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A TIME SERIES ANALYSIS OF WASTE FOR FAST-FOOD OUTLETS IN ZIMBABWE: A CASE STUDY OF SIMBISA BRANDS' BAKERS INN

BY

ESTER TORINGEPI

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SUPERVISOR: DOCTOR MAGODORA

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AUTHORSHIP DECLARATION STATEMENT

TITTLE OF THE THESIS: A TIME SERIES ANALYSIS OF WASTE FOR FAST-FOOD OUTLETS IN ZIMBABWE: A CASE STUDY OF SIMBISA BRANDS' BAKERS INN.

AUTHOR: TORINGEPI ESTER.

PROGRAM: BACHELOR OF SCIENCE HONOURS DEGREE IN STATISTICS AND FINANCIAL MATHEMATICS.

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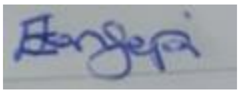
Author's Signature: 

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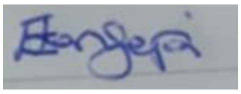

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DEDICATION

I dedicate this work to my family, whose solid support and encouragement have been my constant motivation throughout this research journey. Their belief in my abilities has inspired me to pursue my academic goals with determination and persistence.

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ABSTRACT

This study, "A TIME SERIES ANALYSIS OF WASTE FOR FAST-FOOD OUTLETS IN ZIMBABWE: A CASE STUDY OF SIMBISA BRANDS' BAKERS INN," is a critical analysis of waste generated by fast-food outlets in Zimbabwe. Simbisa Brands' Bakers Inn was the area of focus here. Quantitative data were used in the research and inferred from 29 months of past waste data, November 2021 to March 2024, to determine and analyze trends and patterns in waste creation. Trends were required in knowledge of how operation sustainability and efficiency could be enhanced in the fast-food sector. To achieve its objectives, the study embraced a rational order of activities in terms of statistical approaches in the form of predictive modeling and time series analysis. The models used were ARIMA and FFNN. The activities were applied in forecasting quantities of wastes in the future and forecasting the efficacy of the various interventions of waste management that are being applied. These analytical methods, the study provided general information regarding trends of waste production and their economic effects to business firms. The study identified significant trends in the waste generation patterns at Bakers Inn, such as crucial areas of improvement in coming up with effective waste management systems. The study found that inefficient waste disposal operations and inadequate forecasting led to the production of excess quantities of waste, impacted operating expenses, and resulted in environmental complications. Based on this evidence, the study found pragmatic waste reduction and efficient resource use solutions. Few of the key recommendations included aligning better forecasting techniques to predict waste generation more accurately, improved segregation processes to enable recycling and composting, and customized staff training modules to familiarize them with sustainability initiatives. In general, this study contributed a great deal to sustainable operations within Zimbabwe's fast-foods, and the way is now cleared for Bakers Inn and other such institutions to conduct their operations efficiently and sustainably without leaving an environmental footprint. Of particular interest is the fact that FFNN model attained the best performance regarding forecasting accuracy, thereby pointing to its potential as a useful utility in waste management within the industry.

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ACRONYMS

1 ARIMA - Autoregressive Integrated Moving Average

2 FFNN - Feedforward Neural Network

3 EMA - Environmental Management Agency

4 WST - Waste Generation

5 FC - Food Cost

6 INF - Inflation

7 EXC - Exchange Rate

8 AIC - Akaike Information Criterion

9 BIC - Bayesian Information Criterion

10 MSE - Mean Squared Error

11 MAE - Mean Absolute Error

12 RMSE - Root Mean Squared Error

13 MASE - Mean Absolute Scaled Error

14 GPM - Gross Profit Margin

15 WMP - Waste Management Practice

CHAPTER 1

INTRODUCTION

1.0 INTRODUCTION

Fast-food chains are one of the major sources of wastage in the form of food wastage and packaging. With the rapidly growing business in the sector and numerous new companies coming into the market, the growth has resulted in the production of more wastes, in most instances including the preparation of surplus food. It is a highly serious economic and environmental issue. Bakers Inn, as a leading Zimbabwean fast-food chain under the Simbisa Brands, is no exception to such waste management problems. In order to tackle such problems, it is imperative to employ efficient waste management approaches that can help mitigate environmental effects and foster sustainable business operations. Chapter One forms the background to this study as it presents the background, problem statement and objectives, all of which are crucial in placing the research in context and delineating its significance.

1.1 BACKGROUND

The fast-food industry's worldwide expansion at a rapid pace has positioned the sector in a market of US$645.8 billion in 2020 (Grand View Research, 2020). More waste is generated with this expansion, as the food services industry generates 14.4% of the food waste globally (United Nations Food and Agriculture Organization, 2019).

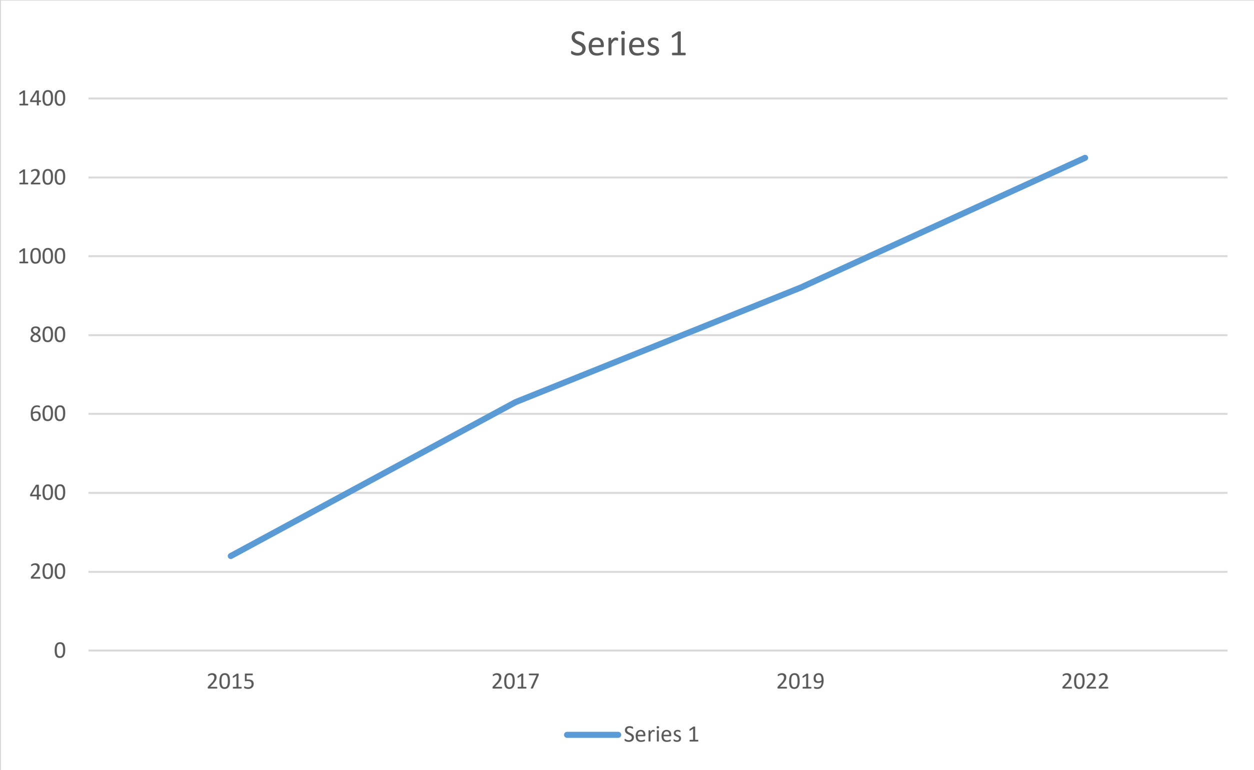
The fast-food market in Africa is set to increase to US$13.4 billion in 2025 because of urbanization and changes in consumer tastes (Research and Markets, 2020). Waste management remains a big problem in Africa, with the majority of African nations lacking appropriate waste management infrastructure (African Development Bank, 2018).

In Zimbabwe, the fast-food sector has grown visibly and among market leaders is Simbisa Brands (Bakers Inn). Simbisa Brands' Bakers Inn food outlets in Zimbabwe generate plenty of waste. Historical evidence shows an upward trend:

Table 1.1 Waste generation

Year	Waste Generation (tonnes)
2015	240
2017	630
2019	920
2022	1250

Figure 1 Waste generation



The graph shows an upward trend in waste generation.

A breakdown of waste composition at Bakers Inn outlets shows:

Food waste: 60%

Packaging waste: 25%

Paper and cardboard: 10%

Other waste: 5%

At Bakers Inn, waste generation has significant impacts, with financial losses estimated at around $500,000 annually due to disposal costs and food spoilage. This not only strains operational budgets but also reflects inefficiencies in inventory management. Environmentally, the high volume of organic waste contributes to landfill overuse, leading to soil and water contamination, while methane emissions from decomposition worsen climate change. Public health risks increase as accumulated waste attracts pests, potentially spreading diseases. Furthermore, inadequate waste management practices can harm the brand's reputation and limit job opportunities in sustainable waste initiatives.

Previous studies have shown that waste generation in Zimbabwe's fast-food industry is characterized by

Seasonal Fluctuations: Research shows that waste generation in Zimbabwe's fast-food sector demonstrates important seasonal fluctuations. Specifically, waste generation is high during festivals such as Christmas, Easter, Valentine's Day, Independence Day, Heroes Day and Defence Forces Day. The explanation for this trend is the increased customer traffic and increased preparation of foods during these festivals, since the outlets overestimate the quantities to cater to the demand. For instance, during holidays, special offers and larger gatherings can increase food waste significantly, overwhelming existing waste management practices. Seasonal patterns such as these must be comprehended to develop targeted waste management practices that are effective during peak waste generation seasons (Meki et al., 2020).

High Organic Waste Composition: The second prominent feature of waste generation by this industry is the high organic content percentage in the waste, which is approximated at around 65% of the generated waste. Such waste is primarily made up of food residues, spoiled ingredients and packaging. The dominance of organic waste creates certain challenges such as odour, pest attractiveness and landfilling. Effective organic waste management is not only central to reducing general levels of waste but also to following sustainable alternatives such as composting. By recycling organic residues from fast-food outlets, we can reduce their footprint on the environment and contribute towards a more sustainable waste management system (Chitakira and Mhlanga, 2018).

Insufficient Waste Supervision Exercise: Unsound waste management methods are a matter of concern in Zimbabwe's fast-food sector. Correct waste disposal measures are a challenge for most outlets, with serious environmental and health consequences. Mismanaged waste can contaminate the surrounding water and land resources, leading to damage to public environment and health. Some of the factors that contribute to this are poor staff training on proper waste disposal measures and insufficient appropriate resources to enable effective waste management. Addressing these problems through increased training and better utilization of resources is key to reinforcing waste management procedures and reducing the environmental footprint of the sector (Mugweni, 2017).

This study targets to bridge the gap by conducting a time series analysis of waste generation data from Simbisa Brands (Bakers Inn) fast-food outlets in Zimbabwe, providing valuable insights into patterns, trends and predictive models for waste generation.

1.2 STATEMENT OF THE PROBLEM

Waste disposal in Simbisa Brands' Bakers Inn fast-foodss in Zimbabwe is faced with a variety of serious issues. Inefficient waste disposal procedures, inadequate forecasting and lacking awareness of waste generation pattern trends are at the heart of these issues. The extensive amount of waste produced makes a significant contribution to the inefficiencies of operations, leading to wastage accumulation, which not only increases the cost of disposal but also poses the threat of causing damage to the environment. This is particularly a problem looking at the requirements by the Environmental Management Agency (EMA) and municipal city councils. Lack of proper prediction of waste generation also leads to inadequate resource use and low storage capacity but also amounts to business losses on products that could not be sold, as well as excess production. As such, the company loses money as these issues of waste management directly affect both operations costs and compliance. This study aims to solve these issues by assessing waste generation patterns, developing predictive models and offering evidence-based recommendations for optimizing waste management practices. The ultimate reason is to reduce cost on waste dumping, enhance sustainability and reduce impacts on the environment, thereby making Bakers Inn more efficient and responsible to run.

1.3 RESEARCH OBJECTIVES

1. To analyse historical waste generation.

2. To determine factors contributing to excessive waste generation.

3. To forecast future waste generation using time series models.

1.4 RESEARCH QUESTIONS

1. How do seasonal fluctuations influence waste generation at Simbisa Brands' Bakers Inn fast-food outlets?

2. How accurately will the developed predictive models forecast waste generation at Simbisa Brands' Bakers Inn fast-food outlets?

3. What are the environmental impacts of current waste management practices at Simbisa Brands' Bakers Inn fast-food outlets?

4. How can Simbisa Brands' Bakers Inn fast-food outlets optimize waste management practices to minimize environmental harm?

5. Can we reliably forecast future waste output?

1.5 ASSUMPTION OF THE STUDY

1. The accuracy and reliability of secondary data from Simbisa Brands' Bakers Inn waste management records and Zimbabwe Waste Management Authority reports.

2. The stability of waste generation patterns over time, with no significant changes in operational practices or external factors.

3. The representativeness of the selected locations (Harare, Chivhu and Masvingo) for the entire Simbisa Brands' Bakers Inn network in Zimbabwe.

4. The adequacy of time series analysis techniques in capturing complex relationships between variables

1.6 SIGNIFICANCE OF THE STUDY

The findings of this study will be beneficial to stakeholders:

This study will enrich the knowledge of the researcher in time series analysis and waste management, with enhanced capacity to carry out research (Kothari, 2004). Findings of the study will also inform future studies.

Likewise, findings of the study will inform policy making for waste management, with the capacity of the government to:

Develop evidence-based waste management policy (Mugweni, 2017)

Strengthen environmental legislation and regulation (Zimbabwe Waste Management Policy, 2017)

Promote sustainable fast-food practices

This study will also:

Contribute to the body of knowledge on Zimbabwe waste management (Chitakira and Mhlanga, 2018)

Provide a model for carrying out future studies on time series analysis of waste management

Help contribute to academic literature on sustainable fast-food practices

The research findings will benefit the business by:

Inform evidence-based decision-making on waste management practices (Meki et al., 2020)

Enhance waste reduction and recycling programs

Encourage cost savings through optimizing waste management

The study findings will benefit the society:

Encourage sustainable waste management to minimize ecological damage (United Nations Food and Agriculture Organization, 2019)

Enhance public health through hazard reduction related to waste

Benefit Zimbabwe in realizing its sustainable development objectives

This study presents trends and patterns of wastage at Simbisa Brands' Bakers Inn FAST-FOODs, giving stakeholders important information that can be used to improve waste management systems and promote sustainability.

1.7 LIMITATIONS OF THE STUDY

1. Data availability and access constraints: Limited historical data availability can constrain the study duration and level of granularity

2. Use of secondary data: The research used existing data, which may be biased or incomplete

3. Lack of generalizability: Results may not be generalizable to other FAST-FOOD restaurants or industries.

4. Limitations of time series analysis: The research may not capture non-linear relationships or structural breaks in the data

5. Externalities: The study may not be in a position to capture the impact of policy changes and economic cycles on waste generation.

6. Small sample: The sample employed by the study may be small and this may affect the reliability of the results.

1.8 DELIMITATIONS OF THE STUDY

1. Geographical scope: The study focuses on Simbisa Brands' Bakers Inn outlets in Zimbabwe only.

2. Timeframe: The study analyses data from 2020 to 2023 only.

3. Data type: The study uses secondary data only.

4. Methodology: The study employs time series analysis techniques only.

1.9 DEFINITION OF KEY TERMS

1. Waste Generation: The process of producing waste resulting from the operations of fast-food outlets (Mugweni, 2017).

2. Time Series Analysis: A statistical technique used to analyse and predict data points composed over time, enabling the identification of patterns, trends and seasonal fluctuations (Box et al., 2015).

3. FAST-FOOD Outlets: Establishments that provide quickly prepared food and beverages, often with take-away or dine-in options, such as Simbisa Brands' Bakers Inn (Kotler et al., 2019).

4. Waste Management: The process of collecting, moving, processing and disposing of waste in an environmentally responsible manner (United Nations Environment Programme, 2019).

5. Organic Waste: Biodegradable waste, including food waste, paper and cardboard that can be composted or recycled (Chitakira and Mhlanga, 2018).

6. Non-Organic Waste: Non-biodegradable waste, including plastics, glass and metals, requiring specialized disposal methods (Zimbabwe Waste Management Authority, 2020).

7. Seasonality: Fluctuations in waste generation patterns due to seasonal changes, holidays, or special events (Meki et al., 2020).

8. ARIMA Model: A statistical model used to forecast future values based on past patterns and trends in time series data (Box et al., 2015).

9. Sustainable Waste Management: Practices and strategies aimed at minimizing waste generation, promoting recycling and reducing environmental impacts (World Health Organization, 2018).

1.10 CONCLUSION

This chapter presented a comprehensive plan for conducting time series analysis of trends in waste generation at Simbisa Brands' Bakers Inn fast-foods in Zimbabwe. The study aimed at providing additional insights on patterns, trends and drivers of waste generation, developing prediction models and providing evidence-based recommendations for improvement.

CHAPTER 2

LITERATURE REVIEW

1.0 INTRODUCTION

The rapid growth of the fast-food industry in Zimbabwe has led to increased concerns about food waste management. Bakers Inn, a popular fast-food outlet, produces weighty amounts of waste, including food waste, packaging materials and other non-food waste. This literature review aims to explore the current state of knowledge on food waste management in the fast-food industry, with a specific focus on Bakers Inn in Zimbabwe. The review will examine the causes and consequences of food waste, as well as strategies for reducing and managing food waste in the fast-food industry. By combining existing research, this review aims to provide insights and recommendations for improving food waste management practices at Bakers Inn.

2.1 THEORETICAL LITERATURE REVIEW

2.1.1 Waste Management Theory

Theory of waste management is an all-encompassing discipline that deals with principles, frameworks and strategies that are developed to dispose of waste in a proper manner to minimize environmental, economic and social effects. Based on the disciplines of environmental science, economics and sustainability studies, this theory was developed by intellectuals and organizations over time.

Most relevant framework in this application is the waste hierarchy that pronounces a scientific method of handling waste. Joining the list of modern waste management policies, the waste hierarchy seeks prevention, reduction, reuse, recycling, energy recovery and finally disposing of the waste. This method was adapted by innovative environmentalists and policy makers as a measure to reduce the economic and environmental impact of waste.

Zero-waste concepts have been advanced by writers like Paul Palmer, while others like Michael Braungart and William McDonough started the Cradle-to-Cradle design, which promoted sustainable use of resources. Governments and institutions like the United Nations Environment Programme and European Union have also been influential in the formation of waste management policy, particularly because of the excess waste caused by industrial activities like fast-foods, which have enormous packaging and food wastage problems.

The waste hierarchy is the most widely accepted approach in waste management with a ranking of approaches in an attempt to most effectively guide successful waste management strategies.

Prevention (Reduce) – Minimizing the amount of waste produced.

Minimization (Reuse) – Utilizing a material repeatedly.

Recycling – Recycling waste to new material.

Energy Recovery – Converting waste to energy (e.g., incineration).

Disposal (Landfilling, Incineration without energy recovery) – This is the least preferred.

In Bakers Inn, a Zimbabwean restaurant, waste management serves to efficiently suppress environmental impacts as well as increase sustainability (Mhiribidi, 2019). Through the application of the waste reduction principles such as suppression of wastage of food and performing recycling operations, Bakers Inn is able to limit its environmental impact and increase its sustainability

The Waste Management Theory Was Developed because of several reasons, some of which include

1. Environmental reasons. In order to minimize pollution, conserve resources and prevent land degradation.
2. Economic efficiency. To conserve money in waste disposal and reduce recycling complexity.
3. Sustainable development. In order to achieve consumption and production that is responsible.
4. Legal regulations. Governments all over the world have passed legislation to manage waste effectively.

2.1.2 Food Waste And Revenue Theory

The connection between food wastage and reduced profitability can be best illustrated in the fast-food industry and with a direct impact on profitability as well as sustainability. As early as 1817, David Ricardo suggested the Law of Diminishing Marginal Returns, where it is suggested that overproduction—such as in food overproduction—will lead to decreasing returns. Not only does such a scenario increase wastage but also reduces operational efficiency.

In addition, the 1970s Waste Management Pyramid places foremost emphasis on waste reduction at source for cost-effectiveness enhancement. Robert Cross's Revenue Management Theory in 1997 targets profit maximization and loss minimization, such as losses due to food waste, through price optimization, inventory control and demand forecasting. Altogether, these theoretical frameworks have the purpose of strengthening business sustainability, eliminating inefficiencies and promoting sustainable consumption patterns.

To business entities such as Bakers Inn and Simbisa Brands in Zimbabwe, the application of these ideas has the capability of enhancing production operations, reducing food wastage and consequently enhancing financial performance due to enhanced forecasting as well as efficient utilization of resources. Food wastage is naturally connected to operational efficiency, stock control and revenue maximization.

Evidence from research by Sibanda and Mhlanga (2020) attests that there might be significant cost savings and additional revenue for Zimbabwean fast-food restaurants if measures to eliminate food wastage are implemented. Additionally, Tristram Stuart's Theory on Food Waste asserts that the major causatives of wastage in food are likely to be overproduction, inadequate forecasting of demands and unrealistic expectations of consumers. To Bakers Inn and other quick-service restaurants, this means enhanced stock management, portioning and the implementation of donation schemes that can effectively reduce wastage.

Pareto Principle or 80/20 Rule was established by Vilfredo Pareto in 1906. When applied to food wastage, the result is that a significant 80% of wastage would generally result from just 20% of foods, which are perishables. Fast-food restaurants can implement this theory to recognize the primary drivers of waste and subsequently introduce menu layout changes and procurement planning adjustments. As food waste has a direct correlation with revenue, it is an area ripe for cost savings intervention. Food Waste and Revenue Theory demands that food waste has a direct link to revenue (Otieno and Omolo, 2017). Therefore, each rise in revenue comes with an increase in food wastage.

Revenue Management Theory (Robert Cross, 1997) is actually selling the right product, to the right customer, at the right time, for the right price. Fast-food translation, in other words. Dynamic pricing (cutting food by discounting at the end of the day to prevent wastage) and Menu engineering (buying low-wastage, high-margin foods).The theory also suggests that reducing food wastage can earn more revenue through cost reduction and improved operating efficiency (Kumar et al., 2017).

Law of Diminishing Returns (David Ricardo, 1817) more production is not always more revenue—excess production is a source of wastage and loss of funds. Production has to be regulated by forecasting in quick food chains to avoid excess production. Theories were established in the aim of minimizing economic loss suffered as a result of food waste, enhancing the sustainability of food production and supply, optimizing the efficiency of business in pricing and inventory control and optimizing the issue of social responsibility because food waste comes with food insecurity.

In utilizing the Food Waste and Revenue Theory in Bakers Inn, there are some steps that can be undertaken.

1. Perform a food wastage audit to determine where things can be done better (Mangwandi and Moyo, 2017).

2. Minimize food waste with practices, i.e., food recovery and redistribution (Kumar et al., 2017).

3. Research and review the impact of food waste minimization initiatives on profitability (Otieno and Omolo, 2017).

2.1.3 The Lean Path Theory

The Lean Path Theory is a valuable model for the understanding and improvement of waste management systems, particularly within the food service industry. Andrew Shakman developed this data-driven method in 2004 specifically for sole targeting of food waste reduction in fast-food restaurants. Based on Lean Management Principles, it emphasizes relentless monitoring, wastage tracking and process optimization to minimize avoidable losses.

Lean Path employs computerized food waste monitoring systems through which businesses can obtain real-time information regarding waste food. This enables them to detect patterns of wastage and adopt methods to eradicate overproduction and wastage. This idea came about as a result of the escalating problem of food wastage in commercial kitchens, where poor forecasting and inefficient processes can cause massive monetary and environmental losses.

With the implementation of Lean Path, fast-food businesses like Simbisa Brands and Bakers Inn in Zimbabwe are able to optimize stock control, standardize portion sizes and optimize overall profitability in addition to enhancing sustainability. The key goals of this theory are to help food businesses track, analyze and reduce food waste using data analytics, leverage technology and induce behavioural change to reduce wastage in commercial kitchens and ultimately become cost-effective while enhancing sustainability in food service operations.

The Lean Path Theory is based on three fundamental principles to effectively reduce wastage in the fast-food industry.

Firstly, waste must be measured with scales, software and AI to monitor wastage in real-time. By doing so, businesses can discover the specifics of food wastage knowing what is wasted, when it happens and why. Based on this, outlets are well-equipped to make sound decisions for their business.

Second, the theory advocates process analysis and improvement. If there is a trend of food wastage, say overproduction or rotting, then necessary adjustments must be made by fast-food restaurants on their inventory, portion size and menu offerings. This leads to more effective functioning and less wastage.

Lastly, Lean Path Theory also creates behavioural change and staff involvement. Workers are encouraged to be involved in the eradication of waste through training and compensation, thus developing a culture of awareness of waste in the workplace. Engaging employees in such a way not only reduces waste but also creates a sense of responsibility and ownership.

Studies have shown that the implementation of Lean principles will help reduce wastes drastically and make the environment sustainable (Otieno and Omolo, 2017). Focusing on such key principles, quick food firms can enhance their operations and also support a sustainable future.

Lean Path Theory is crucial in conducting a Time Series Analysis of Waste, particularly for fast-food restaurants like Bakers Inn. Applying Lean Path principles within a time series analysis allows it to determine waste handling areas for improvement (Mangwandi and Moyo, 2017). Proper production processes and applying good waste management techniques could allow Bakers Inn to reduce waste production and enhance its environmental sustainability.

It makes it possible to monitor food waste patterns every day, every week, or every month, trace seasonal waste patterns—like higher waste after promotion—and reduce costs associated with overproduction, thereby enhancing profitability and sustainability.

To apply the Lean Path Theory successfully in Bakers Inn, the following must be accomplished: identify waste management areas for improvement (Kumar et al., 2017), streamline production processes to minimize wastage (Mangwandi and Moyo, 2017) and adopt effective waste management methods, including composting and recycling (Otieno and Omolo, 2017).

2.1.4 Food Cost And Revenue Theory

Food cost and revenue theories are important in fast-foods like Simbisa Brands and Bakers Inn in Zimbabwe because they make it possible to balance profitability with wastage reduction. The Food Cost Percentage Model, which is based on restaurants, estimates costs to sales revenues as a percentage. This keeps the prices not only cost-covering but competitive in the market.

Revenue Management Theory by Robert Cross, introduced in 1997, focuses on maximizing sales through effective pricing, demand forecasting and inventory control. This is crucial in reducing loss of food and maximizing profit. Additionally, David Ricardo, in 1817, expressed the Law of Diminishing Returns to us, which instructs us that overproduction does not always mean increased revenue but can instead result in wastage and financial loss.

These theories have been developed in a bid to enhance business efficiency, prevent wasteful use and overall profitability for the food service industry. With the use of time series analysis for waste tracking, Simbisa Brands and Bakers Inn can identify patterns, prevent losses and optimize the management of stock. This subsequently results in enhanced financial performance as well as environmental sustainability.

2.1.5 Gross Profit Margin Theory

GPM theory is a vital financial metric that analyzes the profitability of a company's sales (Kumar et al., 2017). GPM is calculated by dividing the gross profit over the total revenue. The theory is based on theories of cost accounting and financial management, where initial economists such as Adam Smith (1776) laid the foundation and John Maynard Keynes (1936) later developed it to enhance comprehension of business profitability.

The GPM formula [(Revenue - Cost of Goods Sold) ÷ Revenue × 100%] is a key indicator of a company's financial health, operations efficiency and pricing strategy. It helps companies determine how efficiently they manage the costs of production as a percentage of their revenue. For the quick-service restaurant businesses like Simbisa Brands and Bakers Inn in Zimbabwe, it is important to maintain a healthy gross profit margin if they are to remain profitable and minimize wastage. Wastage of too much food leads to a high cost of goods sold, which lowers the gross profit margin.

With the use of time series analysis, such businesses are able to track patterns of waste over time, locate inefficiencies and refine their pricing and inventory strategies to maximize profitability and sustainability. In the waste management sector, GPM is a critical measure that allows companies to evaluate the financial effect of waste minimization measures (Mangwandi and Moyo, 2017). Waste reduction not only reduces costs but also increases the GPM.

It was created to measure business profitability by measuring the leftover profit after direct costs in terms of food, labor and packaging have been subtracted. It assists businesses like Simbisa Brands and Bakers Inn to know how efficiently they can convert sales into profits and also uncover losses arising from wastage so that they can improve cost control.

2.1.6 Inflation And Revenue Theory

Inflation is the pace at which prices are rising over a specified interval, usually one year. It measures how much a group of commodities and services has risen in price over a specified span (Olusola et al., 2022). In this context, some of the theories of inflation that are applicable to the study are presented. Revenue Management Theory (Developed by Robert Cross, 1997) is focused on price changes, demand modelling and maximizing sales strategies. Revenue management can be applied to fast-food restaurants in order to. Adjust menu prices in relation to inflation and Offer combo offerings or dynamic pricing to help recover costs.

2.1.7 Income Effect Theory

Income Effect Theory explains how changes in consumers' income may influence their consumption behaviour, which, subsequently, influences demand, revenue and wastage at fast-food outlets like Simbisa Brands and Bakers Inn in Zimbabwe. Developed by John Hicks and Eugen Slutsky in the early 20th century, this theory supposes that with the rise in consumers' incomes, they spend more on goods and services. Conversely, with the fall in income, consumption lessens.

In the case of Simbisa Brands and Bakers Inn, the impact of income is significant in the determination of trends in food wastage and revenues. To illustrate, in times of high inflation or recession, lower purchasing power can find expression in declining volumes sold, thereby resulting in more stock remaining behind and increased food wastage. When disposable incomes are on the rise, demand for fast-foods is likely to increase. But this can equally result in overproduction when companies estimate the true demand incorrectly, hence increasing levels of waste.

Conducting a time series analysis of waste from these stores can reveal trends related to income fluctuations, enabling better forecasting, inventory management and pricing strategies to lower waste and optimize revenue.

Mukucha, P., Jaravaza, D. C. and Chingwaru, T. (2023) – "Solid Waste Management in the Fast-food Restaurant Industry. The Antecedent Role of Institutional Isomorphism" This study examines the impact of institutional pressure, for instance, coercive, mimetic and normative pressures, on the adoption of green food waste management practices in Zimbabwe's fast-food industry. Authors aimed to find out the impact of external and internal pressures on waste management practices in fast-food restaurants.

The study utilized primary data collected from 400 fast-food restaurants businesses in Harare utilizing a self-administered questionnaire. The data was analyzed using Structural Equation Modelling (SEM) with AMOS being used for determining the relationships between institutional pressures and the adoption of waste management practices.

The findings were that institutional pressures were a dominant force in the adoption of environmentally sound waste disposal practices and subsequently this had a positive impact on operational performance by waste reduction. The authors recommended strengthening the regulatory framework and inducing green behaviour adoption by the fast-food industry via coercive regulation and industry-level self-regulation.

While the study provides valuable information on institutional pressures, the absence of time series data to track waste trends during different periods is a shortcoming. Moreover, the application of self-reported data tends to invite biases, posing challenges to making the study representative and taking an accurate view of actual waste practice.

2.1.8 Exchange Rate And Revenue Theory

Exchange rate is the ratio of foreign currency to domestic currency (Bradley and Moles, 2002). It is essentially the key connection between local and international markets for goods, services and money (Okika Christian, Francis and Greg, 2018). The exchange rate can impact the revenues of a company through transactions, translations and economic exposures. The effect is explained by the trade channel and financial channel hypotheses of a company's performance in an economy with a fluctuating exchange rate. While the financial channel will not directly address this notion, it is illustrated that evidence points to it indirectly expressing the presence of the trade channel.

2.1.9 The Financial Channel Theory

Financial Channel Theory explains how Zimbabwean fast-foods like Simbisa Brands and Bakers Inn's performance, for instance, revenues, wastage and cost management are decided by banking systems, interest rates and financial markets.

It was designed by Ben S. Bernanke and Mark Gertler (1989, 1995) In Monetary Policy Transmission Mechanisms. Explains how business conduct and economic activity are regulated by financial conditions.

Financial Channel Theory propounds that financial variables like profitability, revenue and expenses are major drivers of waste management activities in organizations (Kumar et al., 2017). For fast-food chains like Bakers Inn, for instance, Financial Channel Theory propounds that financial variables drive waste management activities, for instance, investment in waste reduction technology or waste minimization practices (Mangwandi and Moyo, 2017).

The theory was built to. Illustrate how monetary policy (central bank action) influences firms beyond the standard interest rate channels and to analyze how credit constraints, exchange rates and inflation influence investment, pricing and production decisions.

2.1.10 The Trade Channel Theory

Trade Channel Theory explains how international trade, exchange rates and international supply chains affect domestic businesses, including fast-food chains Bakers Inn and Simbisa Brands in Zimbabwe. The theory is applied to study how trade policies and importation costs impact food waste, prices and incomes.

Paul Krugman and Maurice Obstfeld (1991) – Done in the backdrop of macroeconomics and international trade For describing how exchange rates, tariffs and trade policy affect home economies, for demonstrating how world market changes affect food availability, prices and business costs and for helping firms to understand how imported goods affect pricing, revenues and waste disposal.

Trade Channel Theory explains that the flow of goods and services through different trade channels can affect the generation of waste (Kumar et al., 2017). For the example of Bakers Inn's fast-food chain, the trade channel theory can explain how different supply chain channels can affect waste generation.

Researchers have also shown that trade channel theory can be applied in order to minimize waste generation within the fast-food industry (Mangwandi and Moyo, 2017). For example, research by Otieno and Omolo (2017) established that the application of efficient supply chain management strategies can decrease waste generation in the industry by up to 20%.

Bakers Inn in Zimbabwe can make use of the theory of trade channels to minimize waste production (Mhiribidi, 2019). Through the examination of the various trade channels employed by Bakers Inn, including suppliers, distributors and transporters, the company is in a position to determine areas to improve on and adopt measures to limit waste production.

For instance, Bakers Inn can adopt just-in-time inventory practices to minimize food wastage (Kumar et al., 2017). The organization can also adopt recycling programs for food packaging materials and food wastage (Mangwandi and Moyo, 2017).

2.2 THE MAGNITUDE, CATEGORIZATION AND MAIN FACTORS INFLUENCING FOOD WASTAGE

2.2.1Magnitude of Food Waste.

Food waste in FAST-FOOD outlets is a significant environmental and economic issue, with studies showing that between 15% and 30% of all purchased food ends up as waste (Silvennoinen et al., 2019). In Zimbabwe, the fast-food industry, including Bakers Inn, generates significant amounts of food waste (Mangwandi and Moyo, 2017).

2.2.2 Categorization of Food Waste.

Food waste can be categorized into different types, including.

1. Preparation waste: Waste generated during food preparation, such as vegetable peels and meat trimmings (Otieno and Omolo, 2017).

2. Cooking waste: waste generated during cooking, such as overcooked or burnt food (Mhiribidi, 2019).

3. Serving waste: waste generated during serving, such as leftover food and packaging materials (Kumar et al., 2017).

4. Customer waste: waste generated by customers, such as food leftovers and packaging materials (Mangwandi and Moyo, 2017).

5. Spoilage Waste (Storage Waste) – Due to improper storage, leading to expiration.

2.2.3 Main Factors Influencing Food Waste.

Several factors influence food waste at Bakers Inn, including.

1. Overproduction: producing more food than demand, leading to waste (Kumar et al., 2017).

2. Food preparation and handling practices: poor food handling and preparation practices can lead to waste (Otieno and Omolo, 2017).

3. Menu engineering: menu design and engineering can influence food waste, with complex menus leading to more waste (Mhiribidi, 2019).

4. Supply chain management: poor supply chain supervision can lead to waste, particularly if food is not stored or transported properly (Mangwandi and Moyo, 2017).

5. Customer behaviour: customer behaviour, such as ordering more food than needed, can also influence food waste (Kumar et al., 2017).

2.3 EMPERICAL LETERATURE

2.3.1 The definition of food waste and how it is treated

Food waste refers to any food that is discarded or intended to be discarded (Kumar et al., 2017). In the context of fast-food outlets like Bakers Inn, food waste can include items such as spoiled or expired food, food preparation waste and customer plate waste (Mangwandi and Moyo, 2017).

Food waste treatment involves the processing and disposal of food waste in an environmentally responsible manner (Otieno and Omolo, 2017). Common methods of food waste treatment include composting, anaerobic digestion and landfilling (Kumar et al., 2017).

In Zimbabwe, food waste treatment is a significant challenge, particularly in urban areas (Mhiribidi, 2019). Bakers Inn, like other fast-food outlets in Zimbabwe, must ensure that its food waste is treated and disposed of in an environmentally responsible manner.

To address food waste treatment, Bakers Inn can implement strategies such as.

1. Composting. Composting involves the breakdown of organic matter, such as food waste, into a nutrient-rich soil amendment (Kumar et al., 2017).

2. Anaerobic digestion. Anaerobic digestion involves the breakdown of organic matter, such as food waste, in the absence of oxygen to produce biogas and nutrient-rich digestant (Otieno and Omolo, 2017).

3. Recycling. Recycling involves the collection and processing of food waste into new products, such as animal feed or biofuels (Mangwandi and Moyo, 2017).

Firstly a study by Mukucha, P., Jaravaza, D. C. and Chingwaru, T. (2023) – explores the impact of institutional pressures, such as coercive, mimetic and normative pressures, on the adoption of sustainable food waste management practices within Zimbabwe's fast-food industry. The authors aimed to identify how external and internal pressures influence waste management strategies at fast-food outlets.

In this study, the researcher utilized primary data collected from 400 fast-food restaurant businesses in Harare via a self-administered survey. The data was analysed using Structural Equation Modelling (SEM) with AMOS to assess the relationships between institutional pressures and the adoption of waste management practices.

The findings indicated that institutional pressures significantly influenced the adoption of sustainable waste disposal practices, which in turn led to improved operational performance in terms of waste reduction. The authors recommended strengthening regulatory frameworks and encouraging the fast-food industry to adopt green practices through both coercive regulations and industry-wide self-regulation.

While the study provides valuable insights into institutional pressures, it does not incorporate time series data to track waste trends over time. Additionally, the reliance on self-reported data could introduce biases, limiting the study's generalizability and accuracy in assessing actual waste practices.

In anpther study by Matinise, S. (2020) – titled "Understanding Waste Management Practices in the Commercial Food Service Sector" Matinise's study investigates waste cooking oil generation and disposal practices in South Africa's food service sector, including fast-food outlets. The study focuses on understanding the specific types of waste generated and the management practices employed by restaurants to handle cooking oil waste.

Primary data was gathered through qualitative interviews with restaurant staff, focusing on their practices regarding cooking oil disposal. The study uses thematic analysis to identify key practices and barriers to effective waste management.

The findings revealed that fast-food restaurants generated substantial amounts of waste cooking oil, averaging 53 litters per week. However, many establishments lacked formalized systems for oil disposal, leading to inconsistent waste management practices. Matinise recommended implementing standardized practices for waste oil disposal and increasing staff training on sustainable waste practices.

The study, while offering valuable insights into the management of cooking oil waste, does not consider other forms of food waste, limiting its applicability to broader waste management issues. Furthermore, the lack of time series data prevents the study from evaluating waste trends over time, which would have been useful for analysing changes in waste generation.

In addition Makarichi, L. and Jutidamrongphan, W. (2023) – in their study titled "Inventory Analysis and Environmental Life Cycle Impact Assessment of Hotel Food Waste Management for Bio-Circular Economy Development in Zimbabwe" Makarichi and Jutidamrongphan's research evaluated the production of food waste from Zimbabwe's hospitality sector and compared alternative practices of waste management. The study examined the environmental consequence of alternative methods of food waste disposal and presented a life cycle impact assessment (LCA) to identify whose practice contributes to a more environmentally sustainable bio-circular economy.

The authors collected primary information on food wastage generation in Zimbabwean hotels. Secondary information was also studied to look at the environmental impact of waste disposal techniques such as landfill disposal, composting and anaerobic digestion. The information was assessed using a life cycle approach to estimate greenhouse gas emissions associated with each disposal technique.

The study found that the generation of food wastage in the hospitality industry averaged 1.63 kg per guest per day. Landfilling of food wastage had the greatest environmental impact with high greenhouse gas emission. This compared to composting and anaerobic digestion, which had low emissions. The authors encouraged the uptake of composting and AD as waste management practices in Zimbabwe's food industry to reduce environmental impact.

While the report provides a broad environmental overview, it focuses on the hospitality sector to a greater extent than on fast-food establishments. Furthermore, the fact that no time series analysis has been performed rules out detailed examination of long-run trends in food wastage generation and control.

Also Principato, L., Secondi, L. and Pratesi, C. A. (2018) – "Reducing Food Waste. An Investigation on the Behaviour of Italian Youths" Principato et al. talk about food waste mentality in young people in Italy and propose how to make waste smaller. The study is not performed directly in fast-food restaurants, but it is interesting information concerning consumer behaviour that could apply to the food sector.

The study used quantitative survey data to assess Italian youths' food consumption and waste behaviours. The findings revealed strong determinants of food waste such as unawareness, share sizes and attitudes towards sustainability.

Studies found that the adolescents who had higher levels of awareness regarding food wastage would likely adopt waste-reduction behaviours. The authors recommend incorporating food wastage education in the curriculum for schools and inculcating sustainable consumption habits among adolescents.

While the study offers excellent insights into consumer behaviour, it is not able to capture organizational behaviour within the foodservice industry. Furthermore, no time series analysis was conducted, which would have been beneficial in seeing how food waste behaviour evolves over time.

Lastly a study by Matinise, S. (2020) – "Understanding Waste Management Practices in the Commercial Food Service Sector" Matinise's study delves into waste cooking oil production and disposal practices within South Africa's food service sector, including fast-foods. The study focuses on gaining an understanding of the specific type of waste generated and the waste management practice used by restaurants to dispose of waste cooking oil.

Primary data were gathered through carrying out qualitative interviews among the restaurant staff, their practices of discarding cooking oil and the study applies thematic analysis to identify the key practices and issues in efficient waste management.

The study revealed that restaurants would generate a significant amount of waste oil cooking, averaging 53 litters of oil weekly. Formalized oil disposal systems were not available in most institutions, with poor waste collection practices. Matinise recommended implementing standard procedures in waste oil disposal and improving personnel training on sustainable waste management procedures.

The study, as enlightening as it is in the management of waste cooking oil, does not consider other forms of food waste and its use to broader waste management can therefore only be limited. Moreover, the lack of time series data renders it impossible for the study to evaluate trends in waste over time, which would have helped in quantifying change in waste generation.

Bulawayo City Council (2021) – "Fast-food Outlets Major Contributors to Sewer Siltation. BCC" This news article explains how Bulawayo's fast-food outlets are causing sewer siltation by releasing hot effluent, which clogs sewer pipes and damages infrastructure. The article was delivered based on statistics from observations collected by Bulawayo City Council that identified specific fast-food outlets as the main perpetrators of sewer system breakdown.

The report is not methodologically detailed but contains findings from the inspections and sewer clog evaluations. The data points out that certain fast-food chains on a regular basis emitted hot waste, which caused clogged-up sewer pipes in the neighborhood.

The research recommends fast-food chains to install pre-treatment facilities for cooling waste before discharging it into the sewerage system and urges municipal governments to improve waste management regulations.

Although the report identifies a significant waste issue that faces fast-food chains in Bulawayo, it is devoid of in-depth empirical data and does not utilize advanced data analysis methods such as time series analysis. As data collection is not performed extensively, its efficacy in terms of suggestions decreases and analysis is limited to one category of waste and not a comprehensive study of all categories of food waste.

2.4 RESEARCH GAP

Despite the heightened amount of research work on waste management within the fast-food industry, there exists a wide gap in research work in the case of Zimbabwe (Mangwandi and Moyo, 2017). Specifically, there is no research work existing on the use of time series analysis for handling waste within the fast-food industry (Mhiribidi, 2019).

Existing literature has focused on the general waste management in the fast-food industry in Zimbabwe (Mangwandi and Moyo, 2017), yet more particular work on the use of time series analysis in the case of waste management in this context is needed.

Furthermore, there is limited research on the unique challenges and opportunities that confront fast-food chains like Bakers Inn in waste management (Otieno and Omolo, 2017). This study seeks to fill this research gap by conducting a time series analysis of waste generation for Bakers Inn in Zimbabwe.

2.5 CONCEPTUAL FRAMWORK

Independent Variables.

1. Time (t) - monthly or quarterly time frames

2. Seasonality (S) - variation due to seasons in waste generation

3. Trend (T) - general long-term trend in waste generation

4. External Factors (EF) - external factors likely to affect waste generation, economic growth, population growth and weather.

Dependent Variable.

1. Waste Generation (WG) - amount of waste generated by Bakers Inn outlets in Zimbabwe

Mediating Variables.

1. Waste Management Practices (WMP) - effectiveness of waste management practices of Bakers Inn, i.e., waste reduction, reuse and recycling

2. Customer Behaviour (CB) - customer behaviour and decision that are able to influence the generation of waste, i.e., purchase of food and packaging type selection

Conceptual Framework.

Time (t) → Waste Generation (WG)

Seasonality (S) → Waste Generation (WG)

Trend (T) → Waste Generation (WG)

External Factors (EF) → Waste Generation (WG)

Waste Management Practices (WMP) → Waste Generation (WG)

Customer Behaviour (CB) → Waste Generation (WG)

Assumptions.

1. There is relationship between time and waste generation.

2. There is high seasonality effect on waste generation.

3. There is high trend effect on waste generation.

4. There is high external factors effect on waste generation.

5. Effective waste management practices decrease waste generation.

6. Customer behaviour and preferences can influence waste generation.

2.6 CONCLUSION

The chapter has highlighted the importance of waste management within the fast-food industry in Zimbabwe. The studies that were reviewed have shown that waste generation is a serious concern within the fast-food industry, with food waste being the most common factor. The literature has also highlighted the importance of embracing actual waste management practices to curb waste generation.

The above analysis has also described a number of theories and models that can be applied to explain waste treatment in the fast-food sector, including the Income Effect Theory, Gross Profit Margin Theory, Lean Path Theory, Financial Channel Theory and Trade Channel Theory. Theories and models provide significant details on what influences the creation of waste and the methods through which the creation of waste can be minimized.

The review of the literature also identified research gaps in waste management in the fast-food industry. Specifically, more studies focusing on the use of time series analysis to treat waste in the fast-food industry are needed.

In all, the review has presented an adequate synopsis of current knowledge concerning waste management in the fast-food sector of Zimbabwe. The outcomes of this review will guide the construction of a time series model for managing waste in Simbisa Brands' Bakers Inn

CHAPTER 3

METHODOLOGY

2.0 INTRODUCTION

Methodology is important in guiding the manner in which this study is conducted. With mounting concerns regarding the management of fast-food waste, efficient waste reduction and management practices are necessary and with urgency. This study will utilize primary transactional data collected from Simbisa Brands' Bakers Inn, a leading fast-food company in Zimbabwe with significant levels of waste generation. To identify the relationship between total sales and other variables of transaction services, the researcher will employ multiple linear stepwise regression analysis. Understanding trends and patterns of waste production in Bakers Inn outlets and how they are crucial in developing operational measures of controlling waste is important. The aim of this study is to perform a time series analysis of waste production in Zimbabwean Bakers Inn outlets to establish trends, patterns and seasonality. Methodology involves a consideration of research techniques, data sources and methods of analysis. In aid of achieving these objectives, the research will utilize ANN, ARIMA and Microsoft Excel in data analysis. With the application of these techniques, the research seeks to provide insightful information on the production and handling of wastes at Bakers Inn towards more sustainable fast-food management.

3.1 RESEARCH DESIGN

This study applies a quantitative research method based on time series analysis to examine the waste generated by fast-food chains, specifically Simbisa Brands Bakers Inn Zimbabwe. This study aims to know the historical trends and patterns of waste generation to inform effective waste management practice. There is causal research design which assists in knowing the problem under investigation better, however, it doesn't give conclusive proof. This is particularly suited when necessity arises to go further in exploring, explaining, forecasting and managing relationships between variables beyond artificial analysis.

3.2 POPULATION AND SAMPLING

The study sample included Bakers Inn outlets across Zimbabwe. There were approximately 100 Bakers Inn outlets during the time of research, spread across various cities and towns within the country, providing a good representation of the fast-food sector. Zimbabwe was researched as a unit to collect regional variation in waste generation pattern and management practices which were influenced by local consumers' behaviour, regulatory mechanisms and environmental conditions.

To ensure a robust sampling framework, cluster sampling was employed and outlets were selected across different provinces and districts. This enabled a wide analysis of waste disposal practices across diverse situations. Specifically, the study sampled from the following provinces: Manicaland, Mashonaland East, Masvingo, Harare and Bulawayo. For each province, 5 Bakers Inn outlets were randomly selected, giving a total sample of 25 outlets.

Inclusion of outlets that were in operation for a duration of not less than 6 years ensured that adequate historical data on waste generation existed to enable a sounder analysis. Through its focus on an exemplary sample of outlets, the study aimed to provide insightful data on waste disposal practices and their implications on operational efficiency and sustainability within the Bakers Inn franchise business in Zimbabwe.

3.3 DATA COLLECTION

Secondary data collection was largely done using the Simbisa Brands database and some of the online resources used for this study. The Simbisa database gave valuable historical waste generation figures, Bakers Inn sales and operational figures over the last couple of years. Through such abundant information, adequate time series analysis was possible in regard to monthly waste quantities in order to identify waste generation trends.

Apart from the internal information, credible online sources such as industry reports and scholarly articles were sourced through websites such as Google Scholar and Research Gate. The resources provided context and enabled benchmarking against standards in the industry to add depth to the analysis.

To analyze and portray the data in a proper manner, quantitative research tools like Microsoft Excel and Microsoft Power BI were used. Using these tools, it was simple to carry out a detailed analysis of waste generation patterns and their impacts on operational efficiency as well as sustainability at Bakers Inn. Having carried out the study in a holistic process with internal and external sources of information, the study was more enlightened on waste management challenges and opportunities.

3.4 DATA SOURCE

The data for the study were gathered from various primary sources with prime focus on Simbisa Brands' Bakers Inn in-house data and database. These were the most informative to gather such knowledge as waste production by day, week and month reports, garbage disposal records and sales data for correlation purposes.

Besides, waste management companies contracted by Bakers Inn offered useful data on waste volumes collected and disposed of, material composition and recycling percentages. Local government agencies like municipalities and local councils offered data on waste management policy, trends in disposal and environmental monitoring data.

This research specifically utilized secondary data, where it utilized monthly time series data spanning 29 months from November 2021 to March 2024. Specifically, this extensive data collection from Bakers Inn and waste management companies engaged gave a good foundation in viewing trends in waste creation and structuring appropriate management procedures.

3.5 DATA VALIDITY AND RELIABILITY

Validity and authenticity of information in a time series study on waste generated by fast-foods, in this instance Simbisa Brands Bakers Inn in Zimbabwe, are essential for deriving accurate and dependable results. Validity of the information lies in its direct use to the research objectives because it reflects patterns of waste over time by leading fast-food businesses in the country. Since this data is from big companies like Simbisa Brands Bakers Inn, which most likely have structured waste tracking procedures in place, this data can be presumed to be reliable and representative of actual waste trends in the industry.

Reliability is seen where the standard techniques of measurement and reporting of waste are followed through different outlets and time periods. Further, the secondary data of such companies usually undergo in-house quality tests, thus, it is standardized. Standardized reporting procedures and periodic audits through such companies render the information reliable so that valid comparisons and conclusions can be drawn over time. This integrative model assists in the production of confidence in findings and aids in the formulation of successful waste management policy.

3.6 TARGET POPULATION AND SAMPLE PERIOD

The target group was all of the fast-food businesses in Zimbabwe and more specifically, the Simbisa Brands Bakers Inn restaurants. These two represent a significant part of the fast-foods industry in Zimbabwe and their waste generation pattern is likely to reflect general industry trends. The sample period of the time series study will be 29 months from 2021 to 2024 to observe short-term variations and long-term patterns in waste generation. The period will allow observation of seasonal patterns, impacts of economic factors and effectiveness of any waste management measures taken over the period. Through this sample timeframe, the study is able to ascertain trends, patterns and relationships in waste generation across different ranges of products and establishments.

3.7 RESEARCH INSTRUMENTS

The study is to be carried out on time series analysis of the waste generated in Zimbabwean fast-foods, specifically Simbisa Brands Bakers Inn. The study will be based on secondary data and quantitative analysis techniques. The data to be utilized would be past data on waste generation in terms of types (food waste, packaging and plastics) and per time scales (monthly or yearly). These statistics will be gathered from waste management software and internal reports, external audit by environmental departments or local council. Data cleaning, checking and time series analysis, including trend analysis, seasonal decomposition and forecast, will be carried out using statistical packages like R or SPSS. Further, interviews with Simbisa Brands Bakers Inn waste management staff will be carried out with the aim of obtaining an overview of waste management practice and minimization strategies. The composite approach will facilitate the analysis of waste trends, determine underlying patterns and determine the effectiveness of waste reduction initiatives over time.

3.8 DESCRIPTION OF VARIABLES

Table 3.1 Description of variables

VARIABLE	UNITS	DESCRIPTION	SYMBOL	MEASURE	SOURCE
Food waste	Percentage (%)	The amount of food that is	FW	TONNES	Bakers Inn

		thrown away as waste			
Exchange rate	ZIG to 1 USD	The value of Zimbabwean dollars relative to USD	ER	USD	RBZ
Inflation	Percentage (%)	The rate of increase in prices for goods and services	INF	CPI	RBZ
Food cost	Amount($)	The total expenditure on food items	FC	USD	Bakers Inn

3.9 DATA ANALYSIS PROCEDURES

3.9.1 Pre-Test

3.9.1.1 Stationary Test

Stationarity is a necessary assumption for time series analysis, especially for models like ARIMA, which depend on stationarity to make good forecasts. Statistical properties of the time series not changing over time means that they are stationary. To establish whether waste data for fast restaurants like Simbisa Brands Bakers Inn is stationary, there are several tests to use. One of the most commonly used is that of the Augmented Dickey-Fuller (ADF). The null hypothesis is that it is not stationary, i.e., there is a unit root and the alternative hypothesis is that it is stationary. If we obtain a P-value from the ADF test which is less than 0.05, then we will reject the null hypothesis and conclude that the data is stationary. The second choice is the Kwiatkowski-Phillips-Schmidt-Shin test and this is the reverse: its null hypothesis is that the data is stationary. Low P-value in this test would lead to rejection of the null hypothesis, i.e., the series is non-stationary. When we have reached the stage where we have determined that the data is non-stationary, we can then use transformation techniques, e.g., differencing or log transformations, to stabilize the mean and also the variance. This will allow us to make a robust analysis in the future. Having our data made stationary, we will increase the accuracy of our observations and forecasts on waste management practice.

3.9.1.2 Normality Test

Checking for normality is a critical stage in data analysis for quick foods like Simbisa Brands Bakers Inn. Data needs to be normally distributed in statistical models and normality checks guarantee that our analysis will hold. Multiple methods exist for checking for normality. Another popular alternative is Shapiro-Wilk test, which tests if a sample is from a normally distributed population. In the test, we are considering the data to be normally distributed under the null hypothesis. We reject the null hypothesis when the P-value is below 0.05 and conclude that the sample is not normally distributed. Graphical methods can also be used. For example, we can use a Q-Q plot and see the distribution by eye. If the points nearly lie on a straight line, the sample would be normally distributed. If we conclude that the waste sample is not normally distributed, we can apply transformation, for instance, logarithmic or Box-Cox transformation to make the data follow the normal distribution more closely. Using this transformation, we can employ standard parametric statistical procedures for model estimation and forecasting. In general, these tests for normality are quite crucial for any statistical models employed for the waste data in order to be reliable and stable. With the verification of normality, we can have accurate and reliable predictions about the waste management practice.

3.9.1.3 Independence Test

The independence test is a statistical test to see whether two categorical variables are independent of each other. The simplest method to do this is the Chi-squared test. This Chi-squared test is performed to compare experimental frequencies within groups with calculated frequencies that would arise if the two variables themselves were independent. The test calculates a Chi-squared statistic, a measure of how much the observed data deviate from what we would have had under the independence hypothesis. Comparison to a Chi-squared distribution-based critical value, a function of degrees of freedom, allows us to make a decision regarding whether or not to reject the null hypothesis of independence. If the test P-value is < 0.05, this implies a statistical significance between the variables indicating that they are not independent. Independence tests are used in the majority of fields of study in the social sciences, market research and epidemiology to test for interactions between various variables. Through these connections, scientists have access to meaningful information that will inform decision-making and strategy.

3.9.1.4 Homoscedasticity Test

Homoscedasticity is one of the most important concepts in time series analysis and is actually the assumption that the volatility of residuals does not change over time. It is important because some models, for example, ARIMA, rely on the assumption in terms of coming up with good forecasts. If the residuals are heteroscedastic, it will lead to inefficient estimation of parameters and also invalidate the validity of the forecast. There are a number of different techniques that can be employed to test homoscedasticity. One common test used is the Breusch-Pagan test, which checks whether the variance of residuals remains constant over time. If the test provides a significant P-value of less than 0.05, this will be an indicator of heteroscedasticity. Visualization also works very effectively. For instance, through residual plots or through plotting squares of residuals versus time, it is possible to see patterns that are indicative of non-constant variance. If heteroscedasticity exists, we are able to use transformations such as log or Box-Cox transformations so as to stabilize the variance before fitting the time series models. Having obtained homoscedasticity, we are able to make our analysis precise and reliable, which will ultimately lead to making better decisions.

3.10 ANALYTICAL MODELS

For FAST-FOOD wastage time series data analysis, there are a number of analytical models that can be employed depending on the type of data. One of the models that can be employed is ARIMA, which is ideal when it comes to modelling data that has trends and autocorrelation. ARIMA models are denoted by ARIMA (p, d and q) in which p is the order of autoregressive, d is the differences to be taken for the data such that it becomes stationary and q is the moving average order. For seasonal data, a variation of ARIMA called SARIMA is taken into consideration in which there are seasonal differences and seasonal lags. Also, Exponential Smoothing can be an effective model for short-run forecasting with seasonality and trend. For if heteroscedasticity is found, volatility in residuals can be modeled by the GARCH model. This diagram illustrates a simplified work flow of how these models can be used in waste data analysis.

Figure 2 Model selection

This flowchart illustrates the way the models such as ARIMA, SARIMA and Holt-Winters are chosen and applied and the most important initial stationarity, independence, homoscedasticity and normality tests. These methods ensure proper use of a suitable model in efficient waste forecasting for fast-food restaurants.

Table 3.2 Steps in models

Step	Description
Data Pre-processing	Initial step for preparing the dataset
Stationarity Test	Test for stationarity (e.g., ADF test)
	If non-stationary, apply Differencing
ACF/PACF Analysis	Analyse autocorrelation and partial autocorrelation
Model Selection	Choose a suitable model:
	- ARIMA
	- SARIMA
	- Holt-Winters
Residuals Analysis	Analyse residuals of the selected model:
	- Homoscedasticity
	- Independence
	- Normality

This flowchart illustrates the way the models such as ARIMA, SARIMA and Holt-Winters are chosen and applied and the most important initial stationarity, independence, homoscedasticity and normality tests. These methods ensure proper use of a suitable model in efficient waste forecasting for fast-food restaurants.

3.11 The Box-Jenkins ARIMA models

The Box-Jenkins ARIMA model is a commonly used method for time series analysis and forecasting mainly when dealing with non-seasonal data. The ARIMA model is composed of three main components. AR, Integrated and MA. The model is denoted as ARIMA (p, d and q), where.

The ARIMA model formula can be expressed as.

$$\boldsymbol{Yt = \emptyset 1 Yt - 1 + \emptyset 2 Yt - 2 + \cdots + \emptyset p Yt - p + \in t + \theta 1 \in t - 1 + \theta 2 \in t - 2 + \cdots + \theta q \in t - q} \qquad (1)$$

Where.

• Yt is the value of the time series at time t.

• ϕ1, ϕ2, ϕp are the parameters of the autoregressive component.

• ϵt is the error term (residuals) at time t, assumed to be white noise.

• $\theta 1$, $\theta 2$, θq are the parameters of the moving average component.

Steps in ARIMA modelling.

Model Selection: We need to make the data stationary before we perform time series analysis and differencing is usually done for that. We need to determine the p and d and q values of the ARIMA model. For that, we consider the ACF and the PACF. The ACF plot shows us the autocorrelation of the series and also the lags of the same and through this, we are able to obtain information about the MA component. Concurrently, the PACF plot shows the immediate relationship between the series and its lags after the impact of the intervening lags has been removed, prompting us to specify the autoregressive (AR) component.

Estimation: Estimation of model coefficients is the second essential step in ARIMA time series modelling. They determine the effects of past values of the time series on the present values. In Simbisa Brands Bakers Inn waste data, this means determining AR coefficients, MA coefficients and constant terms and differencing needed to make the series stationary. This is usually achieved through methods such as MLE or LSE.

Diagnostic Checking: Once the parameters are estimated, model diagnostics then come into play to check whether the fitted ARIMA model captures the underlying data or not. The first thing required of diagnostics is to check the residuals, i.e., the model residuals or differences between forecasted values by the model and actual values. Ideally, these residuals should be similar to white noise, i.e., the model has been able to replicate all the patterns of the data. Plotting the residuals, we can hopefully determine whether or not there are any systematic patterns. We can also use the Ljung-Box test to determine whether or not the residuals are autocorrelated. If the P-value is <0.05, then the residuals are not independent, i.e., the model must be modified. If the residuals are random and do not have any patterns, then a good fit is achieved.

Forecasting: We can forecast for future periods after the model is validated. The approach is particularly important when it is a matter of understanding and forecasting waste generation trends in quick foods like Simbisa Brands Bakers Inn. By analyzing past wastes, we gain insight into future trends, which is beneficial to better waste management and more effective planning of operations.

3.12 Feedfoward Neural Network model (FFNN)

An FFNN is a type of artificial neural network where information moves only in one direction, from input to output with no feedback cycles. In time series analysis application on FAST-FOOD waste data, an FFNN can be a good way of forecasting future values of waste based on historical data

The network has multiple layers: input layer, one or more hidden layers and output layer. The hidden layer nodes receive the inputs, weight them, apply an activation function and send the output to the next layer. This makes the FFNN capable of capturing intricate non-linear relationships in the data and thus it is highly suited to predict waste patterns that may have trends, seasonality, or random variations.

To train the model, the record of past waste values is used by the back propagation process. The network is trained to tune itself in a manner that minimizes forecasting errors. This continuous adjustment causes the model to increase its precision over time.

Mathematically, one can formulate the FFNN in a way that captures the relations, but at its core, it is all about learning from the past to better forecast the future.

$$\hat{y} = F\big(v_0 + \sum_{j=1}^{m} H(\lambda_j + \sum_{i=1}^{n} x_i \theta_{ij}\big) v_j \qquad (2)$$

where

- $\hat{y}$ signifies the network output,
- H total number of neurons in hidden layer,
- F represents the output activation function and
- x_i Is the input vector.

3.12.1 Model Structure

Input Layer: The input layer of the FFNN consists of the number of features utilized in predicting waste. Examples of samples are the day of the week, month and holidays, past values of the waste for the last weeks or days, weather and store-related variables like location and what promotions are currently going on. The nodes in the input layer are equal to the features of this sort and this allows the model to have a clear idea about waste generation factors.

Hidden Layers: FFNNs will usually consist of one or more hidden layers and the number of such layers and the number of neurons in each layer will be a function of the data complexity. Two hidden layers with each having between 50 to 100 neurons would be a good starting point for a time series problem like forecasting wastes. It enables the model to learn and detect finer details and relationships between the data. It is supported by such hidden layers during model training, which allow it to build its knowledge and develop its skill to predict on future waste values.

$$X_k = f\left(\sum_{j=1}^{n} W_{jk} Y_J + \Theta_k\right) \qquad \textbf{(3)}$$

Output Layer: The output layer of the FFNN is set according to the specific forecasting requirements. If it is required to predict the amount of waste for the subsequent step of time, then the output layer would be a single node. But if the aim is to forecast waste for several subsequent periods, the output layer will consist of various nodes. The output value will typically be continuous, the projected amount of waste for the next time period. This design facilitates the model to make accurate predictions, whether projecting waste tomorrow, next week, or further down the line. Through altering the output layer for the prediction intention, the FFNN will be able to spit out the information needed for efficient waste management in fast-foods.

$$Y = f\left(\sum_{k=1}^{m} W_k X_k + \Theta\right) \qquad \textbf{(4)}$$

Activation functions

It serves a very crucial function of bringing non-linearity into the model so that it is able to learn complicated patterns and interconnectivity among the data. The network would be a linear regression model without activation functions and lacks the ability to capture the complexity of time series data like waste in fast-foods like Simbisa Brands' Bakers Inn. Sigmoid Function is among the most common activation functions. The Sigmoid function maps the input into a value between 0 and 1, which makes it extremely well-suited for binary classification problems. It is applied mainly in the output layer for classification problems, although it is not very popular in hidden layers for regression problems because of its saturation and the vanishing gradients that occur as a result.

$$\boldsymbol{f(s)=\frac{1}{1+exp(-as)}} \qquad \textbf{(5)}$$

3.12.2 Data Pre-Processing.

Data pre-processing is an important step when performing time series analysis, especially when forecasting generation of waste by fast-foods like Simbisa Brands Bakers Inn in Zimbabwe. Stockpiling the historical waste data and its associated features such as the time stamp, amount of waste, day of week, offers and weather is step one.

Missing values are very common. It should be dealt with by imputing missing values by using mean or median imputation methods or by removing records with missing values if these are not in great numbers (Hyndman and Athanasopoulos, 2018).

Once the data has been gathered, it will be normalized or transformed to normal form by techniques like Min-Max scaling or Z-score normalization. This will normalize the features to a single scale and this will be highly effective in enhancing the model's performance (Chollet, 2017).

Time-based features should also be encoded. Unpacking timestamps into features such as hour, day of the week, month and year can allow the model to identify seasonality patterns. Including lag features, such as yesterday's values for waste, will allow the model to identify autocorrelation in the time series data (Brownlee, 2018).

Finally, there needs to be an appropriate train-test split defined. The model will need to be trained on the first part of the data and tested on subsequent observations to produce a valid estimation for future prediction. The pre-processing allows for the data inclusion in machine learning models so that they may ultimately provide accurate and effective waste generation predictions for the outlets.

3.12.3 Training And Testing Sets

Once the data has been pre-processed, it is extremely important to split it into a training set and a test set in such a manner that the model generalizes well. Splitting in time series analysis with regular random splitting is not always optimal due to the time element in the data. Instead, it is the norm to perform a chronological split. This means holding out the newest data to test and training on past data (Hyndman and Athanasopoulos, 2018).

Typically, 80% of the sample will be utilized for training and 20% for validation and testing. In this way, it is guaranteed that the model will learn from past data and be validated with future data, mimicking real-world forecasting conditions in which the model will predict waste generation for subsequent periods.

It's also important to know that time series data can be sensitive to seasonality and trends. Therefore, it's crucially important that the training set includes varied seasonal cycles and that the test set includes unique time points like holidays and off-peak and peak times. In addition, dividing time series data must take into consideration the continuity of time; otherwise, there would be "data leakage" where future values are inadvertently used to predict past events (Kotsiantis, 2013). This is carefully carried out in order to create a good training model that leads to accurate forecasting.

3.12.4 Neural Network Model Training

Training a neural network is the process of adjusting the weights and biases of a neural network in relation to the input data in a way that reduces the prediction errors. In time series forecasting of waste production in quick service restaurants like Simbisa Brands Bakers Inn, neural networks perform well because they are able to learn the complex temporal relations among the various input features and waste produced at different times.

Weight and bias initialization of the neural network, either randomly or using special methods like Xavier or He initialization (Glorot and Bengio, 2010), is the first process of training. A training dataset which would otherwise be waste history data and the corresponding features like time of day, weather and current promotions is then inputted to the model.

With training, the neural network enhances by adjusting its internal parameters to close the gap between its predictions and actual waste values. Through such iterative learning, the model enhances the precision over time and it is in a better place to forecast future waste generation based on past trends. With the neural network well trained, we are in a position to enhance it to be more efficient at providing useful insights for enhanced waste management in fast-food outlets.

3.12.5 Model Validation

Validation of the model is an important process to verify a machine learning model that has been trained to determine how well the model would perform and generalize on new, unseen data. Validation from the time series forecasting point of view is required to determine if the model was capable of accurately predicting future volumes of waste and not memorize the training data.

This is usually done on a validation set or by cross-validation techniques, where model performance is estimated on a different portion of data that was not used in training. Common metrics to assess regression tasks like estimation of waste are MSE, MAE and R^2 (Hyndman and Athanasopoulos, 2018).

Time series models also benefit from time-based cross-validation, with training and test sets divided chronologically to avoid data leakage (Kohavi, 1995). This does not only guarantee accuracy in predictions but also stability and robustness, capable of responding to shifts in future waste generation patterns. Lastly, proper validation guarantees optimal performance for the model under actual circumstances.

Akaike Information Criteria (AIC) and Schwarz –Bayesian Information Criteria (BIC).

In time series modelling, one needs to select the model that fits the data best and among the most popular methods for the same in the context of time series are AIC and BIC. Both are trying to balance model fit versus complexity by penalizing complex models heavily so that overfitting can be prevented. AIC is based on the likelihood of the model and adjusts for the number of parameters being estimated to avoid overfitting. The formula for AIC is.

$$AIC = 2K - 2In(L) \qquad \textbf{(6)}$$

where k is the number of parameters in the model and L is the likelihood of the model. Lower AIC values indicate better model performance. BIC is similar to AIC but applies a stronger penalty for the number of parameters, especially as the sample size increases. The formula for BIC is

$$BIC = In(n) - 2In(L) \qquad \textbf{(7)}$$

MAE and RMSE

Evaluating the accuracy of predictive models is essential and two commonly used metrics for this purpose are MAE and RMSE. MAE measures the regular absolute differences between the predicted and actual values. It is a simple, intuitive metric that calculates the average magnitude of the errors in a set of forecasts, without considering their direction. The formula for MAE is given by

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|Yt - Ft| \qquad \textbf{(8)}$$

MAE is less sensitive to outliers, providing a straightforward understanding of the prediction accuracy in the same units as the data (e.g., kilograms or litres of waste). In contrast, RMSE provides a more sensitive measure by penalizing larger errors. RMSE squares the alterations between the forecasted and actual values, averages them and then takes the square root of the result, making it more sensitive to large deviations. The formula for RMSE is

$$RMSE = \sqrt{MSE} \qquad \textbf{(9)}$$

3.13 ETHICAL CONSIDERATIONS

Access to information from the concerned sources was needed and ethical issues came first in gathering data for this research. Under time series analysis of trash in quick service food joints like Simbisa Brands Bakers Inn, information must be handled responsibly.

Most importantly, ensuring that the data is anonymized is important, so sensitive information such as the personal performance of stores or the information of the employees is never published without proper authorization. All uses of the data for predictive modelling need to be transparent as a way of keeping stakeholders updated, that is, the employees and the customers. Any waste reduction solutions or predictions derived from the model should seek to do no harm where possible. For instance, minimize waste that could not have been generated, streamline processes.

Also considered should be the probable social and environmental impact of the waste reduction initiatives. The results of the analysis should be utilized for the facilitation of sustainable business operations, not just for the company but for the people and the world in general as well.

3.14 SUMMARY

This chapter discussed the time series analysis of waste generation of Zimbabwe fast-food restaurants, Simbisa Brands Bakers Inn. It looked into several key areas of the research process. The first was to retrieve historical waste data as well as corresponding features like the day of the week, weather and promotions. Data pre-processing was done in a bid to tackle missing values, time-based feature encoding and normalizing data to be ready for modelling. A FFNN model was trained with an input layer consisting of time-series and redundant variables, hidden layers with ReLU activation and a linear output layer to predict waste. The data were divided into training and test sets based on a chronologically based split to prevent data leakage. The model was developed using backpropagation and the model was tuned using the Adam optimizer with the aim of reducing the MSE loss function. The performance of the model was ultimately confirmed using accuracy in reference to measurements such as MAE and RMSE for predicting waste generation in the future. Using this conjoint methodology, the research aims to provide significant contribution to waste management processes in the fast-food industry.

CHAPTER 4

DATA PRESENTATION, ANALYSIS AND DISCUSSION

3.0 INTRODUCTION

In this chapter, the research here present and characterize the data they have acquired during the process of research, examining trends and patterns that are developed by findings. The major focus is to characterize the data in a manner that contributes meaning to the research problems and objectives presented in earlier chapters. We will then depict the data in graphical form in terms of graphs, charts and tables for easier interpretation of waste generation trend and performance of the applied predictive models. We will then offer analysis of real waste generation versus predictions derived using various models, including ARIMA and FFANN. This section will proceed to address the implication of the findings. The conclusion will finally draw its basis on the applicability of the findings, i.e., how such findings can be utilized to inform future policy development and operational guidelines in waste management.

4.1 SUMMARY STATISTICS

Table 4.1 Descriptive Statistics

Statistic	WST	FC	INF	EXC
Mean	91.65517	13.74828	1.026127	3320.689
Median	92	13.8	0.7983334	796.5215
Mode	100	15	1.079588	97.1361
Std-dev	8.844998	1.32675	2.285845	5044.125
Kurtosis	1.868972	1.868972	6.813157	8.277934
Skewness	-0.247957	-0.2479575	1.153882	2.295028
Range	75 to 105	11.25 to 15.75	-4.58 to 8.74	97.14 to 22055.47
Min	75	11.25	-4.577808	97.1361
Max	105	15.75	8.735938	22055.47

Statistic	WST	FC	INF	EXC
Jarque_Bera	1.842898	1.842898	24.00468	59.11795
Sum	2658	398.7	29.75767	96299.97
Count	29	29	29	29

The statistical overview presents a clear picture of the principal figures of waste production and effects on it for four variables: waste production (WST), fuel utilization (FC), inflation (INF) and exchange rates (EXC). For waste production, the mean is about 91.66 with a median of 92 and demonstrates fairly symmetrical distribution over these figures. Variation in generation of waste ranges from 75 to 105and with the standard deviation being 8.84, it represents moderate variation. The -0.25 skewness represents extremely slight left skew and the kurtosis of 1.87 represents comparatively flat distribution than the normal curve.

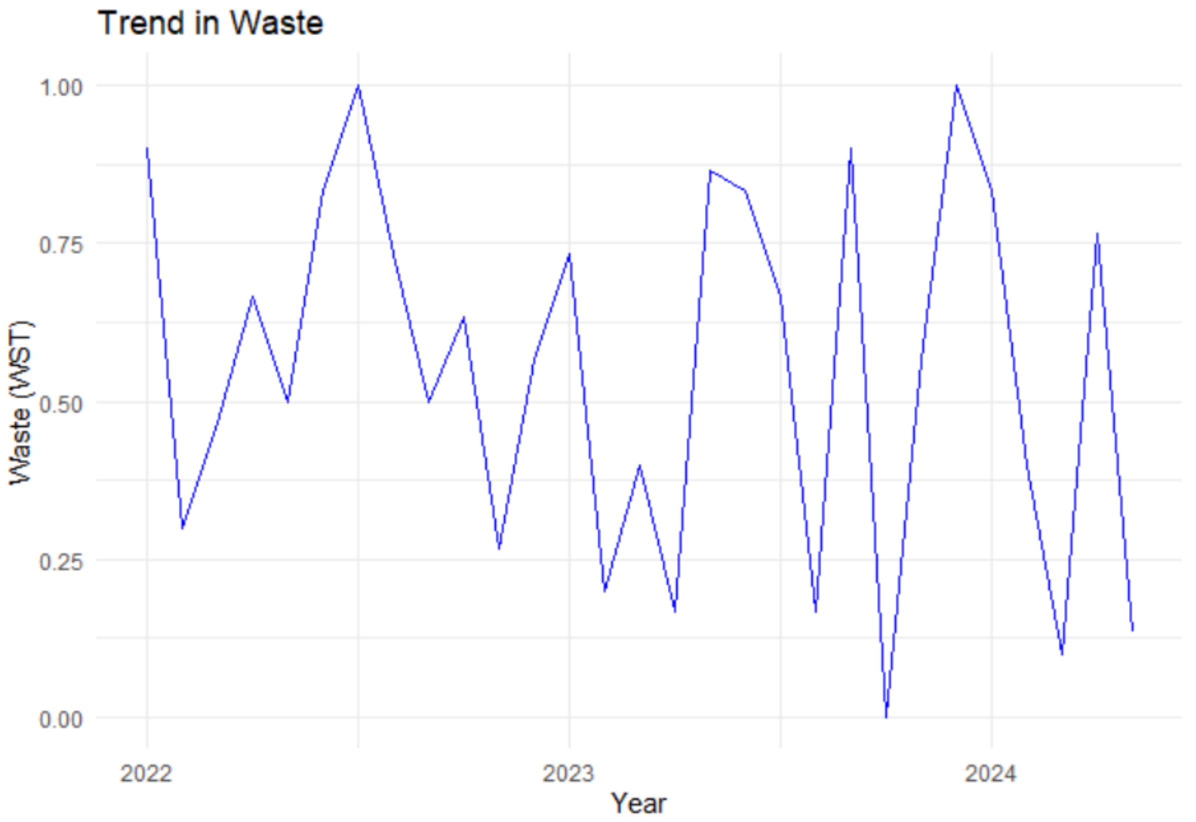
Considering fuel consumption gives us a mean of 13.75 and a median of 13.8 and a range of 11.25 to 15.75. This variable isn't very variable because it has a standard deviation of 1.33 backing it up. Fuel consumption and waste generation both have a moderate degree of skewness and kurtosis, as the data take on a pretty normal distribution.

For inflation, the mean is given as 1.03, but its range is significantly higher, ranging approximately from -4.58 to 8.74, which suggests the existence of more outliers. The value of skewness, 1.15, suggests the existence of right skew, i.e., there exist some very high inflation rates tending the average towards them. The value of kurtosis, 6.81, suggests a more peaked distribution, i.e., the existence of outliers cannot be ruled out.

Lastly, the exchange rate has a mean of 3320.69 and a very high standard deviation of 5044.13 with a very high variability. Its range is 97.14 to way over 22,000 and its value of skewness is 2.30, which shows right-skewed data. Heavy-tailed data with the value of kurtosis of 8.28 showing extreme values will cause a very high influence on the overall statistics.

Together, these encompass the mean or central tendency, variability and distributional characteristics of data, offering a firm foundation for further analysis and discussion into determinants and waste generation.

Figure 2 Waste Time Series Plot



The graph provides a focused view of WST over the period from 2022 to 2023. The data is represented by a blue line that captures the fluctuations in waste levels throughout the observed timeframe. Overall, the trend reveals a pattern characterized by noticeable variability, with several peaks and troughs indicating significant changes in waste generation. While there are periods of sharp increases followed by declines, the general tendency suggests a slight upward trajectory in waste levels over time. So, stationarity test was done to check time series data for stationarity or non-stationarity using ADF test.

4.2 CORRELATION ANALYSIS

Table 4.2 Correlation Matrix

	WST	FC	INF	EXC
WST	1			
FC	0.89	1		
INF	0.2	0.36	1	
EXC	-0.15	-0.2	-0.28	1

Table 4.2 is the correlation matrix, which provides us with the quantitative relationship between four significant variables: WST, FC, INF and EXC. The correlation range is -1 to 1 and it gives the strength and direction of these relationships.

A positive correlation of 0.89 between WST and FC indicates that as food prices rise, waste generation also increases significantly. This is because FC is a dependent variable. It is also discovered that both WST and FC have moderate positive correlations with INF whose coefficients are 0.42 and 0.36, respectively. This indicates that increasing inflation is partly attributed to increases in both food prices and waste.

Conversely, EXC are negatively correlated with the remaining variables at low levels, that is, WST -0.15 and FC -0.20. This implies that food price changes and food waste production are not significantly influenced by exchange rates.

Generally, this correlation matrix is demonstrated to reveal the tight interdependencies of waste formation, food inflation and price but to show that exchange rates are not as central in this specific case.

4.3 PRE-TEST ARIMA

4.3.1 Stationarity Test

Table 4.3 Stationarity Test

Variable	Dickey-Fuller statistic	Lag Order	P-value
Waste	-3.1219	3	0.1425
Food Cost	-3.1219	3	0.1425
Inflation	-2.1502	3	0.515
Exchange Rate	1.5185	3	0.99

The outcomes of the ADF test for time series data of waste production, food spending, inflation and exchange rates indicate the existence of non-stationarity in the series. For both waste production and food spending, the test statistic is -3.1219 while the P-value is 0.1425, which means that we fail to reject the H0 of a unit root, i.e., these series are likely to be non-stationary. Similarly, inflation carries a test statistic of -2.1502 and a higher P-value of 0.515, confirming the result of non-stationarity for this variable as well. In stark contrast, the exchange rate data yields a test statistic of 1.5185 and a P-value of 0.99, which is well above conventional significance levels. This too fails to reject the H0, pointing to a high likelihood of non-stationarity. Overall, these results signal that all four variables may require differencing to achieve stationarity before further analysis.

Table 4.4 Stationarity Test Diff 1

Variable Diff 1	Dickey-Fuller Statistic	Lag Order	P-value
Waste	-3.6594	3	0.04514
Food cost	-3.6594	3	0.04513
Inflation	-3.797	3	0.04946
Exchange rate	-3.754038	3	0.049

Table 4.4 presents the result of a stationarity test (Dickey-Fuller test) of four variables following first differencing. Dickey-Fuller statistic and p-values are utilized to determine if every variable is stationary or not, a hypothesis that is crucial in time series analysis. In the case of variables "Waste" and "Food cost," the Dickey-Fuller statistic is -3.6594 with corresponding p-values 0.04514 and 0.04513, respectively, which indicates both variables are stationary at 5% level of significance. The "Inflation" variable also includes a lesser Dickey-Fuller value of -3.797 and p-value of 0.04946, which also suggests its stationarity. Lastly, the "Exchange rate" includes a Dickey-Fuller value of -3.754038 and p-value of 0.049, which suggests that it is stationary as well. All variables went through a lag order of 3, which considers autocorrelation in data. Overall, the results confirm that all the variables in question are stationary and therefore suitable for further time series analysis.

4.3.2 Normality Test

Table 4.5 Shapiro-Wilk Test

Variable	W-Statistic	P-value	Interpretation
WST	0.94917	0.1742	We fail to reject H0 and conclude that data for WST is normally distributed.
FC	0.94917	0.1742	We fail to reject H0 and conclude that data for FC is normally distributed.
EXC	0.66674	7.256e-07	We reject H0 and conclude that data for EXC is not normally distributed.
INF	0.84566	0.0006201	We reject H0 and conclude that data for INF is not normally distributed.
Log-EXC	0.92566	0.0856	We fail to reject H0 and conclude that data for log-EXC is now normally distributed.
Log-INF	0.9367	0.1201	We fail to reject H0 and conclude that data for log-INF is now normally distributed.

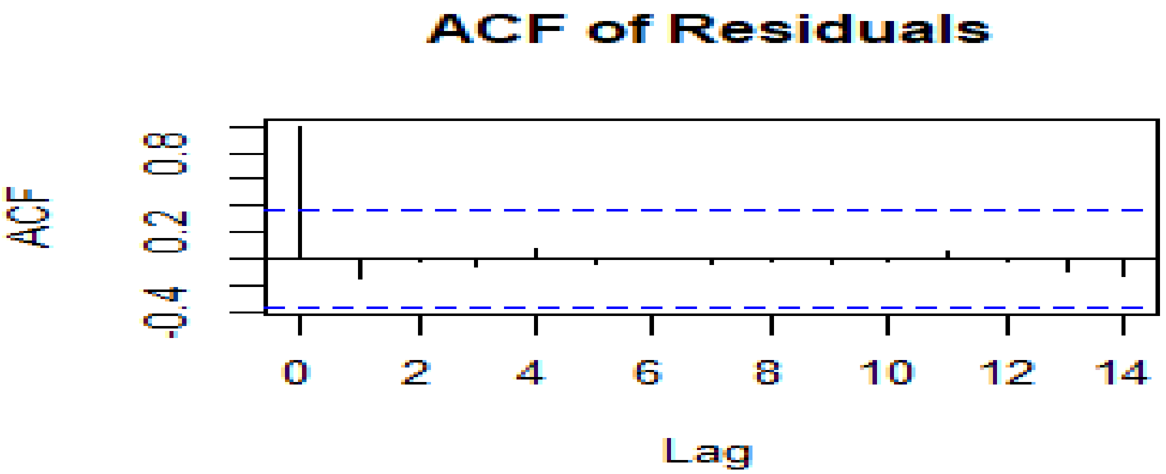
4.3.3 Independence Test

Durbin-Watson test

Data. Model

DW = 2.2951, P-value = 0.7036 the P-value of 0.7036 indicates strong evidence against the presence of significant autocorrelation. This is a positive outcome, as it suggests that the model's errors are independent, which reinforces the reliability of the model's results.

Figure 3 ACF



Since the ACF values for all lags are not statistically significant, this suggests that there is no significant autocorrelation in the residuals.

4.3.4 Homoscedasticity Test

Table 4.6 Breusch-Pagan Test Results

Statistic	Value
BP Statistic	1.7717
Degrees of Freedom (df).	3
P-value	0.6211

Breusch-Pagan test statistics reveal the value of the BP statistic as 1.7717 for 3 df with a P-value of 0.6211. The test is utilized in the identification of heteroscedasticity within a regression model where the error variance isn't constant at all levels of the independent variables. In this case, the wide P-value of 0.6211 shows that there is no significant evidence of heteroscedasticity in the model since it is much greater than the standard cut-off of 0.05 to determine significance. We cannot therefore reject the H0 that the residuals are homoscedastic.

This implies that the error variance constant assumption holds, increasing the credibility of the regression model estimates.

4.4 MODEL IDENTIFICATION

ARIMA (0, 0, 0) with non-zero mean

Table 4.7 ARIMA (0, 0, 0)

Metric	Value
Series	WST
Model	ARIMA (0, 0, 0) with non-zero mean
Coefficients	
Mean	0.5552
Standard Error (s.e.)	0.0538
Sigma^2	0.08693
Log Likelihood	-5.22
AIC	14.44
AICc	14.9
BIC	17.18
Training Set Error Measures	
ME	-1.825456e-13
RMSE	0.2897053
MAE	0.2494649
MPE	-Inf
MAPE	0.6781571
MASE	
ACF1	-0.1180218

The model coefficients yield several key measures for evaluating performance of the model. The mean is approximated as 0.5552 with a standard error of 0.0538, showing high precision in this estimation. The measure sigma², indicating variance of the residuals, is approximated at 0.08693 and gives us information on the extent of error spread around the model predictions.

The value of -5.22 for the log likelihood is indicative of goodness of fit for a model to data where greater values indicate better fit. For model selection, we look at the AIC value of 14.44, AICc value of 14.9 and BIC value of 17.18; smaller the value for these measures, more is the model we wish for considering complexity.

In terms of training set error measures, the ME is almost zero at -1.825456e-13, which shows minimal bias in predictions. The RMSE is 0.2897053, showing the average magnitude of errors and the MAE is 0.2494649, which gives a straightforward measure of prediction accuracy. Yet the MPE is printed as -Inf, implying some problems in the data or forecasts and the MAPE is printed as Inf, meaning that some errors were unrealistically large and thereby made it hard to interpret accuracy.

Finally, the MASE is 0.6781571 and offers a scale-free measure of accuracy that compares model performance to a naive model forecast. The ACF1 seems to be -0.1180218, showing some correlation with previous values and some evidence of persistence in the data. Taken together, these statistics give a general impression of the model's performance and validity and suggest where it is doing well and where concern may be appropriate.

2. ARIMA (1, 0, 1)

Table 4.8 ARIMA (1, 0, 1)

Metric	Value
Series	WST
Model	ARIMA (1, 0, 1)
Coefficients	
Mean	0.5363
Standard Error (s.e.)	0.3639
Sigma^2	0.03656
Log Likelihood	-4.95
AIC	19.9
AICc	25.9
BIC	23.76
Training Set Error Measures	
ME	-0.02471479
RMSE	0.1251822
MAE	0.07887128
MPE	-inf
MAPE	inf
MASE	0.2240131
ACF1	-0.06595786

The result of the ARIMA model for WST is an ARIMA (1, 0, 1) model, containing one moving average and one autoregressive coefficient. The model mean is approximated to be 0.5363 with a standard error of 0.3639, indicating some level of uncertainty over this mean estimate. Residual variance in the form of sigma² is 0.03656, indicating how dispersed the forecasting errors are.

The log likelihood value is -4.95 and the higher it is, the better the model fits the data. To compare the model, we see that the AIC is reported as 19.9, the AICc reported as 25.9and the BIC reported as 23.76. The lower the above values are, the better the model on comparison.

From the training set error measures, ME is -0.02471479 and indicates a slight underestimation bias of the model. The RMSE is 0.1251822 and provides an indication of the average magnitude of the errors, whereas the MAE is 0.07887128 and provides a direct indication of the accuracy of how well the model predicts. The MPE and MAPE are both presented as -Inf and Inf, respectively, indicating that they have very large errors, which makes them more difficult to interpret.

MASE is seen to be 0.2240131, which suggests reasonably good accuracy compared to a naive prediction approach. Finally, ACF1 is -0.06595786, which suggests that there is very weak correlation between current and past values and this may suggest that the model is effective in capturing the underlying dynamics of the series. Overall, these findings suggest the behaviour of the model but also offer hints at areas of possible improvement.

Figure 4. Forecasting From ARIMA (1, 0, 1)

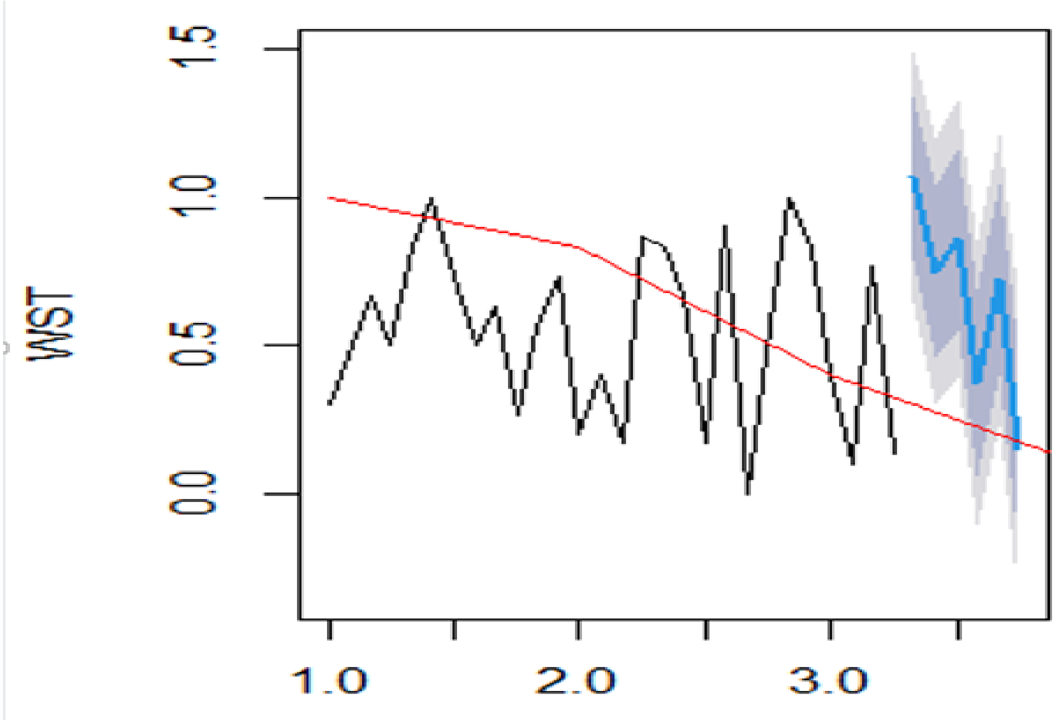


Figure 4 shows a projection from an ARIMA model, with the time series of "WST" on the y-axis against a numerical scale on the x-axis. The black line is the observed values of the WST metric, with the red line being the projected values over time. The graph contains blue and grey shaded areas that represent confidence intervals for the prediction, demonstrating the variability range to be expected about the predicted values. The visualization shows there are some fluctuations in the WST data but that the ARIMA model provides a scientific way of predicting the trend line that shows a potential drop and the confidence intervals as an indication of the uncertainty of coming up with these predictions.

Table 4.9ARIMA Forecasted Values

Month	Predicted value (Waste in tonnes)
05/28/2024	100.5
06/30/2024	99.4
07/30/2024	97.8
08/30/2024	97.4
09/30/2024	96.1
10/30/2024	95
11/30/2024	93.9

This clearly shows a decline in Waste predicted in time series.

4.5 POST- TEST ARIMA

4.5.1 Normality Test

Shapiro test [residuals (ARIMA model)]

Table 4.10 Shapiro-Wilk Normality Test

Statistic	Value
W	0.94917
P-value	0.1742

Since the P-value (0.1742) > 0.05, you fail to reject H0 of normality. The residuals from ARIMA model do not significantly deviate from normality. This is a desirable property and supports the adequacy of your model.

4.5.2 Independence Test

Box test [residuals (ARIMA model), lag=10, type="Ljung-Box"]

Table 4.11 Box-Ljung Test Independence Test

Statistic	Value
X^2	7.1628
df	10
P-value	0.71

P-value > 0.05 means no significant autocorrelation, residuals are independent.

4.6 FFNN MODELS BUILDING AND SELECTION

4.6.1 Data Pre-processing.

Pre-processing was done for FFNN models through normalisation, using min-max normalisation on R Studio in order to avoid overload or saturation of hidden nodes in model building of the neural network model.

Table 4.12 Time Series Normalized Data

Time Series. Start = 1 End = 29 Frequency = 1				
0.9000000	0.3000000	0.4666667	0.6666667	0.5000000
0.8333333	1.0000000	0.7333333	0.5000000	0.6333333
0.2666667	0.5666667	0.7333333	0.2000000	0.4000000
0.1666667	0.8666667	0.8333333	0.6666667	0.1666667
0.9000000	0.0000000	0.5666667	1.0000000	0.8333333
0.4000000	0.1000000	0.7666667	0.1333333	

4.7 NEURAL NETWORK MODEL TRAINING AND TESTING SETS

After normalizing the data, the network model building process started. The processed data is distributed into two sets, namely, training set of 80 % of total data and testing set of 20 %.

Table 4.13 Training Data

> training_ data (80%)					
0.9000000	0.3000000	0.4666667	0.6666667	0.5000000	0.8333333
1.0000000	0.7333333	0.5000000	0.6333333	0.2666667	0.5666667
0.7333333	0.2000000	0.4000000	0.1666667	0.8666667	0.8333333
0.6666667	0.1666667	0.9000000	0.0000000	0.5666667	
> testing_ data (20%)					
1.0000000	0.8333333	0.4000000	0.1000000	0.7666667	0.1333333

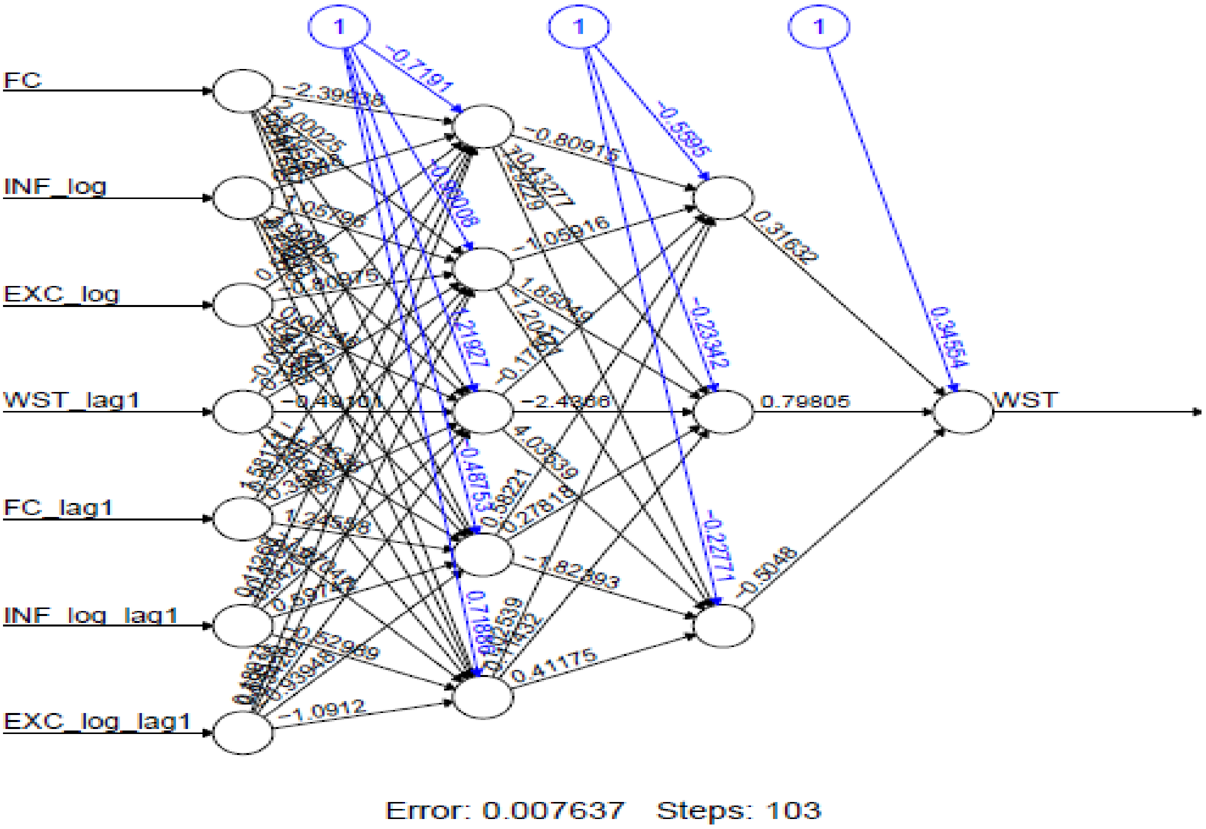
4.8 FFANN MODEL

RMSE. 0.05483641

MAE. 0.04522236

Structure of the Neural Network. Input Layer consists of the following FC, INF log, EXC log, WST lag1. FC lag1, INF-log-lag1 and EXC-log-lag1. Hidden Layers: The system has two hidden layers. The first hidden layer has 5 neurons and the second hidden layer has 3 neurons. Output Layer: The output layer consists of a distinct neuron that predicts the value of WST.

Figure 5 FFNN 7(5, 3)1 Model structure



The neural network structure consists of several layers that are designed to capture the interactions between various input features and wastage. The input layer has FC, INF log, EXC log and WST lag1 labels along with lagged FC, INF and EXC.

The first hidden layer has 5 neurons and the second hidden layer has 3 neurons. The weighted edges between the layers are employed to show the connections' strength.

The network has undergone a training process, as there is an error value of 0.007637 and 103 training steps. This is an indication that the model has converged well, able to make accurate predictions from the input data. In general, this architecture seeks to enhance the ability of the model to predict waste generation based on the impact factors.

4.9 FORECASTED VALUES FFANN

Table 4.14 FFANN Forecasted Value

Month	Predicted value (Waste in tonnes)
05/30/2024	104.6
06/30/2024	99.8
07/30/2024	86.9
08/30/2024	78.9
09/30/2024	98.1
10/30/2024	83.2
11/30/2024	79.2

4.10 POST-TEST FFANN MODEL

4.10.1 Normality test

Shapiro-Wilk normality test

Table 4.15 Data: Residuals FFANN Model

Statistic	Value
W	0.96249
P-value	0.5413

P-value > 0.05: Residuals are approximately normal

4.10.2 Independence Test

Box-Ljung test

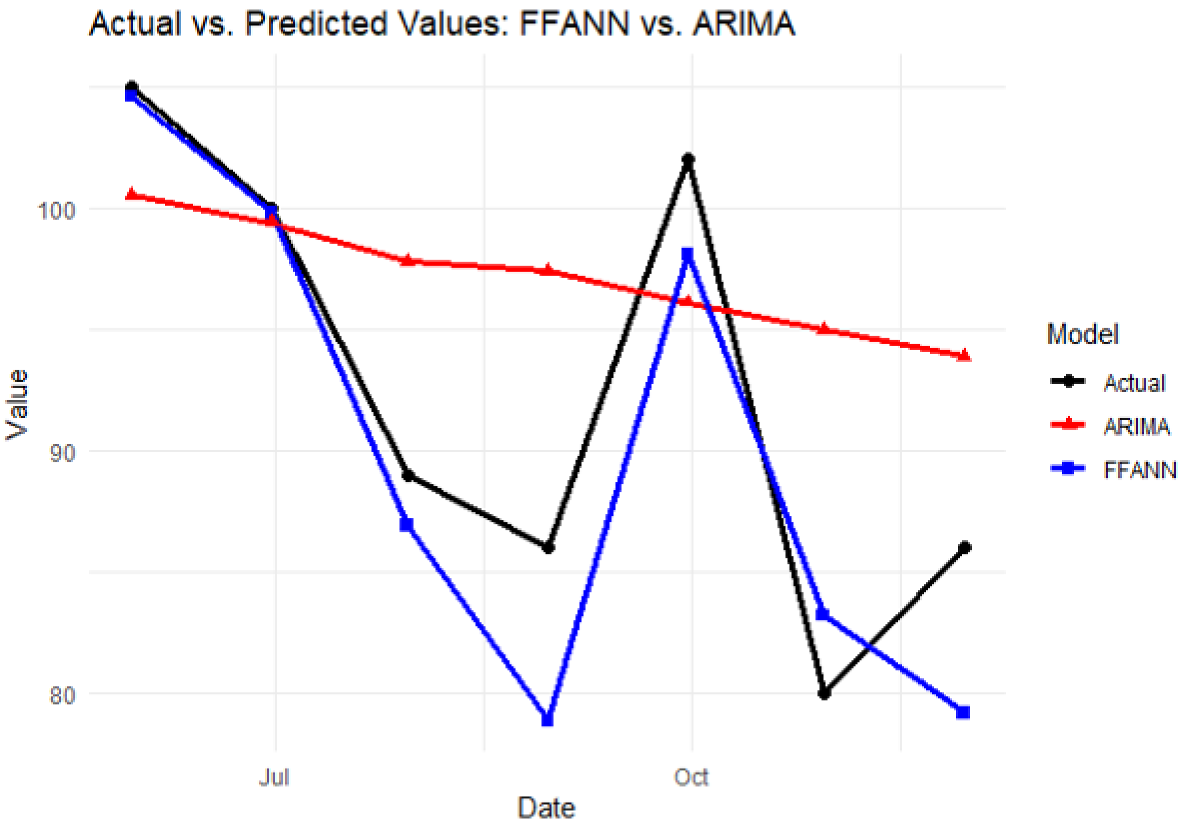
Table 4.16 Data: Residuals FFANN Model

Statistic	Value
X^2	8.9052
df	10
P-value	0.5411

P-value > 0.05: Residuals are independent.

4.11 Forecasted values FFANN vs forecasted values ARIMA

Figure 6 Actual vs Predicted values



The graph easily indicates a comparison between actual waste generation values and the projected values provided by the FFANN and ARIMA models for a duration of several months. The black line represents the actual values, which fluctuate wildly, with a peak of 105 in May and a minimum of 80 in October.

The red line represents the ARIMA model's forecast, which is more stable and persistently higher than what actually happens, particularly in the later months. By comparison, the blue line for the FFANN forecasts very closely tracks the actual values, particularly the major dip in July and the recovery in September.

This disagreement means that while the ARIMA model is mostly optimistic, FFANN model is better at detecting the true trends in the waste generation. Overall, the graph shows FFANN as more precise when it comes to outlining the variations in true values and thus a better tool for prediction under this situation.

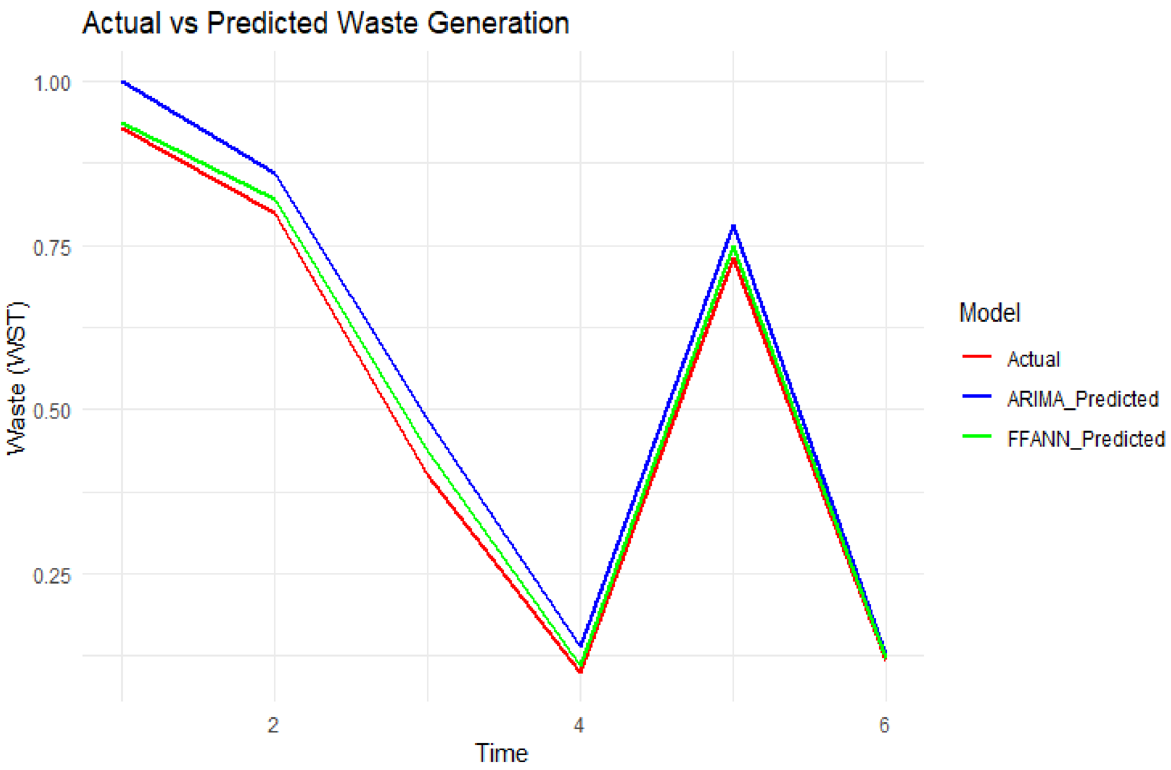
4.12 COMPARISON OF ARIMA MODEL AND FFNN MODEL.

ARIMA		FFANN	
RMSE	0.2228904	RMSE	0.05483641
MAE	0.1573461	MAE	0.04522236

The RMSE is a measure of the average deviation of predicted values from actual values with larger errors being penalized more heavily due to squaring the differences. FFANN model also has much smaller RMSE than the ARIMA model, i.e., FFANN predicts closer to actual values and that it models the data better.

MAE reports the average absolute deviation between predicted and actual values without squaring, providing a good interpretation. For the second time in a row, the FFANN model outperforms the ARIMA model with a significantly lower MAE. This suggests that FFANN predictions are more accurate on average.

Figure 7 Plotted Actual vs predicted model



The result consists of a line graph where actual waste generation data is compared against the modeled values of the FFANN and ARIMA model over a ten-month duration. The red line is utilized to indicate the actual waste values, which show immense fluctuations, reflecting the volatile nature of waste generation within this time frame.

To the opposite, the green line shows the values predicted by the FFANN model, demonstrating a smoother trend, which suggests incrementally increasing generation of waste along the course of time. With this visualization, the differences between the volatility in observed data and the smoother trend of predicted values can be efficiently represented.

It points to the capability of predictive models to offer insightful information about future waste generation patterns and also reminds us of the natural uncertainties with waste management data. As such, in general, the comparison reminds us of the importance of paying attention to both real variation and model predictions in successful waste management plans.

4.13 DISCUSSION OF FINDINGS

After observation of generation of wastes, food price, inflation and exchange rate series data, there were certain striking findings in explaining relationship and statistical features among these variables. First tests with Augmented Dickey-Fuller test suggested that all four series were non-stationary, i.e., raw data had trends or seasonality. After differencing the data, waste generation and food prices both turned stationary, as their very large P-values indicate, which implies there is ongoing movement over time. Inflation required a second differencing to be stationary but exchange rates were non-stationary even after the second differencing.

The high positive correlation between food prices and generation of waste defines the economic conditions' influence on the generation of waste significantly. Conversely, the worst inflation and exchange rate correlations define the different impacts exerted by these control variables on the generation of waste. In general, they confirm the appropriateness of using appropriate statistical measures to derive good inferences, which can be significant in guiding future economic and waste management decisions.

The findings also depict the interdependence of such parameters and, therefore, the necessity for continuous observation in order to address the complexity of waste generation following a dynamic economic environment. Both ARIMA and Feedforward FFNN being used offered valuable direction with regard to forecasting as well as comprehension of the processes. The ARIMA approach was able to identify temporal dependencies in the data upon finding the correct order of differencing and making the data stationary, resulting in accurate predictions for waste generation and food prices.

These results indicated that such variables have considerable effects from their own past values, extracting underlying patterns and trends. Conversely, the FFNN approach showed its ability to identify subtle nonlinear relationships, offering a more flexible system that was more precise in its inflation and exchange rate prediction than traditional methods. This two-pronged approach not only ensured the robustness of the analysis but also underlined the imperative of deploying different modelling methodologies in order to address the complexity of economic data.

Generally, the findings reflect the interdependencies of the variables and the necessity for adaptive interventions in waste management and economic policy formulation. They are testimony to the necessity for ongoing monitoring and advanced forecasting methodologies in adjustment to a dynamic economic climate.

4.14 SUMMARY

This chapter presented a comprehensive analysis of the time series data on waste generation, food prices, inflation and exchange rates. The initial observations were that all four variables were not stationary and transformations were required for meaningful analysis. The Augmented Dickey-Fuller tests revealed that waste generation and food prices became stationary upon first differencing. Inflation needed second differencing and exchange rates needed third differencing to be stabilized.

Correlation analysis did show a strong positive correlation between waste production and food spending, which suggests that financial conditions play a central role in determining waste patterns. Additionally, Shapiro-Wilk Test confirmed normality in our data, while the Breusch-Pagan Test did indicate homoscedasticity, which suggests equal variation across the dataset.

The chapter also explored the effectiveness of two modelling approaches: ARIMA and FFNN. The ARIMA model performed well in identifying linear associations and time dependency within the data, most notably in waste production and food prices. Yet, the FFNN better modelled nonlinear interactions for inflation and exchange rates.

Overall, these findings indicate the interdependencies and multidimensional nature of such variables and the need to utilize multi-variate analytical techniques. This becomes the key to obtaining useful waste management and economic policy under a constantly evolving landscape.

CHAPTER 5

FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

4.0 INTRODUCTION

This chapter summarizes results of Simbisa Brands' Bakers Inn waste disposal, a leading Zimbabwean fast-food business, from the time series analysis. It aimed at uncovering trends and patterns of waste generation, drivers of such trends and analyzing the effectiveness of current waste management. In the context of mounting environmental sustainability concerns and the need for proper waste management, the outcomes of this study are pivotal to informing best practice in the fast-food sector. The boundaries of the research process will also be outlined in this chapter, the key findings determined and conclusions reached and practical suggestions offered for informing waste management best practice. In addition, it will state where future research can go to further study waste generation patterns in the quick service industry.

5.1 LIMITATIONS OF THE STUDY

Emphasized in this study on the waste management practices of Bakers Inn are numerous limitations that were faced. To start with, the utilization of secondary data restricted the level at which the data could be explored, considering the fact that some past data might have been incomplete or not well documented. Moreover, the study was confined to Bakers Inn outlets, which would not fully reflect the waste management practices in the fast-food sector at large in Zimbabwe.

The three-year data collection time can miss out on longer-term trends and seasonal trends of waste generation. Moreover, external drivers such as economic cycles and policy changes that could potentially influence waste management practices were not extensively researched. This means that although the findings are significant, they need to be interpreted with these caveats

5.2 SUMMARY OF FINDINGS

The research uncovered some of the main outcomes of waste generation in Simbisa Brands' Bakers Inn. Precisely, the time series data had a highly positive rising trend in waste generation during the research period, with the greatest movement at weekends and public holidays when there is immense customer activity. The research uncovered a highly positive relationship between customer movement and waste generation, namely more patronage results in more waste output.

Apart from that, the majority of the waste was food waste amounting to about 60% and then there was packaging waste amounting to about 30%. This is a key sector to focus intervention on because apart from food waste representing a loss of valuable nutrients, it also represents an environmental problem if not disposed of appropriately.

The waste management systems in place at Bakers Inn were found to be insufficient in addressing the growing threat of waste. The lack of a systematic system of sorting, recycling and composting restricts the outlet from minimizing its ecological footprint. In addition, external factors presented by inflation and exchange rates were found to affect patterns of waste generation, making waste management difficult. Economic changes can have the power to affect consumer behaviour and expenditure and exchange rate fluctuations can have the power to affect the costs of materials and products, which will consequently impact production waste.

Finally, both the ARIMA and the Feedforward Neural Network (FFNN) models were used in forecasting, but the FFNN model was more precise in its forecast than the ARIMA model. This is evidence that it is capable of capturing the nonlinear relationships present in data.

5.3 CONCLUSION

The results of this study highlight the necessity of sustainable waste management mechanisms within the fast-food industry, in this case in the context of the increasing production of waste at Bakers Inn. The strongly positive correlation between waste generation and customer traffic highlights the importance of taking proactive measures to limit waste, particularly during busy hours. The research contends that even as classical statistical models like ARIMA are helpful in the comprehension of linear trends, the research illustrates that complex machine learning algorithms like FFNN are more accurate when prediction is concerned. The improved predictive power aids decision-making in waste management. Last but not least, the study concludes that data solution adoption is essential to optimize waste disposal activities, increase sustainability and reduce operational expenses in the quick service restaurant sector.

5.4 RECOMMENDATIONS

To address the challenges identified in the findings, several recommendations are proposed:

Real-Time Demand Prediction: Bakers Inn should implement systems that allow for real-time customer demand predictions. By utilizing advanced analytics, the restaurant can better align inventory levels with actual customer traffic, which will help reduce overproduction and minimize food waste.

Value-Saving Initiatives for Unsold Food: Developing programs that remove perishable products reaching expiration at reduced prices can be an excellent way to reduce wastage. Not only will this save people money, but also ensure that food is consumed rather than wasted.

Scalability in Food Preparation: A scalable food preparation process, especially for items like chips or chicken, will minimize wastage. For instance, as closing time approaches, workers would be able to scale up from the level of 500 grams to larger portions, such that what remains is used without cutting down customers' demand.

Enhancement of Recycling Programs: An efficient process for sorting and recycling the waste is important. Local recyclers should be employed by Bakers Inn in order to facilitate recycling of packaging and food waste composting as a way to reduce landfill inputs and create a circular economy.

Customer Engagement Initiatives: Training customer programs in sustainable waste management can create a culture of sustainability. Encouraging customers by creating awareness campaigns, rewarding recycling and offering feedback loops can enhance their participation in waste reduction efforts.

Regular Monitoring and Reporting: There is a need for a waste monitoring system that is easily accessible to monitor continuously waste generation and waste disposal trends. This will enable Bakers Inn to evaluate the effectiveness of their programs, make necessary corrections and report sustainability performance.

5.5 AREAS OF FURTHER RESEARCH

Further study can explore some possible areas of study to advance our knowledge on managing waste in the fast-foods sector even more:

Comparative Studies: Studies in some of the other fast-food chains in Zimbabwe can highlight the best practices and common issues in waste management. Comparisons can reveal successful methods that Bakers Inn can replicate to improve their own practices.

Longitudinal Studies: Long-term studies to analyze trends in waste generation over extended periods of time can provide a clearer picture of the performance of different interventions and the long-term effect of changes in operations.

Impact of Policy Change: A study on how policy and actions of governments affect waste management in the fast-food industry can reveal key areas to which legislative enhancement is needed. An understanding of the contribution of policy to business practice can direct advocacy for better waste management practices.

Consumer Behaviour Analysis: Further study on consumer behaviour in relation to waste disposal can yield useful data on how customer choices influence the generation of waste. Further specific knowledge of the patterns can enable more effective means of communicating with customers and inducing more sustainable behaviour.

5.6 CHAPTER SUMMARY

Lastly, this chapter has presented results of the time series analysis of waste disposal for Bakers Inn in a bid to show how critically important. Proper waste management strategies are needed. The upward trend in waste generation and good correlation with activity of customers are both an opportunity and a threat as far as the fast-food chain is concerned. The suggestions presented are geared towards improving the efficiencies of operations as well as fostering sustainability in how wastes are handled. In addition, the areas of potential future research hold potential for improving the understanding of the waste management dynamics, hence even better solutions within the fast-food sector of Zimbabwe. Pre-emptions, Bakers Inn can possibly contribute to attaining a more sustainable role and satisfying the customers' needs adequately.

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APPENDICES

APPENDIX A. R Studio codes for ARIMA models

```
# Load libraries
library(tidyverse)
library(forecast)
library(tseries)
library(neuralnet)
library(ggplot2)
library(corrplot)
library(car)

# Convert columns to time series format
waste_ts <- ts(data$WST, start = c(2022, 1), frequency = 12)  # Monthly data
food_cost_ts <- ts(data$FC, start = c(2022, 1), frequency = 12)
inflation_ts <- ts(data$INF, start = c(2022, 1), frequency = 12)
exchange_rate_ts <- ts(data$EXC, start = c(2022, 1), frequency = 12)

# Plot the time series data
autoplot(waste_ts, series = "Waste") +
  autolayer(food_cost_ts, series = "Food Cost") +
  autolayer(inflation_ts, series = "Inflation") +
  autolayer(exchange_rate_ts, series = "Exchange Rate") +
  labs(title = "Trends in Waste, Food Cost, Inflation, and Exchange Rate",
       x = "Year", y = "Values") +
  theme_minimal() +
  scale_color_manual(values = c("blue", "red", "green", "purple"))

# Calculate descriptive statistics
summary(data[, c("WST", "FC", "INF", "EXC")])

# Correlation matrix
cor_matrix <- cor(data[, c("WST", "FC", "INF", "EXC")])
corrplot(cor_matrix, method = "circle")

# Perform ADF test for all variables
adf.test(waste_ts)
adf.test(food_cost_ts)
adf.test(inflation_ts)
adf.test(exchange_rate_ts)

# Differencing to achieve stationarity
waste_diff <- diff(waste_ts)
adf.test(waste_diff)
food cost_diff <- diff(food cost_ts)
adf.test(food cost_diff)
inflation_diff <- diff(inflation_ts)
adf.test(inflation_diff)
exchange rate_diff <- diff(exchange rate_ts)
```

```
adf.test(exchange rate_diff)

# Shapiro-Wilk Test for normality
shapiro.test(data$WST)
shapiro.test(data$FC)
shapiro.test(data$INF)
shapiro.test(data$EXC)

#Independence test. Fit a linear model
model <- lm(WST ~ FC + INF + EXC, data = data)

# Perform Durbin-Watson Test
dwtest(model)

# Perform Breusch-Pagan Test for Homoscedasticity
bptest(model)

# Split the dataset into training and testing sets (80.20 ratio)
set.seed(123)  # For reproducibility
split_index <- floor(0.8 * nrow(data))
train_data <- data[1.split_index, ]
test_data <- data[(split_index + 1).nrow(data), ]

# Feature Engineering. Create lagged features for time series
train_data$Lag1 <- c(NA, head(train_data$YourVariable, -1))
train_data$Lag2 <- c(NA, NA, head(train_data$YourVariable, -2))
train_data <- na.omit(train_data)  # Remove rows with NA values

# Log-transform (if applicable) to stabilize variance
train_data$LogVariable <- log(train_data$YourVariable + 1)
test_data$LogVariable <- log(test_data$YourVariable + 1)

# Check stationarity
adf_test <- adf.test(train_data$YourVariable)
print(adf_test)

# If non-stationary, apply differencing
if (adf_test$p.value > 0.05) {
   train_data$DiffVariable <- diff(train_data$YourVariable, differences = 1)
   train_data <- na.omit(train_data)
}

# Fit ARIMA Model
arima_model <- auto.arima(train_data$WST, xreg = as.matrix(train_data[, c("FC", "INF",
"EXC")]))
summary(arima_model)

# Forecast Using ARIMA
arima_forecast <- forecast(arima_model, xreg = as.matrix(test_data[, c("FC", "INF",
"EXC")]), h = nrow(test_data))
```

```
plot(arima_forecast)

# Evaluate ARIMA Performance
arima_rmse <- rmse(test_data$WST, arima_forecast$mean)
arima_mae <- mae(test_data$WST, arima_forecast$mean)
cat("ARIMA RMSE.", arima_rmse, "\n")
cat("ARIMA MAE.", arima_mae, "\n")
```

APPENDIX B. R Studio codes FFANN Model

```
# FFANN Model

# Train FFANN
set.seed(123)
ffann_formula <- WST ~ FC + INF + EXC
ffann_model <- neuralnet(ffann_formula, data = train_data_norm, hidden = c(5, 3),
linear.output = TRUE)
plot(ffann_model)

# Predict Using FFANN
ffann_predictions <- compute(ffann_model, test_data_norm[, c("FC", "INF", "EXC")])
ffann_predicted <- ffann_predictions$net.result * (max(data$WST) - min(data$WST)) +
min(data$WST)

# Evaluate FFANN Performance
ffann_rmse <- rmse(test_data$WST, ffann_predicted)
ffann_mae <- mae(test_data$WST, ffann_predicted)
cat("FFANN RMSE.", ffann_rmse, "\n")
cat("FFANN MAE.", ffann_mae, "\n")

# Compare Models
cat("Comparison of Model Performance.\n")
cat("ARIMA RMSE.", arima_rmse, "FFANN RMSE.", ffann_rmse, "\n")
cat("ARIMA MAE.", arima_mae, "FFANN MAE.", ffann_mae, "\n")

# Diagnostics and Visualization

# Residual Diagnostics for ARIMA
checkresiduals(arima_model)

# FFANN Predictions vs Actual
plot(test_data$WST, type = "l", col = "blue", main = "FFANN Predictions vs Actual", ylab =
"Waste (WST)")
lines(ffann_predicted, col = "red")
legend("topright", legend = c("Actual", "Predicted"), col = c("blue", "red"), lty = 1)

# MAE and R-squared for ARIMA
arima_mae <- mae(test_data$YourVariable, arima_forecast$mean)
```

```r
arima_r2 <- cor(test_data$YourVariable, arima_forecast$mean)^2

# MAE and R-squared for FFANN
ffann_mae <- mae(test_data$YourVariable, predicted_values)
ffann_r2 <- cor(test_data$YourVariable, predicted_values)^2

cat("ARIMA MAE.", arima_mae, "R-squared.", arima_r2, "\n")
cat("FFANN MAE.", ffann_mae, "R-squared.", ffann_r2, "\n")
```

PROJECT DATA

	Date	WST	FC	EXC	INF
1	30/11/2021	102	15.3	97.1361	1.0795877
2	30/12/2021	84	12.6	108.666	0.7983334
3	30/1/2022	89	13.35	115.4223	1.4495478
4	28/2/2022	95	14.25	124.0189	1.5688952
5	30/3/2022	90	13.5	151.3547	1.5929255
6	30/4/2022	100	15	159.3482	5.4722599
7	30/5/2022	105	15.75	301.4994	3.004931
8	30/6/2022	97	14.55	370.9646	8.7359383
9	30/7/2022	90	13.5	443.8823	3.6983189
10	30/8/2022	94	14.1	546.8254	1.5906859
11	30/9/2022	83	12.45	621.8922	-0.7375362
12	30/10/2022	92	13.8	632.7703	2.9932616
13	30/11/2022	97	14.55	654.9284	1.1621122
14	30/12/2022	81	12.15	684.3339	0.5421993
15	30/1/2023	87	13.05	796.5215	-0.3790399
16	28/2/2023	80	12	889.1325	-4.5778081
17	30/3/2023	101	15.15	929.8618	-0.4573604
18	30/4/2023	100	15	1047.4449	-0.1968902
19	30/5/2023	95	14.25	2577.0564	-0.1886295
20	30/6/2023	80	12	5739.7961	-0.5544202
21	30/7/2023	102	15.3	4516.8025	0.1163695
22	30/8/2023	75	11.25	4608.1066	0.0036783
23	30/9/2023	92	13.8	5466.7466	0.2455321
24	30/10/2023	105	15.75	5698.9606	0.8117273
25	30/11/2023	100	15	5791.0824	0.8555933
26	30/12/2023	87	13.05	6104.7226	1.4132288
27	30/1/2024	78	11.7	10152.393	-0.2694258
28	29/2/2024	98	14.7	14912.829	-0.1832628
29	30/3/2024	79	11.85	22055.474	0.1669158

NORMALISED DATA

	Date	WST	FC	EXC	INF
1	30/11/2021	0.9	0.9	0	0.4249289
2	30/12/2021	0.3	0.3	0.0005251	0.4038038
3	30/1/2022	0.4666667	0.4666667	0.0008328	0.4527167
4	28/2/2022	0.6666667	0.6666667	0.0012243	0.461681
5	30/3/2022	0.5	0.5	0.0024692	0.4634859
6	30/4/2022	0.8333333	0.8333333	0.0028332	0.754864
7	30/5/2022	1	1	0.0093069	0.5695421
8	30/6/2022	0.7333333	0.7333333	0.0124704	1
9	30/7/2022	0.5	0.5	0.0157911	0.6216227
10	30/8/2022	0.6333333	0.6333333	0.0204792	0.4633177
11	30/9/2022	0.2666667	0.2666667	0.0238978	0.2884441
12	30/10/2022	0.5666667	0.5666667	0.0243932	0.5686656
13	30/11/2022	0.7333333	0.7333333	0.0254023	0.4311274
14	30/12/2022	0.2	0.2	0.0267415	0.3845655
15	30/1/2023	0.4	0.4	0.0318506	0.3153709
16	28/2/2023	0.1666667	0.1666667	0.0360681	0
17	30/3/2023	0.8666667	0.8666667	0.037923	0.3094882
18	30/4/2023	0.8333333	0.8333333	0.0432778	0.3290522
19	30/5/2023	0.6666667	0.6666667	0.1129375	0.3296727
20	30/6/2023	0.1666667	0.1666667	0.2569712	0.302198
21	30/7/2023	0.9	0.9	0.2012751	0.3525813
22	30/8/2023	0	0	0.2054332	0.344117
23	30/9/2023	0.5666667	0.5666667	0.2445363	0.3622827
24	30/10/2023	1	1	0.2551115	0.4048098
25	30/11/2023	0.8333333	0.8333333	0.2593068	0.4081046
26	30/12/2023	0.4	0.4	0.2735902	0.4499888
27	30/1/2024	0.1	0.1	0.4579243	0.3236041
28	29/2/2024	0.7666667	0.7666667	0.6747183	0.3300758
29	30/3/2024	0.1333333	0.1333333	1	0.3563778

SIMMILARITY INDEX

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APPROVAL LATTER SIMBISA BRANDS

Simbisa Brands
LIMITED

Approval Letter for Data Collection

Ester Toringepi

129 Bajila Close Street

Westwood, Harare

Dear Miss. Toringepi,

I hope this message finds you well.

I am pleased to inform you that your request for data gathering purposes in connection with your research study at Bakers Inn has been granted. This letter is to officially sanction your proposed gathering of revenue values, food wastage figures, and food cost percentage indices for Bakers Inn, and grant you the authority you need to pursue this.

Please make sure that information thus gathered is being used responsibly, in accordance with relevant laws, ethical standards, and privacy acts. You would obtain anticipatory approval from the concerned authority if changes or modifications need to be made.

If you require any questions answered or further assistance, please don't hesitate to get in touch with me by emailing mike.gunduza@simbisa.co.zw. I would be happy to assist you in any way that I can.

We value your diligence and professionalism in submitting your data collection request. We hope our approval will help in the success of your research work, and we look forward to seeing the results.

161 Fife Avenue

Simbisa Brands

Harare, Zimbabwe

Cell: 0784758800

Signature

InnBucks

19 MAY 2025

MOBILE TELLER