to improve South African manufacturing through the use of data and quality management tools like Lean Six Sigma. The subject of the investigation is a company responsible for producing rolling stock components to support the railway industry in Southern Africa. The company of interest operates 24 hours a day, seven days a week. This study aims to sift through the collected data on quality management and identify the factors that had a significant correlation with the amount of waste produced during manufacturing processes. Using machine learning tools, the second objective was to create a model that can predict the amount of waste produced by the manufacturing section. Since the study attempted to analyze waste within a specific company, the case study was selected as the best research method. A case study is the study of a phenomenon within a specific context, without the intent to generalize the results (Sekaran and Bougie 2009; Sreejesh et al. 2014). The entire research process began with a preliminary literature review to identify the problem and formulate the research questions. The procedures included a literature review on waste and prediction models. It was also essential, as part of the research process, to obtain permission to use company data and ensure that the study met the University of Johannesburg's ethical requirements for postgraduate research.

4. Data Collection

For this study, we used a data set with 215924 rows and 13 features or columns spanning the years 2019 to 2021 (Table 1). We had to remove some features such as employee ID (AlpsID), Description SOH, and Employee Name from the data set because they were irrelevant to the purpose of the study.

Table 1. Data features

Data type	Count	Missing Values	Data features
Text	215924	0	WorkDay
Date	215924	0	WorkDay_Formatted
	215924	0	Month
	215924	0	Time
Text	215924	0	Employee Name
Text	215924	0	AlpsID
Text	215924	0	Default Position
	215924	0	Occupation
Text	215924	3116	Description SOH
Date	215924	0	Start time
Date	215924	0	End time
	215924	0	1st connection of the day
Text	215924	686	Comment

The model's independent variables include the time the waste was reported, the occupation which defines the activity, the workday, the month, the position where the waste was reported, and supervisors who represent different teams. The indirect spent time, which essentially defines the time spent on activities that do not contribute to product production, was chosen as the dependent variable for the model. Figure 1 depicts the data preparation and analysis process, as well as the preliminary data analysis step, which entails reading through the data and removing characteristics that were not contributing to the variations. Data visualization involves plotting features in bar charts and scatter plots to gain a better understanding of data distribution and removing features that do not contribute to data variation. We also checked to see if the data set contained any rows with missing values and outliers.

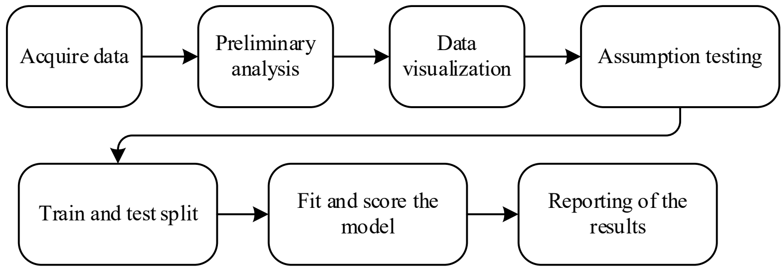

Figure 1. Data preparation and analysis process

Root-mean-square error (RMSE), a measure of model errors, mean absolute percent error (MAPE), a measure of accuracy, and R-squared, a measure of the amount of variance explained by the independent variables to the predicted variable, were all used to assess the model's robustness (Yahya and Olaniran 2014; Egbo 2018). In equations 1 and 2 N denotes the sample data size, y denotes the outcome variable also called the dependent variable, which is waste in this study, $\bar{y}$ is a mean of y, $\check{y}$ represents the model-predicted y-values (Table 2).

Table 2. Evaluation parameters

Statistical index	**Expression**
Root-mean-square error (RMSE)	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y-\check{y})^2}$ (1)
Absolute fraction of variance (R^2)	$R^2 = 1 - \frac{\sum_{i=1}^{N}(y-\check{y})^2}{\sum_{i=1}^{N}(y-\bar{y})^2}$ (2)

4.1 Assumption Testing

The assumptions tested included the relationship among variables (linear relationship, multicollinearity, and autocorrelation) and data behavior (normality of residual and presence of outliers)(Astivia and Zumbo 2019; Rumere et al. 2021). We used a standard split of 70% of the data set for training and 30% for testing. To assess multicollinearity, the Pearson correlation among the input variables was used, and all variables were correlated below the cut-off point ($r = 0.7$) (Astivia and Zumbo 2019). Unlike traditional regression models, CART analysis is not limited by parametric assumptions. Instead, the model is driven by the data. We only tested the above assumptions because we wanted to see how well CART and the traditional regression models performed.

5. Results and Discussion

The section on results is split into two parts: Section 5.1 presents the numerical results, and Section 5.2 the graphical results. It is important to note that the model validation indices are in Section 5.4. We only included findings that we deemed significant, leaving out preliminary findings and results from multiple regression analyses.

5.1 Numerical Results

In this section, we break down the findings by occupation (Table 3). Training new employees (M=3.124; Std=2.334; N=326), inventory (M=3.0179; Std=2.186; N=1970), and customer waiting (M=2.5607; Std=1.5812; N=1943) were the top three wastes. Production stop—Resources not available (M=2.206; Std=1.777; N=88) and union activity (M=2.107; Std=1.424; N=60) should also be reduced. The number of broken machines stopped production (M=1.329; Std=1.676; N=12). Last was cleaning (M=0.7581, Std=1.7763; N=2814).

Table 3. Waste per occupation

Occupation (code)	**Description**	**N**	**Mean**	**Std**	**CoefVar**	**Sum**
102	Training -new position	326	3.124	2.334	74.69	1018.50
110	Inventory	1970	3.018	2.186	72.43	5945.29
108	Waiting due to the customer	1943	2.561	1.5812	61.75	4975.42
107	Production stop - Resource unavailability	88	2.206	1.777	80.57	194.15

Occupation (code)	Description	N	Mean	Std	CoefVar	Sum
103	Union activity	60	2.107	1.424	67.57	126.42
106	Production stop - Machine Breakdown	12	1.329	1.676	126.1	15.95
111	Contractual break	2796	0.787	1.0156	129.05	2200.43
104	Cleaning	2814	0.758	1.7763	234.31	2133.28
105	Meetings	4047	0.557	1.177	211.23	2255.07

5.2 Graphical Results

The first step in developing a CART model in Minitab 20 was to load all the independent and dependent variables and let the software determine the optimal model. The optimal model had 30 terminal nodes, an R-squared of 0.437, and was difficult to read. For this exploratory study, a simplified tree with satisfactory R-square values was required. The final CART model contained five predictors, eight terminal nodes, and an R-squared value of 0.389 as seen in Figure 2.

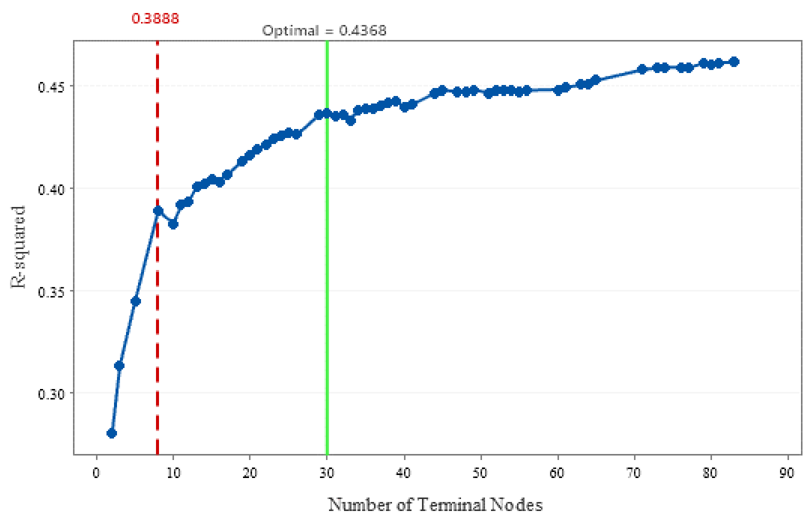

Figure 2. R-squared vs number of terminal nodes

Occupation, which characterizes waste type, was the most significant factor, accounting for one hundred percent of the weight, followed by waste occurrence time (34.2 %) (Figure 3). The relative importance of month and supervisor was 17.6 % and 4.6%, respectively. The supervisor was eliminated as a component of the model in the final version because its contribution was negligible (only 4.6 percent). Figure 4 shows the average monthly waste in hours and monthly waste occurrences. The number of waste occurrences increases from month 1 to month 4, then decreases and increases from month 8 to month 11.

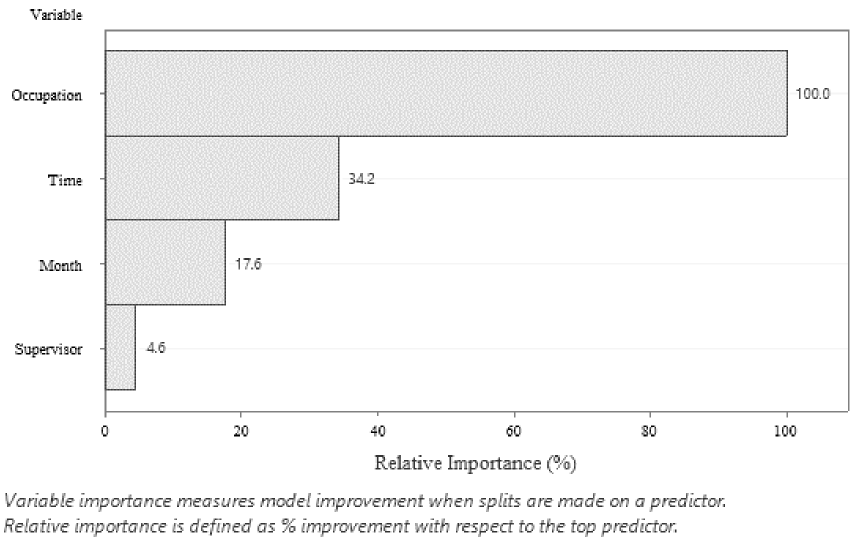

Figure 3. Relative variable importance

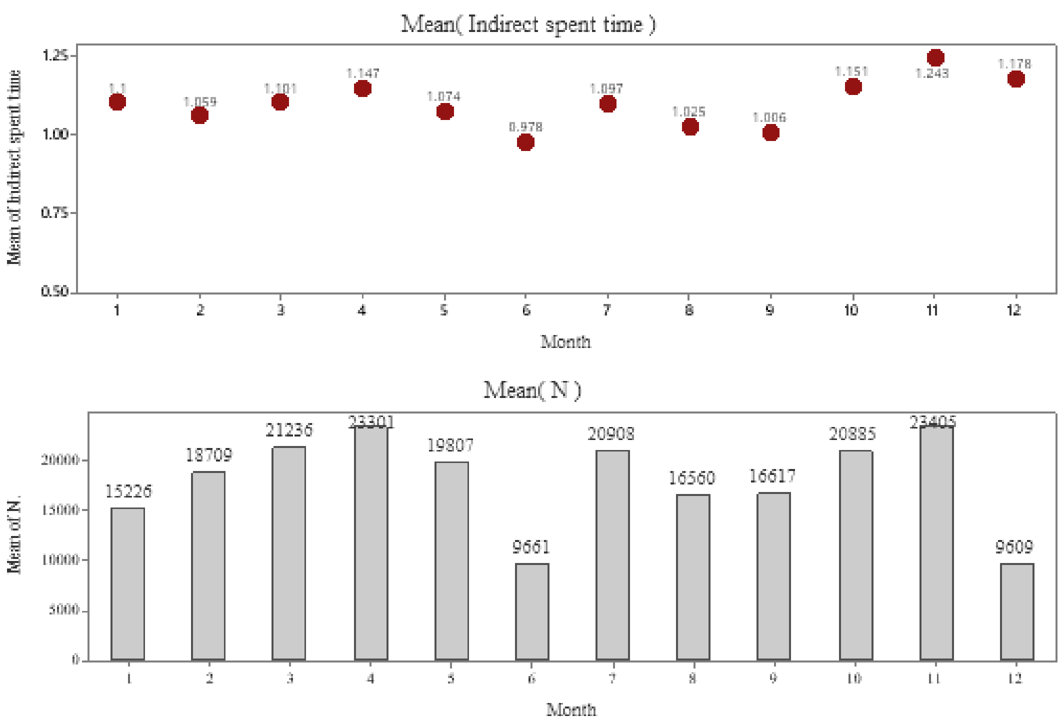

Figure 4. Waste in hours vs month

The company of interest operates 24 hours a day, seven days a week, so it was necessary to compare night and day shift waste. The top graph in Figure 5 shows the average waste per hour, while the bottom graph shows recorded events. Mean waste at midnight was 2.318 hours for 883 records. From 0:00 to 5:00, waste declined. More events were reported from 5:00 to 9:00, and the average amount of waste was highest at 10:00 (M=2.185; N=6552), 12:00 (M=2.034; N=12327), 18:00 (M=1.933; N=3854), and 19:00 (M=1.880; N=669). Figure 6 shows a Pareto chart of occupations, with 110 (Inventory), 108 (Waiting due to the customer), 105 (Meetings), and 111 (Contractual break) causing 80% of waste.

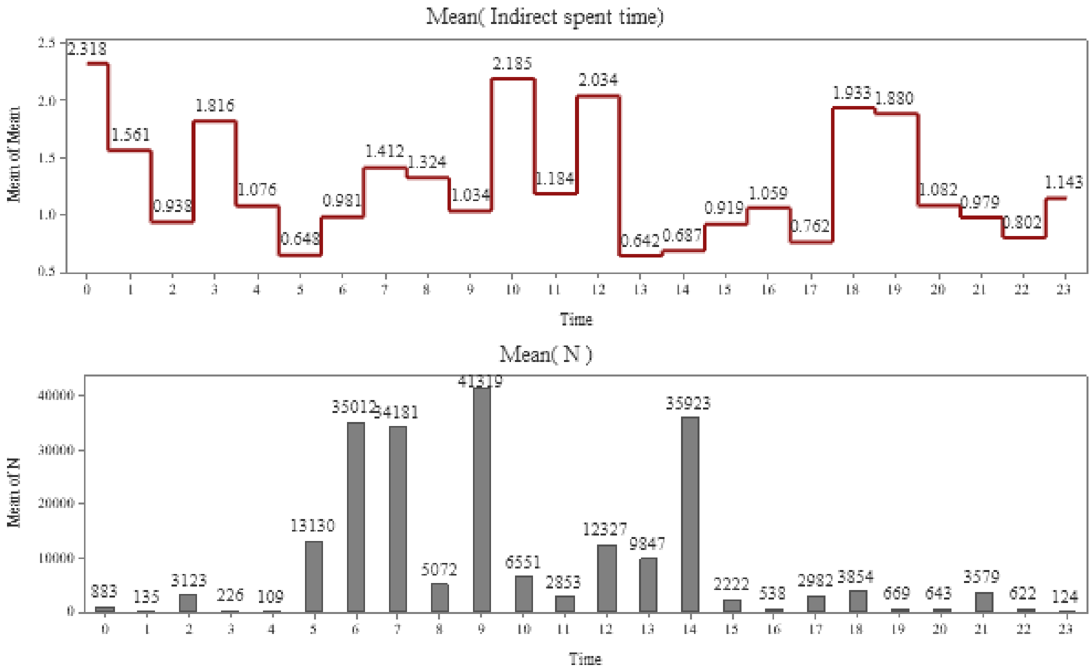

Figure 5. Waste in hours vs time

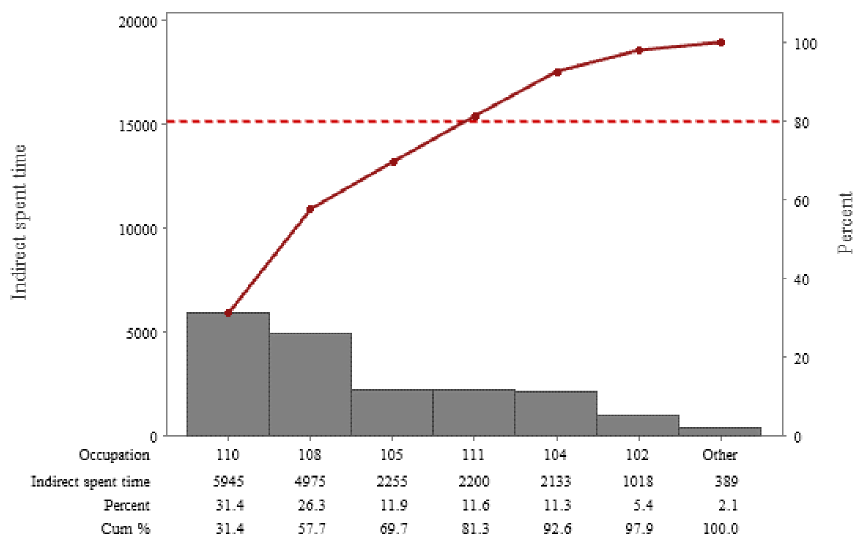

Figure 6. Pareto chart of occupation vs indirect spent time

Figure 7 is a heatmap that shows the major waste drivers over 12 months. Inventory at 110 was high in month 6 with mean waste concentrations of 4.129 hours in month 10 and 3.554 hours in month 11. Customer waiting at 108 averaged 2.97 hours from months 7 to 11. Figure 8 shows Meetings (105) were highly concentrated at 8:00 with a mean waste time of 7.5 hours. The majority of 108 (Waiting due to customer) were reported during the night shift and at 5:00 a.m. Most of the 110 (Inventory) were reported at 7:00 with a 4.3-hour waste time.

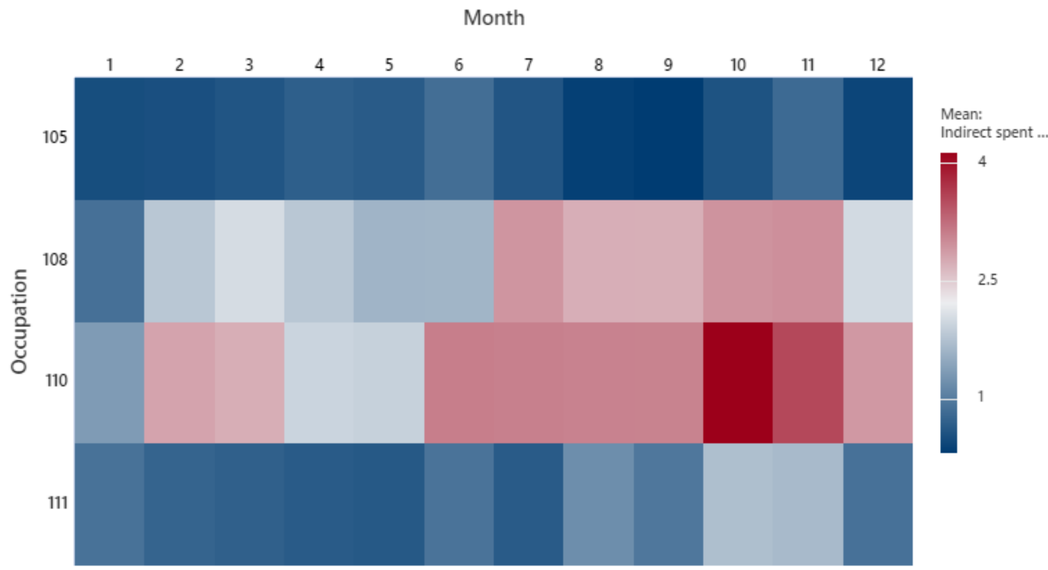

Figure 7. Heatmap of annual waste

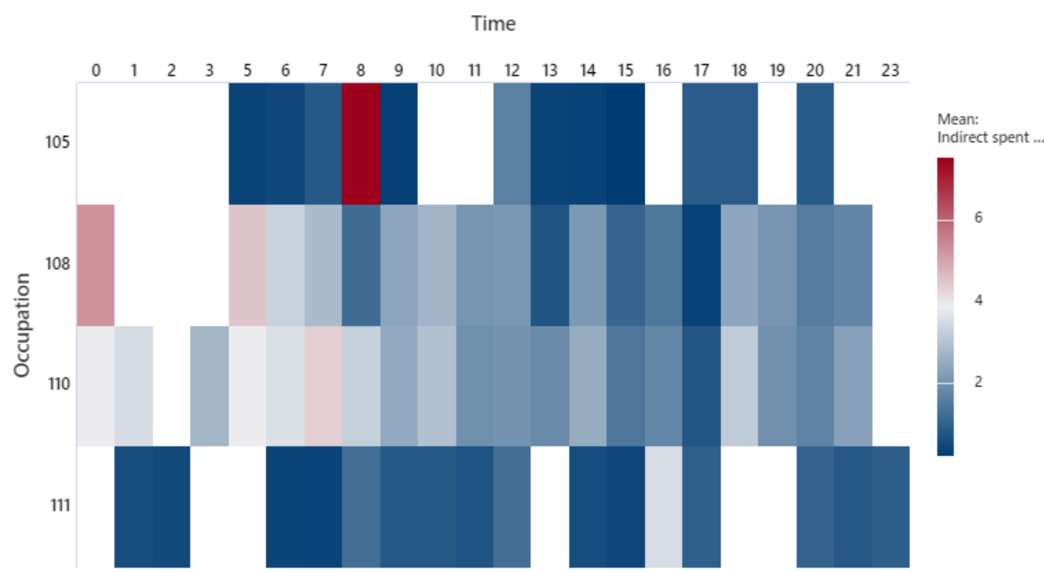

Figure 8. Heatmap of waste time over time

5.3. Model Result

There was a strong correlation between the type of occupation, the time of day, the month of the year, and the amount of waste produced (Figure 4). For example, when the occupation was 104, 105, 106, 111, 115 and the time was within one of these hours 0-6, 11, 13–15, 19, the waste was (M=0.418, Std=0.635, N=3588) (Terminal node 1). The waste was (M=0.755, Std=1. 217, N=2716) when the occupation was 104, 105, 106, 111, and 115 and the time was 7–10, 12, 16–18, 20, 21, 23, and the month was 1, 2, 3, 4, 5, 6, 7, 8, 9, 12 (Terminal node 2). When the occupation was 104, 105, 106, 111, and 115, the time was 7, 8, 9, 10, 12, 16, 17, 18, 20, 21, 23, and the month was 10 and 11, waste increased to (M=2.176; Std=3.332 N=497) (Terminal Node 3).

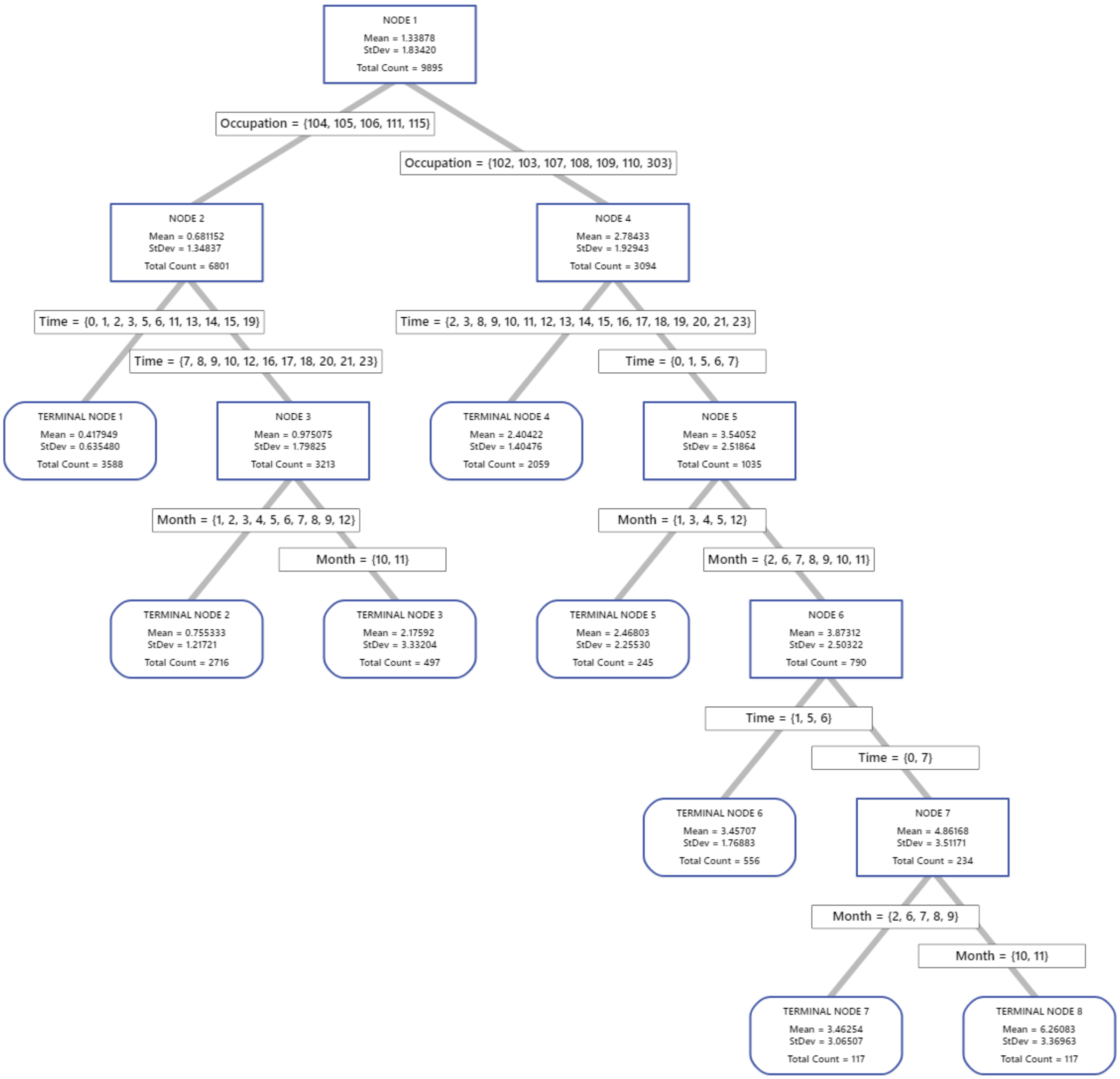

Figure 9 CART diagram

When the occupation involves 102, 103, 107, 108, 109,110, and 303 and time is 2–21, 23 waste was (M=2.404; Std=1.404; N=2059) (Terminal node 4). When the occupation involved 102, 103, 107, 108, 109, 110 and 303, and the time was 0, 1, 5, 6, 7, and the month was 1, 3, 4, 5, 12, the amount of waste was (M=2.468; Std=2.255; N=245) (Terminal node 5). When the occupation was 102, 103, 107, 108, 109, 110 and 303 and the time was 0, 1, 5–7, and the month was 2, 6–11 and time was 1, 5, 6, waste increased to (M=3.457; Std=1.769; N=556) (Terminal node 6). When the occupation was 102, 103, 107, 108, 109, 110, or 303, the time was 0, 1, 5–7, the month was 2, 6–11, and the time was 0–7 and the month was 2, 6–9, the amount of waste was second highest (M=3.462; Std=3.065; N=117) (Terminal node 7). The greatest quantity of waste was produced when the occupation was 102, 103, 107, 108, 109, 110, or 303, the time was 0, 1, 5–7, the month was 2, 6–11, and when the time was 0–7 and the month was 10 or 11 (M=6,260; Std=3,369; N=117). According to the analysis, the main areas that need to be optimized to reduce waste in the production line are terminal node 8 (M=6,260; Std=3,369; N=117), terminal node 7 (M=3.462; Std=3.065; N=117), terminal node 6 (M=3.457; Std=1.769; N=556), terminal node 5 (M=2.468; Std=2.255; N=245), and terminal node 4.

5.3 Proposed Improvements

The goal of this research was to identify the factors that were highly correlated with waste in manufacturing and to create a prediction model that can be used to estimate waste. The findings revealed a strong relationship between the type of occupation, the time of day, the month of the year, and the amount of waste produced. The top five non-value-adding activities that were responsible for the majority of the waste were training – new position, inventory, waiting due to customer, production stop – resource unavailability, and union activity. When the occupation involved 102, 103, 107, 108, 109,110, and 303 and the time was 2–21, 23 waste was found (M=2.404; Std=1.404; N=2059) (Terminal node 4). When the occupation was 102, 103, 107, 108, 109, 110, and 303, the time was 0, 1, 5, 6, 7, and the month was 1, 3, 4, 5, 12, the amount of waste was (M=2.468; Std=2.255; N=245) (Terminal node 5). When the occupation was 102, 103, 107, 108, 109, 110, and 303 and the time was 0, 1, 5–7, and the month was 2, 6–11 and the time was 1, 5, 6, the waste increased to (M=3.457; Std=1.769; N=556) (Terminal node 6). The amount of waste was second highest when the occupation was 102, 103, 107, 108, 109, 110, or 303, the time was 0, 1, 5–7, the month was 2, 6–11, and the time was 0–7 and the month was 2, 6–9 (M=3.462; Std=3.065; N=117) (Terminal node 7). When the occupation was 102, 103, 107, 108, 109, 110, or 303, the time was 0, 1, 5–7, the month was 2, 6–11, and the time was 0–7 and the month was 10 or 11 (M=6.260; Std=3.369; N=117) (Terminal node 8), the most waste was produced. These are areas that were identified as areas that need improvements. The managers can use Figure 6 to estimate the amount of waste by inputting the name of the production line of interest (the default position, the supervisor or the team that will be on duty, the months, the type of waste of interest or occupation, and the time slot), and then click the ok button. This will produce an estimate of the amount of waste.

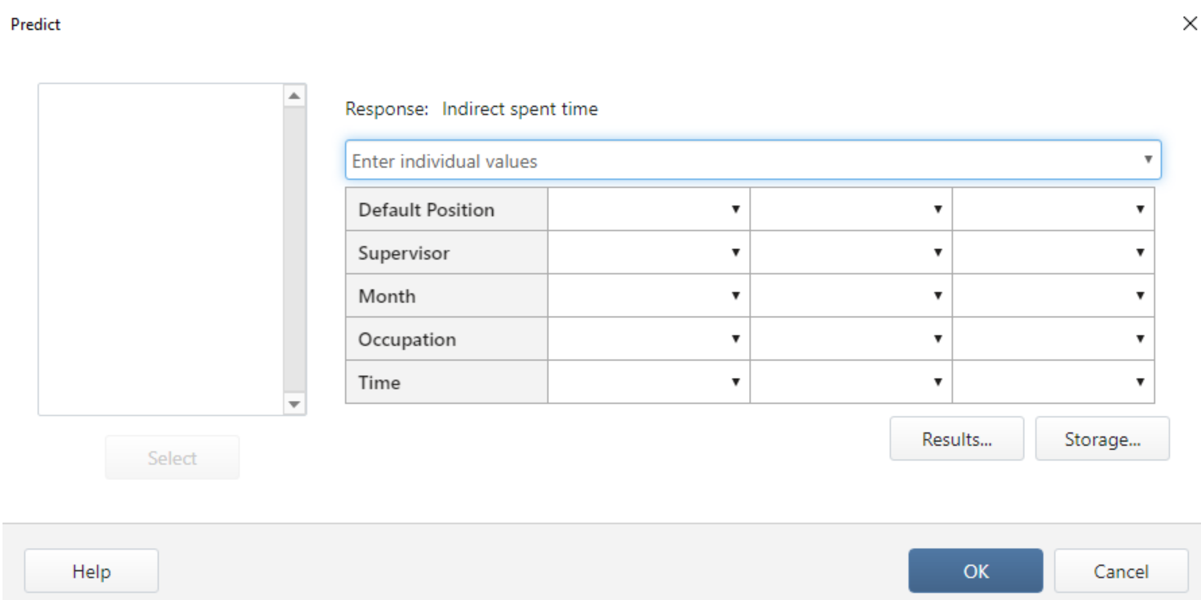

Figure 10. Model application

5.4 Validation

Both the standard regression model and CART analysis used 70% training and 30% test data. The R-Squared was 0.37 for the standard regression model and 0.39 for CART. The CART model had a MAPE of 2.682%, or 97.31% accuracy (Table 4). The model's mean squared error (MSE) was small (2.1195), which means it predicted the observed values well or that the observed values were close to the best-fit line. The CART model accurately predicted production line waste and improvement areas, but further study could benefit from Random Forest and Treenet.

Table 4. CART model validation

Statistics	**Training**	**Test**
R-squared	0.3852	0.3888
Root mean squared error (RMSE)	1.4382	1.4559
Mean squared error (MSE)	2.0685	2.1195
Mean absolute deviation (MAD)	0.7722	0.7848
Mean absolute percent error (MAPE)	2.6145	2.6822

6. Conclusion

To improve manufacturing efficiency, it is necessary to comprehend the sources of waste. This study first analyzed quality management data to establish relationships between data characteristics and manufacturing waste. Secondly, it used tools for machine learning to develop a model that can predict manufacturing waste. A case study was used in this study. We utilized 215924 rows and 13 columns or features spanning 2019 to 2021. The robustness of the model was evaluated using RMSE, MAPE, and R-squared. The optimal model consisted of 30 terminal nodes and an R-squared value of 0.437. This exploratory research required a simplified tree with adequate R-square. The final CART model had five predictors, eight terminal nodes, an R-squared value of 0.389, and an accuracy of 97.31%. There was a strong relationship between occupation, day of the week, month and the amount of waste generated. Eighty percent of waste was attributable to inventory management, waiting on customer, meetings, and contractual breaks. Months 6, 10, and 11 exhibited significant inventory management issues. In months 7 through 11, the average waiting on customer was 2.97 hours. The average duration of 8:00 a.m. meetings was 7.5 hours. The majority of waiting-on customer reports arrived between midnight and 5 a.m. Most inventory issues were reported at 7:00, with a delay of 4.3 hours. The company should improve inventory management, customer relations, and reduce meetings. Future research should employ qualitative methods to better comprehend waste factors, as this study only utilized quantitative secondary data. In addition, there is a strong belief that Random Forest and TreeNet can improve waste prediction in future research.

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Biography / Biographies

Bheki Makhanya is a Senior researcher in the Postgraduate School of Engineering Management at the University of Johannesburg. He holds a PhD in engineering management from the University of Johannesburg. His research interests include the cost of quality, total quality management, reliability improvement and risk management.

Hannelie Nel is based in Abu Dhabi, United Arab Emirates and appointed as the Senior Regional Assurance Manager for Worley UAE, Oman, North Africa and Iraq. She is an Associate Visiting Professor with the Postgraduate School of Engineering Management at the University of Johannesburg and a registered Professional Engineer. She holds a DEng Engineering Management, an MSc in Industrial Engineering, and a BEng in Chemical Engineering; and has over 25 years of experience in both industry and academia. She served as Past President of the Southern African Institute for Industrial Engineering and is currently an Honorary Fellow of the Institute. She is also a professional member of the American Society for Engineering Management. She has received numerous international awards for her contribution to industry and academia; the most recent being the global IEOM Lifetime Women in Industry and Academia Award for outstanding leadership received in Sydney, Australia in December 2022.

Jan Harm Christiaan Pretorius obtained his BSc Hons (Electrotechnics) (1980), MIng (1982) and DIng (1997) degrees in Electrical and Electronic Engineering at the Rand Afrikaans University and an MSc (Laser Engineering and Pulse Power) at the University of St Andrews in Scotland (1989), the latter cum laude. He worked at the South African Atomic Energy Corporation (AEC) as a Senior Consulting Engineer for 15 years. He also worked as the Technology Manager at the Satellite Applications Centre (SAC) of the Council for Scientific and Industrial Research (CSIR). He is currently a Professor at the Postgraduate School of Engineering Management in the Faculty of

Engineering and the Built Environment where he worked since 1998. He has co-authored over 250 research papers and supervised 68 PhD and over 300 Master's students. He is a registered professional engineer, professional Measurement and Verification (M&V) practitioner, senior member of the Institute of Electrical and Electronic Engineering (IEEE), fellow of the South African Institute of Electrical Engineers (SAIEE) and a fellow of the South African Academy of Engineering.