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Energy Assessment and Scheduling for Energy Optimisation of a Hot Dip Galvanising Process

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Declaration

I hereby declare that this submission is my own and to the best of my knowledge, it neither contains material previously published nor written by another person, nor material that to a major extent has been accepted for the award of any other degree at the Durban University of Technology or any other educational institution. I also declare that the intellectual content of this thesis is a product of my work. Any contribution made to the research by others especially in the use of equipment for sample analysis has been explicitly acknowledged in the dissertation.

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___11/09/2021________________________

Date

Dedication

I dedicate my thesis work to my wife Sindisiwe and my daughter Michelle who has been my best cheerleader as well as a source of motivation and strength during moments of despair and discouragement. A special feeling of gratitude to my loving parents, Malvern and Elizabeth Dewa whose words of encouragement and push for tenacity ring in my ears in my life journey.

I dedicate this thesis to my friends, Gift and Doreen Mheta who have supported me throughout the research process. I will always appreciate all they have done, both of you have been awesome and great cheerleaders.

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Abstract

The dearth of energy sustainability is posing major challenges both locally and globally. Galvanising furnaces are categorised as dominant consumers of electricity in the overall galvanising industry. Relatively little research has been carried out concerning energy optimisation through sequencing or scheduling algorithms by way of enhancing the performance of galvanising lines. In this regard, the research centres on evaluating overall energy performance in this industry. The research sought to introduce an optimal energy optimisation-scheduling algorithm for a hot dip galvanising process.

A DMAIC based methodology was presented for the provisioning of a structured problem-solving process for improving energy efficiency in a galvanising process. Its framework embraces an energy sustainability assessment of four batch hot-dip galvanising plants. Four energy minimisation opportunities were identified and quantifiable energy and cost savings, as well as avoided carbon dioxide emissions were derived from the analysis of one of the plants. Production or zinc used was identified as the main driver for electricity consumption for Plant 1, while the number of dips per month, amount of zinc used, and ambient temperature conditions were identified as the relevant variables for developing a regression model for Plant 2. The amount of zinc used and ambient temperature conditions were found to be the relevant variables for Plant 3. The derived regression model for Plant 4 was based on the amount of zinc used and ambient temperature conditions.

The energy performance indicators for a galvanising plant were established through a comparison of actual and expected consumption, energy intensity index, cumulative sum, and specific energy consumption. A bi-objective GECOS algorithm was further introduced to reduce the total energy consumption as well as makespan. The simulation results revealed that the GECOS algorithm outperforms McNaughton's algorithm, Shortest Processing Time Algorithm, and Integer Linear Programming algorithms on minimising makespan on parallel processing machines.

The key contributions to the body of knowledge from the study include a unique evaluation of electrical energy consumption by a hot-dip galvanising plant, development of an energy consumption baseline and performance indices, and the developed novel bi-objective GECOS algorithm that considers reducing total energy consumption by the process tanks as well as makespan. Future research work may focus on hybrid genetic algorithm-artificial immune system scheduling tools that would derive synergy from the advantages of both algorithms to improve energy performance.

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List of Acronyms

CP	Cleaner Production
CUSUM	Cumulative Savings
DE	Differential Equation
DMAIC	Define-Measure-Analyse-Improve-Control
DUT	Durban University of Technology
EnB	Energy Baseline
EE	Energy Efficiency
EII	Energy Intensity Index
EnPIs	Energy Performance Indicators
ESKOM	Electricity Supply Commission
GA	Genetic Algorithm
GECOS	Greedy Energy Consumption Optimisation Scheduling
HDG	Hot Dip Galvanising
HDGASA	Hot Dip Galvanisers Association of Southern Africa
JIT	Just in Time
ILP	Integer Linear Programming
IPMVP	International Performance Measurement and Verification Protocol
MILP	Mixed Integer Linear Programming
NP-hard	Non-deterministic Polynomial-time hard
NDSGA	Non-dominant Sorting Genetic Algorithm
NERSA	National Energy Regulator of South Africa
NHEMOtree	Non-Hierarchical Evolutionary Multi-Objective Tree

PEC	Processing Energy Consumption
RSSR	Remainder Stochastic Sampling with Replacement
SA	South Africa
SEC	Specific Energy Consumption
SBX	Simulated Binary Crossover
SPT	Shortest Processing Time
SSR	Stochastic Sampling with Replacement
SSPR	Stochastic Sampling with Partial Replacement
SUS	Stochastic Universal Sampling
TEC	Total Energy Consumption
TORSCHE	Time Optimisation, Resources, SCHEduling
VIM	Variable Importance Measure
WEC	Waiting Energy Consumption

Research Outputs

1. Dewa, M. and Dzwairo, B. 2020. Optimisation of Electricity Consumption for a Galvanising Plant through Comparative Analysis of Regression Analysis and Genetic Algorithm, *Proceedings of the International Conference on Industrial Engineering and Operations Management*, Harare, Zimbabwe, December 08-10, 2020.
2. Dewa, M. and Nleya, B. 2020. Comparison of Parallel Processors Scheduling Algorithms to Minimise Makespan in a Galvanising Plant. *Ponte Multidisciplinary Journal of Sciences and Research*. Vol 76, Issue 3, p255 -263.
3. Dewa, M., Dzwairo, B. and Nleya, B. 2017. *Development of an energy consumption baseline and performance indices for a galvanising plant*, 28th Annual Southern African Institute for Industrial Engineering Conference, p365 -373, Vanderbijlpark, South Africa.
4. Dewa, M., Dzwairo, B. and Nleya, B. 2016. *Evaluation of Electrical Energy Consumption by a Hot-Dip Galvanising Plant*, 27th Annual Conference of the SA Institute for Industrial Engineering, p75-86, Parys, South Africa.

CHAPTER 1 : BACKGROUND

1.1 Introduction

Manufacturing plants are currently regarded as significant contributors to overall carbon gas emissions due to high-energy usage (Sibanda and Ndlela 2020). By definition, the carbon footprint is a measure of the environmental impact of human lifestyles and processes (Pandey, Agrawal and Pandey 2011). Quantitatively, it is a metric measurement indicative of the amount of carbon dioxide and other gases that are emitted to the environment. The accumulative effect of carbon dioxide results in the " greenhouse effect", which is the capacity of all these gases to heat insulate the earth's surface thus resulting in the latter's temperatures gradually rising (Kweku *et al.* 2017). These include the use of substitute materials such as biopolymers/biodegradable polymers, vehicle light-weighting to improve fuel efficiency, remanufacturing, additive manufacturing, and energy efficiency.

It is noted that promoting energy efficiencies in manufacturing industries will generally reduce both the carbon footprint as well as operational costs. The earlier could be augmented by renewable generation such as solar, wind, hydroelectric, and biomass and less dependence on the traditional fossils-based fuels. However, the large-scale dependence on renewables is still limited. In the interim fossils, generation will still dominate, and thus promotion of energy minimisation in plants will help significantly curb the carbon gas emissions.

Increasing the Energy Efficiency (EE) of production processes and management approaches has a greater potential of reducing energy costs and avoiding a high carbon footprint (Weinert, Chiotellis and Seliger 2011; Shrouf *et al.* 2014). New advances in cleaner production technologies are designed to aid in ensuring sustainable social development that is based upon healthy ecosystems. It is crucial for organisations to embrace process integration, modelling, and optimisation for energy saving and pollution reduction, as they strive to emphasise the criticality of issues such as environmental impact assessments and sustainable consumption (Klemeš, Varbanov and Huisingh 2012).

Hot-dip galvanising is a process of coating fabricated steel by immersing it in a bath of molten zinc. It has been generally acknowledged that hot-dip galvanising is a cost-effective and adequate protection system for components and fabrications required to operate with minimum or zero maintenance for extended periods in any environment (Hornsby 1995). The subject of energy optimisation is vital in any industry, especially in hot-dip galvanising processes that are used to fabricate a wide variety of steel products such as large pre-fabricated items, structural steel, small washers, threaded parts, and so forth. About half of the zinc produced worldwide is used to protect steel from corrosion through galvanising steel or iron (Blake and Beck 2004b).

Not much research has been conducted to enhance the performance of the galvanizing lines in terms of energy optimisation through sequencing or scheduling algorithms, and thus this research seeks to add that niche to the body of knowledge. The roadmap for this chapter commences with the research context and problem, to research aims, objectives, and research questions as well as the rationale for the study. It also embraces the methodology which was followed to achieve results, the research constraints, limitations and assumptions, structure of the thesis, as well as the significance of the study.

1.2 Research Context

The ubiquity of climate change challenges, insecure energy supply, and rising energy generation costs are factors of increasing importance in today's society. According to White (2014), most galvanisers in South Africa (SA) use electric heating systems, originally prompted by the low price of electricity. However, electricity prices have been rising and the National Energy Regulator of South Africa (NERSA) approved an electricity tariff increase of 8% for 2014 to 2015 (Eskom 2014). NERSA approved Electricity Supply Commission's (ESKOM) allowable revenue rise from standard tariff customers to be 8.76% in March for Eskom's direct customers, which was implemented on 1 April 2020, and 6.9% for municipalities, which was implemented from July 2020. The average standard Eskom tariff approved by NERSA would also increase from 116.72 c/kWh to 128.24 c/kWh in 2021, which is an increase of 9.8% (Eskom 2020).

Given the background of rising electricity costs, it becomes imperative to comprehend the energy losses that characterise galvanising processes. Krzywicki and Langill (2003), asserted that furnaces used to heat galvanising furnaces are the largest consumers of heat in the galvanising plant. The key factors that contribute to large energy consumption by the galvanising furnace are heat losses by convection, conduction, and radiation through pot components as well as the galvanised products. Heat losses from the galvanising bath are dependent on the sequencing of the raw steel material which enters the galvanising furnace. It is also a function of the accumulation of dross in the galvanising furnace and environmental conditions such as wind speed and temperature. Substantial energy losses are also realised from the degreasing and pickling tanks.

Essentially, galvanising is a commonly used method to protect metallic surfaces from corrosion. This involves the application of a thin layer of zinc on a base metal to help shield the same from oxygen and the general surrounding environment. Note that oxygen chemically reacts with iron (Fe) to yield iron oxide (rusting, which is a form of corrosion). Rahrig (2002) cited batch hot-dip galvanising and inline, continuous galvanising as the two common methods of applying zinc metal to steel. With batch hot-dip galvanising, the parts or jobs are immersed as a discrete "batch" into the zinc bath. The common methods involved in the galvanising of metals include but are not limited to hot-dip galvanizing, pre-galvanising, and electro galvanizing.

Pertaining continuous galvanising, molten zinc is applied on a continuous ribbon of steel sheet as it passes through a bath of molten zinc at high speeds and the process may operate for days without interruption. The duration for the steel in the zinc bath is about two to four seconds and despite the favourably faster galvanization rate, continuous galvanising is limited to very thin, flexible sheets of steel (Behrens 2012). The context of this study is focused on batch hot-dip galvanising since the scope of the study had more hot-dip galvanising plants than continuous galvanising, with readily accessible production and energy data. The research focuses on energy assessment, regression prediction model and proposes a schedule for galvanising line as an energy-saving initiative.

1.3 Research Problem

The dearth of energy sustainability is continuously posing major challenges to the South African government and globally. Galvanising furnaces are the predominant consumers of energy in the galvanising industry. The key factors that contribute to large energy consumption by the galvanising furnace are heat losses through convection, conduction, and radiation through pot components as well as the galvanised products.

There are 32 existing hot-dip galvanising companies in South Africa, all under the auspices of the Hot Dip Galvanisers Association of Southern Africa (HDGASA). Twenty-eight of the companies rely on electric furnaces (Wilmot 2007). As a way of curbing the usage of huge amounts of energy, there is a gradual shift from open to closed galvanising furnaces.

Previous research focused on continuous galvanizing plants with gas-fired furnaces and less attention has been given to batch-mode galvanising plants that utilise electric furnaces. It has also focused on design issues such as reduced number of welds and shaping of galvanising furnaces but no research has been conducted to reduce energy consumption by the galvanise furnaces through optimal sequencing of the raw steel material. It is generally accepted that hot-dip galvanising plants are characterised by high energy consumption indices coupled with low energy efficiencies since even outside production periods, the zinc is kept molten in the furnace at all times (Blake and

Beck 2004b). Huge energy losses emanate from the degreasing, pickling, and galvanising tanks that are left open during idle periods.

The cited galvanising sector is also devoid of methodologies for establishing and documenting energy baselines for improving their energy performance for hot-dip galvanising process, which adversely impinges on tractability in the analysis of energy consumption. The outlying challenge faced in computing the energy consumption benchmark for the galvanising plants lies in the fact that even plants that are processing the same raw materials have variable equipment sizes and throughputs. This poses a challenge to develop a scheduling algorithm for optimising the energy consumption of the degreasing, pickling, and galvanising tanks of galvanising process to evade unwarranted energy losses.

1.4 Research Questions

A good research question is vital to guide the researcher and it should be specific and pinpoint exactly the focus of the problem, feasible to provide answers within the required timeframe and practical constraints, as well as complex enough to develop the answers and relevant to a specified field of study (Bairagi and Munot 2019). This research intends to answer the following descriptive research questions:

- What are the potential opportunities that would characterise a batch hot-dip galvanising process concerning the reduction of the use of electrical energy, considering the galvaniser's energy management and consumption data?
- What are the relevant electricity consumption drivers for a galvanising line considering the number of dips per day, amount of zinc used, galvanised product tonnage, and the ambient temperature conditions?
- What are the energy performance indicators for a galvanising plant concerning the comparison of actual consumption and expected consumption, energy intensity index, cumulative sum, and specific energy consumption?

- Which parameters should be deployed to develop an optimal scheduling algorithm for energy optimisation of the galvanising process?

1.5 Research Aim and Objectives

This research was aimed to evaluate energy performance and derive a novel optimal scheduling algorithm for energy optimisation of the hot-dip galvanising process, against the backdrop of rising energy costs. The research objectives are:

- To conduct an energy assessment and evaluation of a batch hot-dip galvanising process to identify potential opportunities for the reduction and more efficient use of electrical energy;
- To identify the relevant electricity consumption drivers for a galvanising process;
- To develop energy performance indicators for a galvanising plant;
- To develop an optimal scheduling algorithm for energy optimisation of the galvanising process.

1.6 Rationale

The operational environment of manufacturing plants is characterised by increasing pressure to reduce carbon footprint, motivated by trepidations associated with high-energy costs and climate change, with energy as one of the most vital resources for manufacturing. Krzywicki and Langill (2003), asserted that natural gas is the most common fuel used to heat galvanising furnaces, and for instance in the United States of America, natural gas is readily available so abundant such that nearly all galvanisers use this fuel as their heat source. Consequently, less research has succinctly addressed galvanising furnaces, which utilise electric heating, thus calling for in-depth research in that dimension.

Fripp (2015) posited that Eskom's tariff increases were set relatively below inflation for the period from 1987 to 2007, and from 2008 to 2015, electricity tariffs in SA increased by 300%, tripling in 8 years whilst inflation over this period was 45%. The biggest challenge was that South Africa's electricity prices were set to escalate even further. It is against the background of rising electricity costs that it became imperative to conduct a study that would promote sustainable consumption of electricity to reduce operational expenditure.

Fang *et al.* (2013) asserted that research on adopting sequencing or scheduling as a tool for reducing the consumption of energy and power by manufacturing organisations is rather scarce. A lot of research up to date has been conducted on minimising energy consumption in manufacturing companies, striving to improve the efficiency of the equipment, fundamentally disregarding the potential for energy reduction at the system-level where the operational method can be employed as the energy-saving approach (Liu *et al.* 2014). The benefit of the scheduling approach is applicable across existing galvanising plants and does not require a large investment. Therefore, this research proposes a novel scheduling algorithm for energy optimisation of a jobbing hot-dip galvanising process.

1.7 Research Methods

The literature review was conducted using a range of information sources that include books, commercial magazines, bibliographic databases, and Internet search engines to acquire background information on hot-dip galvanising, heat modelling, scheduling algorithms, and energy optimisation. The research adopted a unique Define-Measure-Analyse-Improve-Control (DMAIC) research approach for the provision of a structured and rigorous problem-solving process for improving energy efficiency in a galvanising process. The issues of research misconduct, plagiarism, ethical approval of the study, and data presentation or analysis were taken as ethical considerations in scientific research.

Methods for Objective 1

Initially, the case study organisations were evaluated in terms of their awareness of energy management and commitment to improving energy efficiency. Questionnaires were used to elicit information from management at the case-in-point galvanising plants. The method also entailed compiling a detailed electrical energy balance and identifying the most significant energy users of electricity using Pareto Analysis. A heat loss calculator was then developed for evaluating energy-saving initiatives for the significant energy users after which recommendations were made for reducing the energy consumption of the galvanisers.

Methods for Objective 2

The methods which were adopted for identifying the relevant electricity consumption drivers entailed defining the boundaries, identifying energy sources, outlining the baseline period, and definition of relevant consumption drivers. Multiple regression analysis was used to determine the relevant variables and to validate the strength of statistical relationships between the variables.

Methods for Objective 3

The research method for objective 3 embraced determining and calculating energy performance indicators. Four Energy Performance Indicators (EnPIs) that include Actual versus expected consumption, Energy Intensity Index (EII), Cumulative Savings (CUSUM), and Specific energy consumption (SEC), were adopted for the study.

Methods for Objective 4

The method for developing a scheduling algorithm comprises optimisation problem formulation, objective and fitness function, and constraint identification, encoding, selection, crossover, mutation, and termination. The first step of the research approach comprised the development of a mathematical model for energy consumption optimisation scheduling. The study adopted a bi-objective optimisation scheduling approach that considers two criteria, that is to minimise the electrical energy consumption and makespan simultaneously. The Genetic Algorithm (GA) was simulated and the results were compared against McNaughton’s algorithm, Shortest Processing Time, and Integer Linear Programming (ILP) algorithm on a Time Optimisation, Resources, SCHEduling (TORSCHE) platform in terms of minimising makespan for a galvanising plant.

1.8 Research Scope, Constraints and Limitations

It was crucial to establish the boundaries or scope for the study with the view to establish what could be accomplished. Several constraints limited the options in conducting the study, and for instance, four hot-dip galvanising plants were elected due to financial and time constraints. The study focused on four galvanisers in KwaZulu-Natal, South Africa, and these plants primarily use electricity as the source of energy for the galvanising furnace and other process tanks.

One key limitation was the inability to accurately measure the temperature variation across the galvanising tank surface, as a function of weather conditions such as wind and temperature, due to the limited technology that prevailed when the study was conducted. The collection of primary data for the study was conducted throughout twelve months and the timeframe was characterised by variation in temperature and wind speed from day to day. Thermal imaging during the galvanising step was also compromised since it was imperative to comply with safety guidelines regarding getting to the proximity of the furnace.

The spattering of the molten zinc from the galvanising bath frequently occurs when the steel part is introduced into the galvanising furnace and can be a source of burn injuries to workmen in the galvanising area. Only the energy consumption by the galvanising process equipment was taken into consideration since energy consumed by equipment is the primary source of energy consumption in production scheduling. Other kinds of energy consumption, such as illumination and ventilation were not considered.

1.9 Research Assumptions

It was assumed in this research that the degreasing, pickling, and galvanising tanks will be fully open when a full length of raw steel is being dipped and can be partially closed depending on the length of the raw material. In pursuit of the study, it was assumed that partial covering of the galvanising furnace would result in zero heat losses through the insulating cover and heat losses were only to be realised from the uncovered zinc surface. Heat loss from the surface was calculated with the assumption that the temperature distribution is uniform and only one emissivity is applied to the surface material. It was assumed that since these plants are almost similar in size, the identified energy-saving initiatives would be applicable in all four plants.

In developing the scheduling algorithm for energy optimisation, it was assumed there was no double dipping of galvanising work, which is a process of galvanising an item that is longer, wider, or deeper than the relevant available bath dimensions. In double-dipping, the part is dipped into a zinc bath so that half or more of its ‘over dimension’ is immersed in the molten zinc.

1.10 Structure of the Thesis

Chapter 1 covers the background, problem statement, aims and objectives, and rationale for the study. Chapter 2 carries out an extensive literature survey on hot-dip galvanising, galvanising processes, and energy efficiency-related issues in such plants. The key issues that are reviewed in this section include an overview of consumption drivers, energy loss in surface preparation, and energy losses in galvanising. The literature reviews cover energy consumption baselines, specific energy consumption, regression analysis and energy consumption benchmarking. The other key issues that are reviewed in this section also include scheduling algorithms and genetic algorithms.

Chapter 3 establishes the base research framework, ethical considerations as well methodologies for energy efficiency-related issues in a galvanising process. Key energy efficiency indicators are formulated as well as discussed in the same chapter.

Chapter 4 carries out an in-depth analysis of galvanising plants concerning energy efficiency. The chapter also covers the results for energy performance indicators and the development of an optimal scheduling algorithm for energy optimisation.

Chapter 5 proposes a novel Greedy Energy Consumption Optimisation Scheduling (GECOS) algorithm that considers reducing total energy consumption by the process tanks, as well as makespan. Simulation results for bi-objective optimisation and comparison of scheduling algorithms are also covered in this chapter.

Chapter 6 concludes the work and provides recommendations for future research direction.

1.11 Significance of the Study

The regulation of carbon dioxide emissions has been imposed globally, and because of the climate change convention, reducing energy consumption is a strong factor in the manufacturing industry. Hence, the results of this study will significantly add to the knowledge base on striving to reduce the energy consumed by galvanising processes, improve sustainability in manufacturing, and foster the reduction of global carbon footprint. The envisaged measurable outputs include conference proceedings and journal publications. The research output can be positively exploited by the galvanising communities such as Hot Dip Galvanisers Southern Africa and expected effects of research results include substantial energy savings and better sustainability by implementing companies.

1.12 Conclusion

This chapter was a preamble that provided a context for the research and a description of the research problem. It also touched on the research aims, objectives, and research questions. The research context of climate change challenges, unsecured energy supply, and rising energy prices was outlined. The lack of methodologies for establishing and documenting energy baselines for improving their energy performance for the hot-dip galvanising process was also stated as part of the research problem. A research approach was also elucidated, commencing with a review of the relevant literature, cascading to preliminary time studies, ethical considerations, methodologies for energy assessment, and identification of the relevant electricity consumption drivers for a galvanising process. The research approach for determining and calculating energy performance indicators as well as mathematical formulation and bi-objective scheduling algorithm was also outlined in this chapter. The following chapter will embrace a detailed literature review of hot-dip galvanising, heat modelling, scheduling algorithms and energy optimisation.

CHAPTER 2 : LITERATURE REVIEW

2.1 Introduction

It is crucial to conduct a literature review in order to compare, contrast and encapsulate what research has been done in the past with regard to hot dip galvanising, energy optimisation and scheduling algorithm. In particular, the focus of this literature review is on energy requirements, together with its use, and optimisation in such industries. An overview summary of scheduling algorithms that gear towards optimising energy usage in such industries is presented. The review is carried out as a basis for the identification of any existing gaps in the body of literature and provides a rationale for a niche that is added to the existing body of knowledge. It also facilitates unveiling of research strategies and specific data collection approaches that are commonly used for hot-dip galvanising processes. Likewise, emphasis is on familiarising with existing measures to optimise energy usage in such industries.

Moreover, embracing previous research also facilitates interpretation and discussion of results, regardless of whether they tally (concur) with previous findings (Gay, Mills and Airasian 2006). There should be a provision for a rationale for the discrepancies if the results contradict previous findings. The key literature that is reviewed under this chapter includes galvanising processes, energy losses in galvanizing, energy performance indicators, energy consumption benchmarking, heat transfer models, and genetic algorithms.

2.2 Batch Hot-Dip Galvanising Process and Energy Optimisation

This section focuses on the literature survey regarding the first research objective, which is to conduct an energy assessment and evaluation of a batch hot-dip galvanising process to identify potential opportunities for the reduction and more efficient use of electrical energy. Although less research work has been conducted to optimise galvanising processes operating in a jobbing environment from an energy-saving perspective, significant research has been undertaken `concerning minimising makespan and maximizing production. For instance, Burkard and Hatzl (2005) investigated scheduling in batch processes striving to minimise makespan. An event-driven model was used to accelerate the running time for the uniform discretisation of a time model and the results demonstrated that one can store some products in batches if the processing times are prolonged.

Sundaramoorthy *et al.* (2016) posited that hot-dip galvanising facilities are energy-intensive, with electrical, oil, or gaseous fuel energy representing a substantial portion of total energy usage. Sundaramoorthy *et al.* (2016) then developed a heat balance model for annealing and zinc furnaces in continuous hot-dip galvanising processes using data gathered from several manufacturing plants. The results of the study revealed that less than half the amount of heat supplied to the furnace was absorbed by the product; the remainder of the input heat energy was dissipated as energy losses. It was also found that there was significant heat loss from the flue gas stack and wall surfaces, while the heat lost due to phase changes and openings was minimal. In that scenario, dimensions of the furnace, emissivity, galvanising furnace temperatures, thermal conductivity of insulation materials, as well as entry and exit steel strip temperature for the individual zones have a substantial influence on the total heat loss. Heat balance analysis can aid galvanisers to identify prospects to reduce energy losses and optimise system performance.

On the other hand, the work of Fernández *et al.* (2012) revealed that several mathematical optimisation techniques can be utilised to reduce the energy consumption of a batch process. The results demonstrated that scheduling is crucial for heat integration and the establishment of efficient heat exchanger networks would aid to reduce energy consumption in batch processing.

Additionally, Shrouf *et al.* (2014) developed a mathematical model for scheduling production on a single machine with the view to optimise the machine's energy consumption. Machine-level decisions were made to establish optimal launch times for job processing, "turning on" time, "turning off" time, and when the machine must be shut down. A genetic algorithm was used to obtain ‘near’ optimal solutions while an analytical method was used to generate an optimal solution for minimising cost and the best possible schedule for minimising energy costs. The results demonstrated that a substantial reduction in energy cost can be derived from avoiding high-energy price periods. It was noted that this model would enable operations managers to implement the cheapest production scheduling during a production shift.

The work of Dewa, Dzwairo and Nleya (2016) revealed that galvanising plants may be sub-categorised according to the type of fuel used to heat the surface preparation and galvanising tanks. Less research has been conducted on galvanising processes that use electricity as the main source of heating the surface preparation and galvanising tanks and thus this research is aimed at adding the missing gaps to the body of knowledge concerning that niche. Concerning gas-fired furnaces, these furnaces heat the zinc directly or indirectly. Furnaces that heat the zinc directly use immersion burners and furnaces that heat the zinc indirectly have a combustion gallery between the furnace and the exterior of the furnace to facilitate the transfer of heat from the combustion gases to the zinc. Flat-flame, forced-circulation and high-velocity furnaces are the major types of indirect gas-fired furnaces prevailing within the galvanising industry (Krzywicki and Langill 2003). The hot-dip galvanising process is characterised by the following key three steps and these include pre-treatment (degreasing, pickling, fluxing, and drying), galvanising and post-treatment (quenching, passivating and inspection).

2.2.1 Hot Dip Galvanising Process

Hot-dip galvanising is a complex metallurgical process in which steel material is rapidly immersed zinc alloy bath whose temperature is normally between 450˚C and 480˚C (Marder 2000; Ilinca *et al.* 2007). Marder (2000) posited that the manufacture of zinc and zinc alloy coatings on steel is one of the industrially widely used processing techniques that is deployed to protect steel components that operate under corrosive environments. Hot-dip zinc coating methods that include batch and continuous processes were reviewed along with iron-zinc phase equilibria and iron-zinc kinetics. Iron-

Zinc-Aluminium equilibrium was also reviewed in the light of studies of solubility and inhibition layer formation and breakdown. The effect of the microstructures of these coatings on the crucial properties of corrosion, weldability, formability, and paintability was also discussed.

The hot-dip galvanising process is characterised by massive heat losses and concerning heat transfer, and thus, Blake and Beck (2004a) modelled the effect of combined radiation and convection on hot-dip galvanising furnace wear. It was established that natural gas is the most commonly used heating medium for galvanising furnaces in the UK and abroad. The results of the study revealed that the alloying reaction between the steel kettle wall and the molten zinc was temperature-dependent, and this forms a non-adherent alloy above a certain rate of heat transfer. This scenario allows the molten zinc to erode the kettle wall faster, thereby diminishing the kettle life span and the production rate for the furnace. Computational Fluid Dynamics software was used to build a model and investigate the cause of higher localised wear of the kettle walls of a hot-dip galvanising furnace. The comparison of the model with wear data of the kettle walls after the serviceable life as well as data from an actual furnace in operation was done. The results demonstrated that as opposed to direct contact between the flame and kettle wall, radiation and convection exchange from the flame were found to be the major cause for kettle wear.

Thereafter, Cook (2005) presented basis data for calculations for heat lost at the zinc-air interface for "open" and "enclosed" furnace. It was established that many gas-fired kettles cannot be covered since the burners cannot be turned off completely or "turned-down" sufficiently. The annual radiation and convection heat loss at the zinc-air interface during non-production was found to be quite substantial because about half of the burner energy passes through the heating zone of the walls. Additionally, a well-constructed kettle in a properly designed furnace would normally have a useful life of ten years and capturing waste heat from the kettle flue to heat the flux and caustic tanks would significantly lowering energy costs for the galvanisers.

Electrical heating is preferred for a galvanising furnace since the radiant heat produced by resistance elements is very uniform, though the high cost of electricity usually precludes the use of electrical heating (Krzywicki and Langill 2003; Sommer, Walton and Cotchen 2004). There are three steps to the galvanising process which include preparation, galvanising, and post-treatment, with the preparation step being divided into degreasing, pickling, and fluxing (Behrens 2012; Dewa, Dzwairo and Nleya 2016). It is worth noting that the appreciation of the hot-dip galvanising process and the operating temperature that characterise it, is a crucial precursor to the execution of an energy assessment and evaluation of such processes to identify potential opportunities for more efficient use of energy.

2.2.2 Surface Preparation

The initial process tank in the galvanising plant is the degreasing tank which usually contains a caustic soda solution used to get rid of organic contaminants such as oils and dirt from the surface of the steel. The degreasing tanks are generally heated to a temperature of about 80°C and can be agitated to hasten the cleaning process (Krzywicki and Langill 2003). These surface contaminants need to be eliminated before pickling so that the surface can be "wetted" by the pickling solution.

The second surface preparation step is pickling where the degreased steel is immersed into a tank containing acid solution. These tanks either contain sulphuric or hydrochloric acid solution which is used to remove any mill scale or other oxides that may have developed on the surface of the steel (Prasad, Prasad and Patel 2015). Hydrochloric tanks may be used at ambient temperatures without heating since the cleaning action of the hydrochloric solution is sufficient at room temperature. Conversely, in order to increase the cleaning action, sulphuric acid must be heated to a temperature of about 60°C.

The third surface preparation step is fluxing which involves the application of a fluxing chemical coating, usually zinc ammonium chloride, onto the surface of the steel part (Behrens 2012). The discussion revealed that the fluxing chemical would chemically remove the last vestiges of oxides prior to steel immersion into the molten zinc, and allows the steel to be wetted by the molten zinc. Two types of fluxing include “dry” or “wet” fluxing. With dry fluxing, the steel part is immersed into an aqueous solution of the zinc ammonium chloride flux, of which upon removal, the flux solution is dried prior to immersion into the zinc bath.

The amount of flux deposited on the components is a function of the flux concentration, and the cleaning performance is a function of the drying time and temperature conditions (Hornsby 1995). On the other hand, in wet fluxing, a blanket of liquid zinc ammonium chloride is floated on top of the molten zinc bath so that the steel part to be zinc coated first passes through the molten flux as it is being immersed into the zinc bath. Zinc ammonium chloride is less dense and has a lower melting point than molten zinc and thus floats on the bath surface. Wet fluxing is preferred for workloads that consist of small fasteners, mixes of shapes and sizes, and when centrifuging is executed (Hornsby 1995). It is noted from the description of operating temperatures that characterise the surface preparation for galvanising that some heat is lost to the environment. A successful energy assessment of the galvanising process is dependent on acknowledging the steps undertaken in accomplishing such tasks and identifying potential opportunities for reducing use of energy.

2.2.3 Galvanising

Hot-dip galvanising is a hot process whereby cleaned steel is immersed in molten zinc usually at a temperature of between 445˚C and 450˚C (Wilmot 2007). When perfectly cleaned steel is immersed into molten zinc a metallurgical (chemical) reaction results, forming a thick coating comprising of a series of zinc and/or zinc-iron alloy layers. Generally, the duration for the steel to reach bath temperature and to react with the zinc is usually less than ten minutes (Behrens 2012). The adhesion of the resultant coating to carbon steel is therefore determined by employing metallurgical laws and forms a chemical bond to the substrate. Chemical bonding is considered to be superior when compared to mechanical bonding. The galvanised steel product is withdrawn slowly from the galvanising bath once the coating growth is complete, and the left-over zinc is removed by draining, centrifuging or vibrating.

Vourlias *et al.* (2005) conducted a study on the negative effect of insoluble dross particles on the quality of the galvanised coatings. It was found that one key by-product of hot-dip galvanising is dross that is formed inside or on top of the molten zinc as floating (galvanising ashes) or bottom dross. The intermetallic compounds of the floating and bottom dross develop when the concentration of elements of iron oxides and zinc ammonium chloride exceed their solubility limits in the zinc furnace. The floating dross is characterised by a mixture of oxides and chlorides. Despite perfect control of the zinc bath and the deliberate addition of elements such as aluminum to reduce the iron dissolution, the temperature gradient between the immersed objects and the zinc bath necessitates the crystallisation of dross (Vourlias *et al.* 2005). The temperature at which the zinc bath is maintained has a direct effect on the galvanising furnace life since at galvanising temperatures, the partially soluble iron from the furnace wall dissolve in the liquid zinc and form dross (Blake and Beck 2004a). One of the objectives of the study was to identify the relevant electricity consumption drivers for a galvanising process. It was noted that hot-dip galvanising process operates at a temperature of around 450ºC hence the need to comprehend the energy consumed by the process. Hence, the subject of energy optimisation is vital for the galvanising industry, especially during hot-dip galvanising procedure.

2.2.4 Post Treatment and Inspection

Kong and White (2010) conducted a study on Cleaner Production (CP) of hot-dip galvanising industry in China and also cited pre-treatment (degreasing, pickling, fluxing, and drying), galvanising and post-treatment (quenching, passivating), as the key steps for a galvanising process. Kong and White (2010) posted that post-galvanising treatment can be characterised by air cooling or quenching into water and the galvanising operation was found to produce atmospheric emissions, solid waste emissions and contaminated wastewaters that could harm the environment and hence the need for CP options. Generally, quenching is the last step in most Hot Dip Galvanising (HDG) processes used to promote passivation of the zinc surface and to control the growth of the zinc-iron alloy layers, with chromium-free passivating technology being preferred to toxic hexavalent chromium passivation (Kong and White 2010).

The inspection of hot-dip galvanised steel is simple, zinc does not adhere to contaminated steel, and thus, a visual inspection of the galvanised steel provides an adequate evaluation of the quality of the coating (GAA 2012). A variety of simple physical tests can be performed to determine thickness, uniformity, adherence, and appearance. The duration to first maintenance of HDG products is directly proportional to the thickness of the zinc coating, given any operational environment. This is a function of the coating thickness which is a critical parameter in the specification and effectiveness of hot-dip galvanising as a corrosion protection system. Thus, an inspection of the coating thickness is a key feature of hot-dip galvanised (HDG) products since thicker coatings yields enhanced durability and decades of maintenance-free performance (AGA 2011).

In order to relate the extent to which various coatings provide protection against corrosion, salt-fog tests are generally used for relative comparison concerning service conditions (Rahrig 2002). This test produces quick results and is characterised by low cost although the correlation between the duration in salt spray test and the expected life of some HDG coatings is generally weak (ISSF 2008). It was noted that post-treatment and inspection would generally consume less energy when compared to the preceding steps that characterise a galvanising process. Therefore, this study will pay less attention to post treatment and inspection since there are bound to be no potential opportunities for the reduction and more efficient use of electrical energy.

2.3 Energy Consumption Drivers for Processes

Relevant variables or energy consumption drivers are quantifiable factors that would influence a plant’s energy consumption, such as production, weather conditions, and hours of operation or production (ENS 2013). This section focuses on the literature survey regarding the second research objective, which is to identify the relevant electricity consumption drivers for a galvanising process.

2.3.1 Overview of Consumption Drivers for Processes

Soytas and Sari (2007) used a multivariate framework to investigate the relationship between energy and production in the manufacturing industry. The results demonstrated that fixed investment, labour, and electricity consumption were related, with energy consumption showing a strong correlation with production. Therefore, increased energy efficiency and energy-saving technologies may enhance the growth in manufacturing value addition.

Depree *et al.* (2010) conducted a study on model development and validation of control of annealing furnace from basic heat transfer principles. This has been used to compare the measured pyrometer and thermocouple temperatures against predicted strip temperature distribution and furnace wall temperatures. The simple model had a short solution time and was found to be suitable for rapid simulation of alternative operating conditions of a furnace to optimise plant throughput, heat treatment quality and energy consumption.

Fikru and Gautier (2015) conducted a study on the influence of weather variation on energy consumption using five-minute interval weather-energy data obtained from residential houses. The results demonstrated that sensitivity of energy use to weather depends on the specific time of the day or night and season. It was anticipated in this current study that the electricity consumption for a galvanising process would also be affected by weather conditions, especially temperature and humidity.

Nota *et al.* (2020) conducted a study on energy efficiency and derived a methodology for reducing the energy consumption in batch manufacturing processes from a combination of management techniques and Industry 4.0 technologies. Commencing with the analysis of loss cause identification, a method that obtains quantitative data about energy losses in batch manufacturing was proposed. By implementing manufacturing execution system software, energy management strategies for minimizing the energy consumption and the energy costs of the production for each machine were constructed. The research contributes positively to the body of knowledge since decision-makers can reduce carbon footprint and energy costs while achieving production goals. The appreciation of the correlation between production and energy by top management can enable managers to conduct a bottom-line analysis on how to improve the overall productivity while keeping the energy cost low.

The literature has demonstrated it is vital to comprehend the energy consumption drivers for processes since that would enlighten or give a better perspective of measures that can be undertaken to reduce the energy consumption from manufacturing processes.

2.3.2 Energy Loss in Surface Preparation

There is energy consumption during surface preparation of steel when heating caustic soda solution to a temperature of about 80°C in a degreasing tank, or when sulphuric acid is heated to a temperature of about 60°C during pickling (Prasad, Prasad and Patel 2015). The degreasing and pickling tanks are characterised by heat loss through convection, conduction and radiation. Newton’s law of cooling states that the heat flux is a function of a difference of temperatures between the wall and the environment (Newton 1929). A classic equation of exponential decline over time is derived from Newton’s law of cooling which can be used to predict the heat loss from the uncovered surface of the degreasing, pickling and galvanising tanks. The heat transfer per unit surface through convection was first described by Newton and the relation is known as the Newton's Law of Cooling as shown in Equation 2.1.

$$q = h_c A dT \tag{2.1}$$

where;

q - is the heat transferred per unit time (W);

A - is the heat transfer area of the surface (m^2);

h_c- is the convective heat transfer coefficient of the process ($W/m^2{}^\circ C$);

dT - is the temperature difference between the surface and the bulk fluid ($^\circ C$).

The convective heat transfer coefficient of air shown in Equation 2.2 can be expressed as:

$$h_c = 10.45 - v + 10\, v^{1/2} \tag{2.2}$$

where;

v - is the relative speed of the object through the air (m/s).

However, Davidzon (2012) concluded that Newton's law of cooling was ambiguous in theory and practice of heat transfer since it was an approximation of the exponential model applicable only when certain conditions are met. Hence, further research is required for modeling the phenomenon of heat exchange.

Conduction is heat transfer that takes place if there is a temperature gradient in a solid or stationary fluid medium. Fourier's Law is used to express conductive heat transfer as shown in Equation 2.3:

$$q = k\, A\, dT\, /\, s \tag{2.3}$$

where;

q - is heat transfer (W, J/s);

A - is heat transfer area (m^2);

k - is thermal conductivity of the material ($W/m\ ^\circ C$);

dT - is temperature difference across the material (°C);

s - is material thickness (m).

Heat transfer through radiation takes place in form of electromagnetic waves mainly in the infrared region. The radiation energy per unit time from a blackbody is proportional to the fourth power of the absolute temperature and can be expressed with Stefan-Boltzmann Law as shown in Equation 2.4:

$$q = \sigma T^4 A \tag{2.4}$$

where;

q - is heat transfer per unit time (W);

σ - is The Stefan-Boltzmann Constant = 5.6703 10-8 (W/m^2K^4);

T - is absolute temperature Kelvin (K);

A - is area of the emitting body (m^2).

For objects other than ideal blackbodies ('gray bodies') the Stefan-Boltzmann Law can be expressed as shown in Equation 2.5.

$$q = \varepsilon \sigma T^4 A \tag{2.5}$$

where;

ε - is emissivity of the object (ε for zinc tarnished = 0.25, zinc polished = 0.045, = 1 for a black body).

If a hot object is radiating energy to its cooler surroundings the net radiation heat loss rate can be expressed as shown in Equation 2.6.

$$q = \varepsilon\,\sigma\,(T_h^4 - T_c^4)\,A_c \tag{2.6}$$

where;

T_h - is hot body absolute temperature (K);

T_c - is cold surroundings absolute temperature (K);

A_c - is area of the object (m^2).

Overall, with regard to surface energy balance, the law of conservation of energy applies at the control surface and would hold for both steady-state and transient conditions (Incropera *et al.* 2013).

Figure 2.1 shows the conduction of the medium to the control surface (q''_{cond}), convection from the surface to the fluid (q''_{conv}) and net radiation exchange from the surface to the surroundings (q''_{rad}), given T_1 and T_2 as the temperature between within the conducting material.

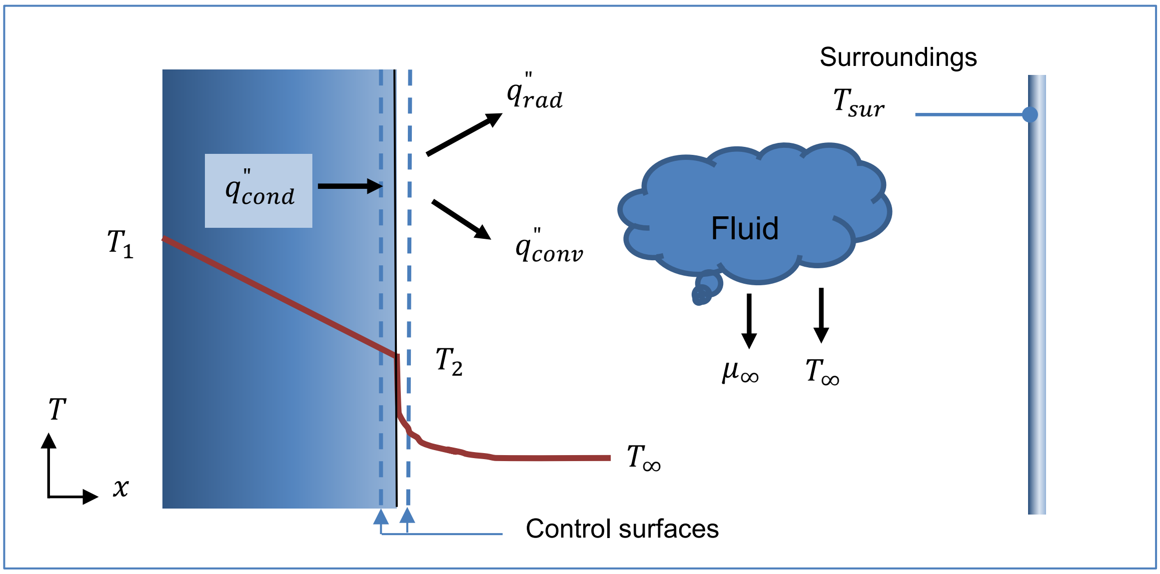

Figure 2.1: Energy balance at surface of a medium

Source: Incropera et al. (2013)

The energy balance equation can be expressed as shown in Equation 2.7:

$$q^{"}_{cond} - q^{"}_{conv} - q^{"}_{rad} = 0 \tag{2.7}$$

Understanding the various modes of energy loss in surface preparation is vital for comprehending the analysis for galvanising process energy consumption, which is required for the development of an optimal scheduling algorithm for energy optimisation.

2.3.3 Energy Losses in Galvanising

The galvanising furnace is the most significant energy user in most galvanising plants, and energy is consumed even during idling periods when no product is being produced since the zinc must be maintained in a molten state. Newton’s law of cooling, Fourier's Law on conductive heat transfer, and the Stefan-Boltzmann Law of ‘gray bodies’, also characterise the energy losses during the galvanising phase of steel products. Wubbenhorst (1956) established an implicit energy balance for gas-fired galvanising furnaces as energy supplied is equal to the sum of the heat required to galvanize and melt out replacement zinc, and the heat lost from the exposed surface of molten zinc, and the energy lost through the exterior walls of the furnace and the energy lost through the furnace exhaust. The energy lost through the exterior walls of the furnace was assumed to be negligible and is roughly 2 percent of the total consumption ((Wubbenhorst 1956); (Blake and Beck 2004a).

Meunier (1988) developed a general expression for the specific energy consumption (SEC) of a galvanising furnace as shown in Equation 2.8:

$$SEC_{supply} = \frac{\hat{q}_w}{\eta_{prod}} + \frac{A_s \dot{q}_s}{\eta_{prod} \dot{m}} \left(\frac{t_{uncovered}}{t_{prod}} \right) + \frac{\dot{Q}_{losses}}{\eta \, \dot{m}} \tag{2.8}$$

where;

$\hat{q}_w$- is the heat required to galvanize the work in kW h/t;

η - is the overall efficiency;

η_{prod} - is the efficiency of the furnace during production periods;

A_s - is the surface area of the molten zinc in m^2;

$\dot{q}_s$ - is heat flux on the surface of the molten zinc in kW/m^2;

$\dot{m}$ - is the absolute production rate in tons/hr;

$t_{uncovered}$ - is the time of operating while the covers are not in use;

t_{prod} - is production time in hrs;

$\dot{Q}_{losses}$ - is the sum of heat losses during production and idling periods.

The equation exhibits the SEC is a function of production rate, when the production rate is low, the energy losses from the walls and the surface galvanising tank become more significant. Heat is transferred from the molten zinc surface of the tank by convection and radiation and since radiation is included, the problem is nonlinear. Both steady-state and transient analysis can be performed, whereby with steady-state analysis, the focus is on the final temperature at different points molten zinc surface after it has reached an equilibrium state. With transient analysis, thrust on the temperature of zinc surface as a function of time with interest on the duration molten zinc surface to reach an equilibrium temperature.

The thermal energy supplied from the galvanising furnace must be efficiently transferred to the molten zinc bath and inefficient heating results in irregular heating of the furnace walls and large temperature gradients to which the steel furnace is exposed (Prasad, Prasad and Patel 2015). Galvanising furnace steel degrades faster when exposed to high-temperature gradients and this generally occurs because sections of the furnace wall remain hotter than other portions of the furnace. This is largely due to the constant temperature changes in the zinc bath when steel objects which were initially at ambient temperatures are immersed and drawn out during the galvanising process. Heat energy should be applied as evenly as possible to the furnace walls, and the zinc bath temperature variation should be narrow, to prolong the life of the galvanising furnace (Krzywicki and Langill 2003; Prasad, Prasad and Patel 2015).

When heat is not supplied to the furnace fast enough when large work is immersed into the bath, large temperature gradients would occur. The energy source must be able to supply heat energy to the furnace as soon as it is lost since the steel being dipped into the zinc would initially be at room temperature. The temperature drop of the furnace is also dependent on the amount of zinc in the furnace, and large furnaces have enough heat capacity to avert high-temperature drops when compared to smaller furnaces when the same size of steel is immersed into the furnaces (Krzywicki and Langill 2003; Prasad, Prasad and Patel 2015).

Heat losses also occur on the inner side of the furnace wall where there exists a layer of iron-zinc intermetallic compound. Heat must be transferred through this solid layer to heat the liquid zinc. Thus, significantly more heat energy is required in the furnace in order to maintain galvanising temperatures in the bath (Krzywicki and Langill 2003). Understanding the various modes of energy loss from the galvanising furnace is also vital for comprehending the analysis for galvanising process energy consumption, which is required for the development of an optimal scheduling algorithm for energy optimisation. The principles of heat transfer are a fundamental input to the mathematical model for energy consumption optimisation scheduling.

2.4 Energy Performance Indicators and Energy Consumption Benchmarking

It is vital to comprehend that energy performance indicators are crucial for providing the relevant information on energy performance that would enable the galvaniser to appreciate its energy performance and develop interventions to save energy. This section focuses on the literature survey regarding the third research objective, which is to develop energy performance indicators for a galvanising plant. The key issues that are reviewed in this section include energy consumption baselines, energy performance indicators, specific energy consumption, regression analysis, engineering energy simulation, and modelling and energy consumption benchmarking.

2.4.1 Energy Consumption Baselines

The energy consumption baseline establishes the “before” scenario by capturing a system’s total energy use before initiating improvements (Reichl and Kollmann 2011). Valencia-Ochoa, Ramos and Meriño (2017) conducted a study on the application of energy planning to reduce the gas consumption for a hot-dip galvanizing process in a metallurgy company basing on ISO 50001 standards. The gas consumption for the organisation represented about 75% of total energy consumption, an indicator that there were energy saving potentials in gas usage. Gas consumption, level of production, and time were the three variables that were considered from real data to obtain energy performance indicators that included baseline and goal line, consumption ratio concerning production level, and CUSUM. The implementation of this method realised energy saving potentials, reduced greenhouse gas emissions as well as reduced operational costs for the plant.

The energy consumption baseline energy serves as a good preliminary point for setting improvement goals for energy efficiency, and it is a comparison point for trending overall performance and appraising future efforts. According to ISO 50001:2011, an Energy Baseline (EnB) is a quantitative reference that can be used to compare Energy Performance Indicator (EnPI) values over time and to quantify changes in the energy performance (da Silva Gonçalves and dos Santos 2019). Figure 2.2 shows a comparison between the baseline period and the reporting period, revealing improved performance over time relative to the baseline consumption. Determination of baseline consumption can be achieved through artificial neural networks and one can recreate the post-retrofit energy consumption and production of the system in case it would be operating in its past configuration that before energy-saving measures (Rossi and Velázquez 2015).

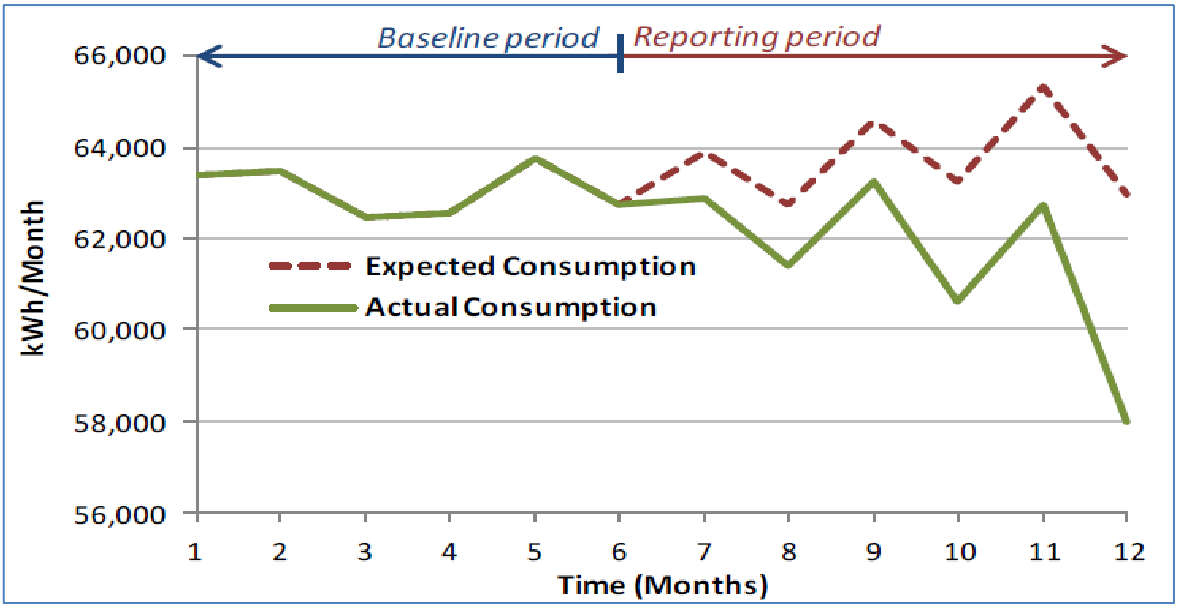

Figure 2.2: Improved performance over time relative to baseline

Source: ENS (2013)

Many industrial facilities face challenges concerning the development of methodologies for establishing and documenting energy baselines for energy performance improvements (ENS 2013). The process encompasses defining system boundaries, identifying energy sources, defining baseline timeframe, relevant variable definition, followed by determination and calculation of energy performance indicators, and finally addressing baseline adjustments. The International Performance Measurement and Verification Protocol (IPMVP) is an international reference for measurement and verification (M&V) of energy savings from energy efficiency projects and energy cost reduction highlights the determination of baseline consumption as a crucial factor measurement and verification of savings (EVO 2012).

Rossi *et al.* (2014) used Artificial Neural Networks (ANN) modelling and thermodynamic simulation to determine the baseline of energy consumption and production in a plant. ANN modelling showed high accuracy and robustness in the results, although it was vulnerable to fluctuations in operating parameters beyond the range for which the model was trained. The thermodynamic simulator is not conditioned by the richness of historical data available, since it is not based on statistics, and in circumstances where the acquisition of reliable measurements is a problem, thermodynamic modelling becomes more useful. It was capable of predicting the behaviour and performance of the plant with a satisfactory level of accuracy although it was more susceptible to measurement errors.

2.4.2 Energy Performance Indicators

Energy Performance Indicators (EnPIs) are used to quantify the energy performance of the whole business or its various parts, and thus would be a measure of energy intensity used to gauge the effectiveness of energy management efforts (da Silva Gonçalves and dos Santos 2019). The basic types of EnPIs include measured energy value, ratio, and Cumulative Sum (CUSUM). A typical example of measured energy value is annualised consumption, and typical problems that characterise the EnPI include misleading results, non-capture of relevant variables and does not measure energy efficiency. A typical example of ratio EnPI is kWh per unit which is generally characterised by misleading results and does not account for baseload and non-linear effects (Valencia-Ochoa *et al.* 2017).

Specific energy consumption (SEC) is also another ratio EnPI in energy consumption benchmarking, and it is an indicator of the amount of primary energy consumed by a process to produce one physical unit of product. Equations can be used for comparing furnaces of different designs and fuel types objectively, and to emphasise the need for energy optimisation, Blake and Beck (2004b) presented a set of equations that describe the energy efficiency of a galvanising furnace. These equations can be used to describe furnace efficiency and comparing different furnace designs and fuel types objectively. The reliance on production rates to analyse furnace energy consumption would be eliminated and burner manufacture and set-up would be easier, and also reduce the energy consumption of the furnace.

2.4.3 Specific Energy Consumption

Several studies have embraced specific energy consumption as an indicator for improvement in energy efficiency in facilities. Close monitoring of the SEC value in production processes is significant given the intense global market competition and increasing environmental concerns surrounding the manufacturing sector. There has been a growing interest in conducting an in-depth analysis of the pros and cons of using SEC, given the increasing importance of monitoring improved industrial energy efficiency and the rising popularity of SEC as a key performance indicator for energy monitoring (Lawrence *et al.* 2019). The use of SEC is simple and is one of the basic approaches for calculating energy usage per unit of a product. The average energy consumed, the quantity of energy-consuming devices, and the quantity produced during the period of interest are used for the calculation of SEC (Palamutçu 2015).

ISO 50006:2017 makes provision for establishing energy baselines and energy performance indicators cover the process of measuring energy performance and determining whether the energy performance meets the targets set by the organisation (ISO 2017). ISO 50006:2017 states energy performance as the measurable results that are related to energy efficiency or energy use, of which the results can be expressed as SEC such as kWh per unit. In circumstances where several forms of energy are used, a conversion can be done to a common unit of measure, and that should be performed in such a manner that it embraces the total energy used as well as energy losses. Deng *et al.* (2017) developed an optimisation model that optimised the process parameters, specific energy consumption and minimum processing time under the actual constraint conditions of a manufacturing process to reduce the energy consumption of a machine tool.

2.4.4 Regression Analysis

Regression analysis is a statistical approach for estimating the relationships between variables or the extent to which one dependent variable relates to one or more independent variables (Therkelsen *et al.* 2016). Regression models have proved to be reliable in situations where the input data embraces the full annual variation in operating conditions and is generally employed for deriving energy savings estimates through the measurement and verification of energy efficiency projects. Regression modelling on energy consumption uses the relevant variables and baseload and it can be more complex if the scenario is non-linear, may clouded by uncertainty if multiple relevant drivers are considered, and would require some adjustments if there is a change in operational conditions (Amber *et al.* 2017).

In order to estimate a single regression model with more than one outcome variable, a multivariate regression technique can be used. An R^2 of 0.75 indicates a reasonable correlation between energy consumption and dependent variable, 0.9 or above is very good, while an R^2 much below 0.7 or so is likely an indication of poor control or room for improvement of the analysis research approach (Moletsane *et al.* 2018).

2.4.5 Engineering Energy Simulation and Modelling

The engineering analysis of a system's inputs and outputs can reveal the relevant variables that would influence energy consumption through visual assessment of a process, using more advanced approaches such as energy mapping or deliberating flows with operations team members to identify possible energy influences (ENS 2013). Energy simulation tool, eQUEST is commonly used for simulating energy consumption for facilities and subsequently verifying the results with actual electricity consumption data. The crucial input data for such software would include building footprint, climate data, occupancy and heat load (equipment, people and lighting), space allocation (zoning), material properties for doors and windows, design of HVAC system, indoor temperature and operating schedule.

Building footprint can be composed of original Computer-Aided Design drawings of architectural and HVAC designs while occupancy schedule can be investigated through a paper survey (Kuo *et al.* 2017). However, the present study focuses on simulating the scheduling process to derive energy savings from a hot-dip galvanising process.

2.4.6 Energy Consumption Benchmarking

Energy consumption benchmarking is a process by which one collects and analyses energy performance data of comparable activities to evaluate and compare performance between or within entities (Saygin *et al.* 2011). Saygin *et al.* (2011) posited that improved energy efficiency is one of the key measures that is used to abate CO_2 emissions in the industry. Energy benchmark curves were plotted for individual plants to offer a basis for estimating sectoral energy efficiency improvement potentials compared to current global best practice technology. Best practice technology data was compared with current energy use to estimate the energy efficiency improvement potentials. The results demonstrated that best practice technology offers improvement potentials worldwide.

Energy consumption benchmarking is an energy consumption indicator as a function of the raw materials, process and product output (Worrell and Price 2006). It can be used for comparison of the energy performance of several plants within the same industry, to compare the dynamics in the energy performance of one plant at different periods, with the view to improve energy performance (Ke *et al.* 2013).

Energy consumption benchmarking can also be useful for estimating the energy-efficiency improvement potentials within a particular sector whereby the results are compared against best practice technology currently in operation (Saygin *et al.* 2011). It increases general awareness of energy efficiency among facility owners and occupiers which in turn may influence a behaviour change provides objective, reliable information on energy use and the benefits of improvements. Energy consumption benchmarking can be focused on poorly performing facilities and necessitates the identification of best practices that can be replicated within a facility or across facilities. Within a particular sector, the results of energy consumption benchmarking can be compared against best practice technology currently in operation and it can be quite handy for estimating the energy-efficiency improvement potentials. According to Phuong (2010), energy consumption varies with different raw steel materials and each item has its product and process parameter which determines how much energy is consumed.

One of the key performance metrics in energy consumption benchmarking is specific energy consumption (SEC) which is an indicator of the amount of primary energy consumed by a process to produce one physical unit of product (Laurijssen, Faaij and Worrell 2013). To emphasise the need for energy optimisation, Blake and Beck (2004b) presented a set of equations that describe the energy efficiency of a galvanising furnace and can be used for comparing furnaces of different designs and fuel types in a completely objective fashion. Cook (2005) elaborated that future furnace furnaces will have to operate using less energy and have higher production capabilities to be competitive. Ben-Nasr *et al.* (2008) optimised the hot-dip galvanising process of reactive steels by minimising zinc consumption without alloy additions.

The essence of lean manufacturing principles is to diminish waste that exists in many forms including setups and energy consumption. A lean system may be realised by processing jobs in batches. Mouzon, Yildirim and Twomey (2007) proposed a method for reducing the energy consumption by deploying a batch dispatching rule there should be a sizeable batch size in the queue before machine processing commences, and that particular machine processes all jobs until the queue is empty. The machine will then be switched off so as derive substantial energy savings if there is abundant time pending the arrival of the next batch of jobs.

Mouzon and Yildirim (2008) further posited that considerations should be taken to minimise energy consumption while concurrently optimising scheduling decisions to reduce the carbon footprint of industrial processes. They proposed a framework that minimises total energy consumption and total tardiness to solve a multi-objective optimisation problem. They deployed a greedy randomised multi-objective adaptive search metaheuristic to attain a fairly accurate Pareto front since the total tardiness problem with release dates is a Non-deterministic Polynomial-time hard (NP-hard) problem. Illustrating the proposed framework in a case study, they achieved a wide variety of dispersed solutions and demonstrated that total energy consumption decreases as total tardiness decreases.

He *et al.* (2012) also indicated that machine tools consume a huge amount of energy and consideration and characterisation of task-oriented energy consumption is ominously crucial for the exploration of potential energy-saving initiatives. He *et al.* (2012) proposed a model for task-oriented energy consumption for machining systems, taking into consideration that energy consumption is a function of flexibility and variability of task flow and would thus dynamically depend on these parameters in production processes. An event graph methodology solved in Simulink simulation environment was used to model the energy consumption driven by tasks, basing on the task-oriented energy consumption characteristics. The results gave insight on energy consumption in a machining system, which necessitated robust decision making for enhancing energy efficiency.

The literature on energy consumption benchmarking has shown that the quality of data used for benchmarking should be good and more data yields better results. It was also noted that energy benchmarking could become a key tool to estimate energy saving potentials and energy indicators could function as strong complementary methodology.

2.5 Scheduling Algorithms for Energy Optimisation

This section focuses on the literature survey regarding the fourth research objective, which is to develop an optimal scheduling algorithm for energy optimisation of the galvanising process. Arbiza *et al.* (2008) scheduled batch processes using mathematical framework aimed at improving the makespan, financial and environmental performance. The study adopted an advanced planning and scheduling tool, which includes a temporisation algorithm, an environmental evaluation module based on life cycle assessment, and a financial module, coupled with multi-objective genetic algorithms. The methodology enabled the computation of a set of non-dominated solutions in terms of some predefined criteria and the decision-makers can select a solution that would trade-off between the different objectives could use the set of solutions that were derived.

Scheduling is about assigning products and processes to available production equipment. Time is key in scheduling since the decision has to be made at what time the product is processed. Sequencing also complements scheduling since it leads to optimisation where a decision on the order to be taken is made, based on the algorithm designed for the optimisation considering various constraints such as cost, energy consumption, and other parameters. Mcmullen, Tarasewich and Frazier (2000) presented a research approach to solve the Just-in-Time (JIT) sequencing combinatorial problem for multiple product scenarios when set-ups between products are required. Until around the year 2010 to 2011, inadequate research had focused on production scheduling as an energy-saving initiative. Martínez-de-Pisón *et al.* (2006) modelled a process for optimising the annealing cycle on a hot-dip galvanising process, based on a combination of the techniques of artificial intelligence and genetic algorithms.

Verdejo, Alarcó and Sorlí (2009) solved a production sequencing problem of continuous galvanising using an algorithm based on the Tabu Search, primarily through grouping and sequencing. They successively divided an unfinished cold coils pool into groups of coils (production campaigns) mainly according to their due dates and their required galvanising types within stated campaign sizes. The continuous galvanising line would process the coils of a production campaign continuously one after another with each new campaign requiring major set-up changes of the line. The sequence in which the coils were to be processed was then determined after ascertaining the coil composition of a campaign and this phase is a complex exercise taking consideration of a myriad of constraints.

Weinert, Chiotellis and Seliger (2011) posited that scheduling would influence the energy consumption behaviour of the whole system, and by integrating energy efficiency criteria into scheduling, a reduction of energy costs is to be expected. A requirement for the integration of energy efficiency benchmarks in planning undertakings is a comprehensive prediction of the energy consumption which should be executed at the machine level.

Ben-Nasr *et al.* (2012) demonstrated that there is a serious opportunity to optimise the galvanising process at a minimum thickness, playing on the physical parameters such as bath temperature, immersion time, withdrawal speed and silver addition. In their article, Zhou *et al.* (2013) modelled the performance of inductors attached to a galvanising bath where the zinc flow and temperature distribution in the inductors of a galvanising bath were simulated numerically. However, less research has been conducted to enhance the performance of the galvanising processes in terms of energy optimisation through sequencing or scheduling algorithms, thus this research seeks to add that niche to the body of knowledge.

Liu *et al.* (2014) applied Non-dominant Sorting Genetic Algorithm (NDSGA) to develop a model to minimise total non-processing electricity and consumption as well as the total weighted tardiness for a job shop scheduling problem. NDSGA performance was then tested on an extended version of Fisher and Thompson job shop which integrated the electrical consumption profiles for the equipment. The result demonstrated that the total non-processing electrical energy consumption in the job shop was decreasing considerably, however at the detriment of its performance on the total weighted tardiness objective up to a certain level. On the other hand, Fernandez *et al.* (2014) utilised ant colony optimisation to schedule a galvanising process. Given a combinatorial NP-hard problem, it was critical to develop an intelligent algorithm for scheduling able to optimisation by translating the scheduling rules and prevailing operational criteria into technical constraints and cost functions, which guaranteed a satisfactory solution within a reasonably short computation time.

Giret, Trentesaux and Prabhu (2015) analysed the flow shop scheduling with machines arranged in series and jobs processed in the same order. A novel Bat heuristic for achieving minimal makespan by reaching the lower bound through a reverse engineering method was proposed for the flow shop problems. The heuristic was applied with the Genetic Algorithm (GA) in a MATLAB environment. The results were compared with traditional heuristics and it was found that the GA applied Bat heuristic yielded better results. However, multi-objective studies for more complex scheduling problems with additional features such as parallel machines and setup time are uncommon and new algorithms for such problems are desirable in practice (Parveen and Ullah 2010).

Multi-objective flow shop scheduling with sequence-dependent setup time can be regarded as NP-hard since it is characterised by greater complexity toward optimality in a reasonable time. Mohammadi (2015) discussed the application of the Robust Genetic Algorithm to solve a flow-shop scheduling problem. Garen (2002) presented a multi-objective GA for job-shop scheduling with a novel representation that enabled the use of simple recombination operators and the simulation results demonstrated that the proposed approach was able to generate a set of solutions close to the Pareto-optimal front. Madivada and Rao (2012) had also earlier proposed a new meta-heuristic solution approach for multi-objective job shop scheduling problems. The concept of fuzzy dominance was employed for performance evaluation of solutions in a multi-objective scenario and the results obtained from the study demonstrated that the proposed algorithm can be used as a new alternative technique for scheduling complex multi-objective job shop problems.

Zhang *et al.* (2015) designed and applied a self-adaptive differential evolution (DE) algorithm to solve production scheduling concerned with energy consumption optimisation for the process industry by introducing a self-adaptive parameter mechanism into the basic DE algorithm. The simulation results from the algorithm demonstrated that the designed self-adaptive DE algorithm had gains of reduced solution time and faster operation, coupled with reduced energy consumption.

Zlobinsky and Cheng (2018) investigated the performance of the Simulated Annealing (SA) with Metropolis-Hastings algorithm combining it with other sampling methods to solve a single machine weighted earliness and tardiness scheduling problem. The search space of possible feasible schedules was divided into several sections for initialisation to obtain characteristics of a likelihood function over the sections such that a section with a high likelihood of containing the optimal schedule was chosen for the second step. SA was then run on the pruned search space to find an optimal schedule with a better performance of about 4.5 times reduction in the run time of the algorithm in less than 1000 iterations.

2.6 Measurement and Verification

Many approaches have been developed by different organizations to determine savings and some of these approaches are described by the International Performance Measurement and Verification Protocol (IPMVP) (Organisation 2012). When considering projects aimed at improving energy efficiency and reducing energy costs, international organisations and governments are considering IPMVP as the international reference text on measurement and verification (M&V) of energy savings. The protocol highlights the criticality of the selection of the method that aims to solve the problem of determining the baseline consumption, as a key factor during the planning phase of a program that embraces M&V of savings (Rossi *et al.* 2014). It is worth mentioning that South Africa has also adapted the IPMVP for the Energy Efficiency and Demand-Side Management, and is referred to as the SA M&V guideline. There is a need to formalise the energy baseline development process and the most easily applicable approach for determining the baseline consumption is the engineering method, based on the use of standard formulae and assumptions for calculating the energy use before energy retrofit initiatives (Trianni *et al.* 2019).

2.7 Work Measurement

Work measurement can be described as the application of methods that are designed to establish the duration of specified manufacturing tasks when executed by an average worker at a defined level of performance (Sookdeo 2019). It is applied to ensure improvements in productivity and quality and Sookdeo (2019) demonstrated the necessity for a performance measurement system to ensure that operations and employees are managed, and performance is measured. The results indicated that organisations with no measurement systems are unable to measure their output and thus fail to improve productivity.

Work measurement can also play a vital role in the energy optimisation of a hot-dip galvanising process. There are three basic work measurement techniques used for determining the cycle time for jobs. These include direct observation methods (stop-watch time study), estimating methods, and predetermined motion time systems (synthetic). The challenges for the stopwatch time study method include the fact that it is very tedious is not applicable in non-existent work environments (Razmi and Shakhs-Niyaee 2008). On the other hand, work measurement estimating methods are not precise times while synthetic time standards are rather complicated and will require experienced time study workmanship to achieve accurate results.

Research on work measurement with a special focus on galvanising is rather scarce. This research adopted a direct observation method through a stopwatch time study, given that an accurate estimate of the duration of each step of the galvanising process is required to establish the heat loss from the process tanks. For instance, concerning the speed of withdrawal from the bath, 1 metre/minute is regarded as the best speed and 1.5 metres/minute as the maximum speed. Slow speed allows excess molten zinc to drain back into the bath and if the speed is too fast, the zinc layer in the coating is too thick (wasting zinc).

2.8 Genetic Algorithms

2.8.1 Background

Holland invented a genetic algorithm (Rumelhart *et al.* 1975), a directed random search technique that can find the global optimal solution in complex multi-dimensional search spaces (Pham and Karaboga 2012). A genetic algorithm (GA) is a search heuristic that mimics the process of natural evolution by generating useful solutions to optimisation and search problems. GAs are part of a larger class of Evolutionary Algorithms (Beck *et al.*), which are inspired by natural evolution, such as inheritance, mutation, selection, and crossover to generate solutions for optimisation problems (Deepak 2011). The genetic algorithm generates the final result of the best individual of each generation through a repetitive process of creating generations of individuals based on other individuals from previous generations (Martínez-de-Pisón *et al.* 2006). GA would be convergent as the generation index tends to infinity if the probability of containing the global optimum inside the current generation tends to one in a finite-population paradigm (Agapie and Wright 2014).

GAs are characterised by a population of strings called chromosomes, which will then encode the individuals or candidate solutions to an optimisation problem. Genetic operators are then applied to the candidate solutions of the population through a process of selecting individuals according to their level of fitness in the problem domain and breeding them together for the next generation (Tsai, Eberle and Chu 2013). Emulating from natural adaptation, populations of individuals that are better suited to their environment are evolved. Individuals are encoded as strings such that the chromosome values are uniquely mapped onto the decision variable domain with the view to assess the fitness of these individuals in the given population (Pham and Karaboga 2012).

2.8.2 Population Representation

A population is a set of potential solutions on which GAs operate through the encoding of a parameter set simultaneously. The method of representation directly influences the performance of a GA in terms of computation time and accuracy (Pham and Karaboga 2012). A single-level binary string is perceived as the most commonly used representation of chromosomes in the GA whereby each decision variable in the parameter set is encoded as a binary string and these are linked to form a chromosome. However, the standard binary representation can result in the search process being deceived or fail to effectively locate the global minimum due to large Hamming distances in the representational mapping between adjacent values (Caruana and Schaffer 1988). Adoption of logarithmic scaling in the conversion of binary-coded chromosomes to their real phenotypic values would embrace a larger search space with an identical number of bits than a linear mapping scheme, thus enabling reduction of the computational encumbrance of exploring unknown search spaces to a more workable level (Schmitendorf and Forrest 1992).

Although binary-coded GAs were widely used, researchers are in pursuit of alternative encoding strategies such as integer and real-valued representations. Bramlette (1991) argued that for some problem domains, binary representation would be unreliable since it would obscure the nature of the search. Under such circumstances, adoption of integer representation and look-up tables offers a convenient and acceptable manner of mapping from representation to problem domain (Lucasius and Kateman 1992).

Applying real-valued genes in GAs is superior in numerical function optimisation over binary encodings since efficient floating-point internal computer representations can be used directly thus using less memory. Moreover, the efficiency of the GA is enhanced since there is not essential to convert chromosomes to phenotypes before each function evaluation. There is greater liberty to implement diverse genetic operators and precision is maintained by discretisation to binary or other values (Wright 1991). If all the parameters for the system under study are real numbers, a real-coded GA would be more efficient than a binary-coded GA concerning run time, simplicity, resolution of solution space as well as efficiency of program coding. This coding employs vectors or strings of real numbers instead of chromosomes of binary-coded GA and takes reproduction, crossover, and mutation operators of real vectors (Kim *et al.* 2002).

2.8.3 Initialisation

The next step after population representation is to create an initial population and this is generally accomplished through utilising a random number generator to uniformly generate the required number of individuals and distribute them over a desired range. Bramlette (1991) developed an extended random initialisation method by which an individual with the best performance is chosen for the initial population after a quantified number of random initialisations are tested for each individual. The random number generation is the normally used method for creating an initial population in the absence of a priori information about the solution (Rahnamayan, Tizhoosh and Salama 2007). Cheng, Yang and Cao (2013) also chose random initialization of a population as the appropriate technique for combinatorial optimisation problems with discrete search space since under such circumstances, it is difficult to predict the regions where optimal solutions are likely to be derived.

On the other hand, some researchers such as Grefenstette (1987) and Whitley, Mathias and Fitzhorn (1991) seeded the initial population with some individuals which were known to be in the propinquity of the global minimum. A piece of prior knowledge about the optimisation problem is required for this approach and the GA will use less amount of time to converge to an optimal solution (Pham and Karaboga 2012).

The GA Toolbox for MATLAB (2014) supports binary, integer, and floating-point chromosome representations. Binary and integer populations may be initialised using the Toolbox function to create binary populations and a supplementary function is provided for building vectors that describe the integer representation used. Real-valued populations can also be initialised and conversion between real values and binary strings is provided through routines that support the usage of Gray codes and logarithmic scaling.

2.8.4 Objective and Fitness Function

The objective function is used to provide a measure of how individuals have performed in the problem domain. In a minimisation problem, the fit individuals will have the lowest numerical value of the associated problem objective function. This raw measure of fitness is usually only used in an intermediate stage in determining the relative performance of individuals in a GA (Hassanein, Aly and Abo-Ismail 2012). An objective function is used to evaluate the performance of the phenotypes in the problem domain. Objective function values can be scalar or, in the case of multi-objective problems can be vectorial.

Multi-objective problems are characterised by a family of equally fit solutions with different values of decision variables instead of a single unique solution and it is imperative to adopt some mechanism to ensure that the population can evolve the set of

Pareto optimal solutions (Goldberg and Richardson 1987). Multi-objective options define parameters characteristic of the multi-objective genetic algorithm and one can define a handle to the function that computes distance measure of individuals, computed in decision variable or design space (genotype) or function space (phenotype). While the solver selects individuals from higher fronts, Pareto Fraction can also be deployed to set the fraction of individuals to keep on the first Pareto front.

Another function, the fitness function, is usually exploited for transforming the objective function value into a measure of relative fitness. It acts as an interface between the GA and the optimisation problem and the quality of the proposed solution is evaluated as a function of how well the solution performs the required function and satisfying the stated constraints (Pham and Karaboga 2012). A fitness function is a performance index, used to pick the outstanding solution in the population to be parents to the offsprings which will embody the next generation and this mimics the evolutionary process of "survival of the fittest" (Hassanein, Aly and Abo-Ismail 2012).

2.8.5 Encoding

Encoding is a process of representation of individual genes through the use of bits, numbers, trees, arrays, and depending on the structure of encoding, they can be classified into one-dimensional and two-dimensional. one-dimensional encoding embodies binary, octal, hexadecimal, permutation, and value encoding while tree encoding is two-dimensional (Cheng and Gen 1997). The most common representation of chromosomes in GAs is binary encoding whereby chromosomes are represented by the binary string of zeros and ones. With octal encoding, the string of chromosomes is represented by the octal numbers, zero to seven. Hexadecimal encoding is executed by utilising the hexadecimal numbers from 0- to 9 (Sivanandam and Deepa 2008).

Concerning permutation encoding, every chromosome is a string of numbers that represent a position in a sequence whereas, with value encoding, every chromosome is a string of some values. With tree encoding, every chromosome is a tree of some objects, such as functions or commands in a programming language, and is widely applied in evolving programs or expressions for genetic programming (Rajasekaran and Pai 2011).

GAs operate on an encoding of the problem's input data and the selection of an encoding scheme is strikingly crucial for the computational performance of the algorithm, with a poor encoding yielding lengthy running searches that are characterised by unsatisfactory results (Hassanein, Aly and Abo-Ismail 2012).

2.8.6 Selection

During each successive iteration, a part of the existing population is selected to form a new generation sample pool. This is accomplished by an objective function that establishes the basis for the selection of pairs of individuals that would be bred in the problem domain (Reeves and Rowe 2013). The fitness function is utilised to assess the quality of an individual to increase the probability that the single bit can survive throughout the evolutionary process. Highly fit individuals, relative to the whole population, have a high probability of being selected for mating whereas fewer fit individuals have a correspondingly low probability of being selected (Tokhi and Azad 2008).

The Roulette Wheel mechanism is the most widely used selection technique for probabilistically selecting individuals based on some measure of their performance. Stochastic sampling with replacement (SSR) is the basic roulette wheel selection whereby the individuals are selected according to some measure of their performance and the segment size and selection probability remain the same throughout the selection phase. Stochastic sampling with partial replacement (SSPR) is an extension of SSR whereby an individual's segment is resized through reduction if it is selected. SSR gives zero bias but a potentially unlimited spread such that any individual with a segment size greater than zero would fill the next population (Man, Tang and Kwong 2012).

Instead of the single selection pointer employed in SSR, SSPR and RSSR, Stochastic Universal Sampling (SUS) uses equally spaced pointers, which are equivalent to the number of selections required. The population is shuffled randomly and a single random number is generated, and a percentage of individuals is then chosen by generating the pointers spaced, and selecting the individuals whose fitness span the positions of the pointers. SUS is a single-phase sampling algorithm with minimum spread and zero bias since an individual is thus guaranteed to be selected a minimum of times, based on their position in the population thus achieving minimum spread. (Man, Tang and Kwong 2012).

Assuming that certain individual's gene codes would generally produce better performing individuals, genetic operators manipulate the characters or genes of the chromosomes directly, with the recombination operator being employed to exchange genetic information between pairs. There are two primary methods of reproduction in GAs and these include crossover and mutation.

2.8.7 Crossover

Crossover is "a must" operator in GA, usually applied with high probability to produce new individuals that exhibit some parts of both parent's genetic material. Single-point crossover is the simplest recombination operator which creates two offspring strings from two-parent strings by replicating selected bits from each parent (Zalzala and Fleming 1997).

Concerning multi-point crossover, the crossover positions are the crossover are chosen at random on a given length of chromosome with no duplicates, and these crossover points are then sorted into ascending order. The bits between successive crossover points are then exchanged between the two parents to produce two new chromosomes. This results in a more robust search due to its disruptive nature which encourages exploration of the search space restricting early convergence to highly fit chromosomes (Rani *et al.* 2012). On the other hand, with uniform crossover, an offspring is obtained by choosing bits uniformly from a random subset from each of the two parents with a given probability and then exchanging the bits uniformly to other positions (Rani *et al.* 2012). Other crossover variants include heuristic, arithmetic, geometric, and scattered cross-over functions.

The simulated binary crossover (SBX) operator uses two-parent vectors and uses a blending operator on a variable to generate two offspring solutions, using a distribution index parameter that is kept fixed to a non-negative value in program execution (García-Martínez, Rodríguez and Lozano 2018). If a small value of the distribution index is chosen, offspring solutions are likely to be created further away from parents. On the other hand, if a large value of the distribution index is used, the resulting offspring solutions are closer to the parent. Thus, the distribution index parameter has a direct influence on the spread of offspring solutions. Ahmed, Mohialden and Abdulrazzaq (2018) proposed a self-adaptive procedure of updating the distribution index parameter by adopting an extension-contraction concept in a conventional genetic algorithm. If the child solution that is created is superior to the participating parent solutions, the child solution is extended further with the view to create a much better solution. Conversely, if a worse solution is created, a contraction is executed. Either task will result in an update of the distribution index, so that the newly- contracted or newly-created extended offspring solution has an identical probability of creation with an updated distribution index.

Casjens *et al.* (2015) developed a non-hierarchical evolutionary multi-objective tree learner (NHEMOtree) using a binary decision tree representation based on genetic programming to handle multi-objective optimisation problems with unbiased optimisation criteria. Multi-objective variable importance measure (VIM) was calculated for each new population and used to improve the standard crossover operator of GP. A naive VIM was used as selection frequency in tree-based multi-objective classifiers for multi-objective optimisation as the variables within the individuals are selected considering all optimisation criteria. The position of the selected variable within a tree is also valuable since variables close to the leaves are less important than variables close to the root. As the tree gets bigger, there are higher chances of overfitting, and given that scenario, the weighting of a variable's position is important. Casjens *et al.* (2015) modelled the node position using an exponential weighted relative frequency, VIM_e defined by Equation 2.9:

$$VIM_e(X\,j;t) \ = \begin{pmatrix} \sum_{n \in N_t(X_j)} \frac{1}{N_t} w(\vartheta t(v);t) \ if \ X_j \ j \in t \\ 0 \qquad\qquad\qquad\qquad if \ X_j \ \notin t \end{pmatrix} \tag{2.9}$$

where;

$N_t(X_j)$ is the set of nodes comprising variable (X_j) in tree t, N_t the number of all variables in t, and from Equation 2.10

$$w(\vartheta_t(v);t) \ = \frac{1}{2^{\vartheta_t(v)-1}} \tag{2.10}$$

where;

the weight of node v with depth $\vartheta_t(v)$; and $\vartheta_t(root)$ = 1.

The VIM_e decreased exponentially with increased tree depth. The VIM-based crossover operator aimed to generate good solutions at a faster rate by selecting the nodes for crossover basing on the VIMs of the variables in the nodes. That way, the nodes with a more important variable were more likely to be selected as crossover points. Based on their VIMs, ranks were assigned to the variables and the corresponding nodes and the selection probability $p_x \in [0;\ 1]$ for variable X_j in tree t was determined by Equation 2.11:

$$p_x\ (X_j\ ;t) \ = \frac{rank(VIM_e(X_j;t))}{\sum_{X_j \in t} rank(VIM_e(X_j\ ;t))} \tag{2.11}$$

The crossover point was selected randomly from all nodes comprising a variable, if a variable was contained in more than one node of a tree, t.

2.8.8 Mutation

A mutation is a secondary operator which assures that the chances of searching a particular subspace of the problem space are never zero by inhibiting the possibility of converging to a local optimum, rather than the global optimum. It is a low rate unary operator whereby one or more of the offspring is slightly disturbed to get a clone and this is crucial to sustaining an acceptable diversification degree in the population (Eldos 2013).

Mutation operators are usually applied with a small probability to stimulate small local disturbance of the individuals, giving more impact on individuals as opposed to crossover operators which transmit genetic information from parents to offsprings, with less impact on individuals (Barolli *et al.* 2012). Traditional GA exploits a mutation operator to stimulate a chance that a bit of a chromosome will be changed from its original state and this is characterised by randomness and adds diversity to the current generation of the population. The basic modes of mutation functions that can be exploited in GAs include constraint-dependent, Gaussian, uniform, and adaptive feasible mutation functions.

As opposed to the traditional GA, Raghava (2013) adopted an adaptive mutation where patterns among the high-performing chromosomes were detected and the current population will then be mutated according to it. The mutation probability is adaptive in the sense that mutation would only affect those chromosomes that were not performing well without affecting the high-performing chromosomes.

2.8.9 Termination of the GA

The process of recombination, mutation, decoding the individual strings, evaluation of the objective functions, and assigning fitness values to chromosomes continues through subsequent generations as shown in Figure 2.3. As a result, good individuals are preserved and mated with one another while the fewer fit individuals are deceased, leading to an increase in the average performance of individuals in a population. The GA will then be terminated after a certain number of generations, or when a particular point in the search space is encountered if some criteria are satisfied (Zalzala and Fleming 1997).

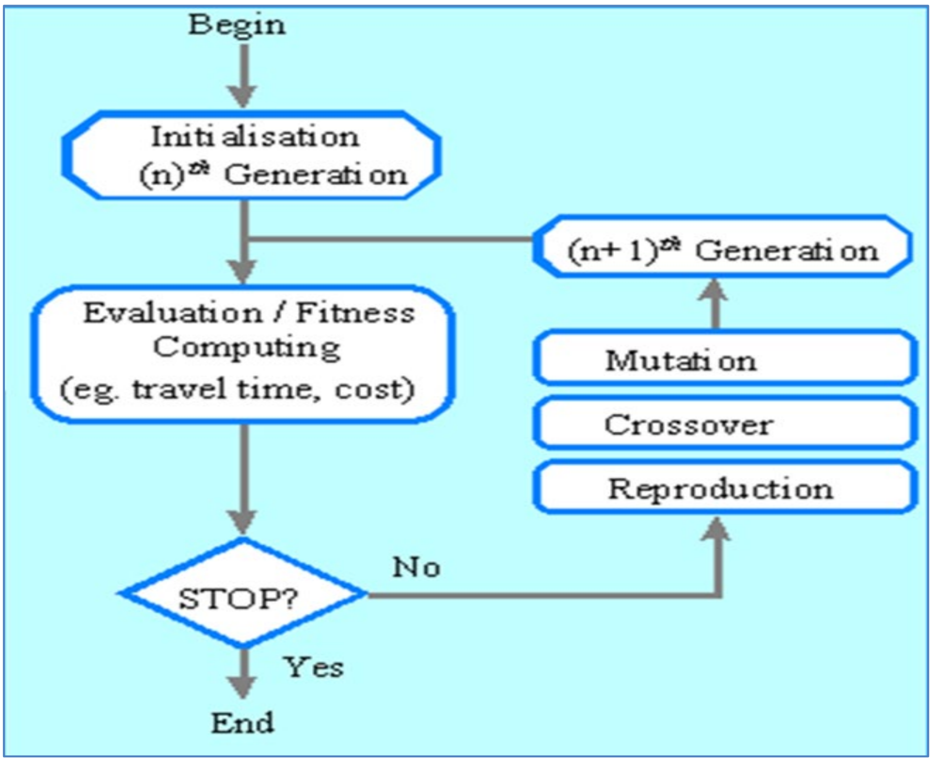

Figure 2.3: General structure of a genetic algorithm

Source: Zalzala and Fleming (1997)

Xu *et al.* (2014) also indicated the fitness limit, stall generation, and stall time limit as function-based stopping criteria, while generation number is an iteration-based stopping criterion. With fitness limit, the algorithm discontinues if the best fitness value is less than or equal to the value of the fitness limit. Stall generations termination is whereby the algorithm discontinues when the weighted average change in the fitness function value (change in the spread of the Pareto solutions) over the stall generations is less than the function tolerance. The spread is a measure of the movement of the Pareto front In this case. Stall time limit is whereby the algorithm stops if there is no improvement in the objective function during an interval of time in seconds equal to the stall time limit (Xu *et al.* 2014). A fresh search may be initiated for the GA if no acceptable solutions are found.

2.9 Comparison of Genetic Algorithms and Traditional Search

Genetic algorithms differ substantially from other traditional search and optimisation methods in the sense that a GA would search a population of points in parallel, as opposed to a single point. As opposed to deterministic methods, GAs do not require derivative information or other auxiliary knowledge but would exploit probabilistic transition rules. It would operate on an encoding of the parameter set rather than the parameter set itself (Wang 2010).

GA would deliver a substantial number of possible solutions for a cited problem and when considering scenarios that characterise multi-objective optimisation and scheduling problems where an individual problem does not have one individual solution. Under such circumstances, GA is potentially valuable for identifying these Pareto-optimal solutions simultaneously (Martinez-Falero, Martin-Fernandez and Garcia-Abri 2013).

This research adopted GA to derive a novel optimal scheduling algorithm for energy optimisation of the hot-dip galvanising process considering that the scheduling problem required a simultaneous multi-objective optimisation of energy and processing times.

2.10 Conclusion

The literature review provided a deep appreciation of the theoretical and research issues related to hot-dip galvanising, energy losses and consumption benchmarking, potential scheduling algorithms, and genetic algorithms. The literature review identified the missing gaps in research on the hot-dip galvanising process where most researchers tended to focus on gas-fired tanks and less focus on the use of electricity as the main source of heating the surface preparation and galvanising tanks. No work on standard times for the activities that characterise the galvanising process was obtained from the literature.

The review also revealed that electrically fired galvanising lines have not received a fair share of research time by most researchers globally. Although until recently, researchers have tried to pay more attention to scheduling for energy optimisation, no work to date, according to the author’s knowledge has specifically targeted the hot-dip galvanising plants, which are major consumers of electricity. Therefore, this research gives an impetus to fill this major knowledge vacuum. There was also comprehensive coverage of genetic algorithms spanning from population representation, through encoding, selection, crossover, mutation, up to the termination of the genetic algorithm. The next chapter will unveil the research approach that was employed for energy assessment to derive a novel optimal scheduling algorithm for energy optimisation of the hot-dip galvanising process.

CHAPTER 3 : METHODS AND MATERIALS

3.1 Introduction

It is vital to use a proper research approach as the path through which a researcher would need to conduct their research. The previous chapter gave a detailed literature review on hot-dip galvanising plants, energy losses in galvanising, energy performance indicators, energy consumption benchmarking, and potential optimisation algorithms for scheduling. This chapter focuses on the research methods that were adopted for the study. It commences with a research framework that is used as a guide for the focus of the study and ethical considerations in scientific research since the level of attention on ethical conduct has both amplified and widened in response to expectations for greater accountability and reduce research misconduct. The chapter then focuses on methods that were adopted to achieve the four research objectives.

3.2 Research Framework

A research framework is generally used by researchers as a guide to focus on the scope of the study (Harrison *et al.* 2017). It is an elementary structure of the ideas that serve as the basis for a phenomenon that is to be investigated, and would thus provide a structure for conceptualising and designing a research study, making it possible to make sense of data, and allows the researcher to transcend common sense (Beck *et al.* 2020).

Since sustainable scheduling is drawing more attention from many manufacturing organisations, with energy as a central concern regarding sustainability, Gahm *et al.* (2016) developed a research framework for energy-efficient scheduling. Using an iterative research approach, after reviewing, analysing, and synthesising the current state of the literature, a new research framework that embraces three dimensions, which are energy supply, energetic coverage and energy demand, was proposed. Tobi and Kampen (2018) posited that a conceptual framework is the product of the conceptual design that would comprise of the research objective (what is to be achieved by the research), the underlying theory or theories that are pivotal to the research study, the research questions (knowledge produced, and the operationalisation of concepts and constructs that will be measured during the research process.

A research framework would guide research activities through reference to formal theory, such as a conceptual framework, which is an argument that the selected concept is relevant and useful, given the lack of methodologies for establishing and documenting energy baselines for improving their energy performance for hot-dip galvanising process, which adversely impinges on tractability in the analysis of energy consumption.

The research proposes a unique DMAIC (Define – Measure – Analyse – Improve – Control) research approach for the provision of a structured and rigorous problem-solving process for improving energy efficiency in a galvanising process. Kaushik, Mittal and Rana (2016) conducted a study in energy paybacks for the manufacturing industry using the six-sigma DMAIC research approach and found that industries are currently concerned about energy consumption and the race to clean; green and less energy-consuming manufacturing is prevalent in the world.

Menghi *et al.* (2019) conducted a review of energy assessment methods and tools such as DMAIC for energy efficiency of manufacturing systems and found that assessment tools and methods are vital for energy management activities. DMAIC would enable the identification of improvement opportunities and tracking the effects of management decisions on energy use. DMAIC can help industrial organisations to cope with the knowledge and organizational barriers of implementing energy reduction measures, with monitoring and analysis of the energy consumption representing the vital initial step towards increasing energy efficiency (Jamil *et al.* 2020). Guided by the DMAIC research approach, as shown in Figure 3.1, the research framework encompasses the underlying factors that determine the development of an optimal scheduling algorithm for energy optimisation of the galvanising process.

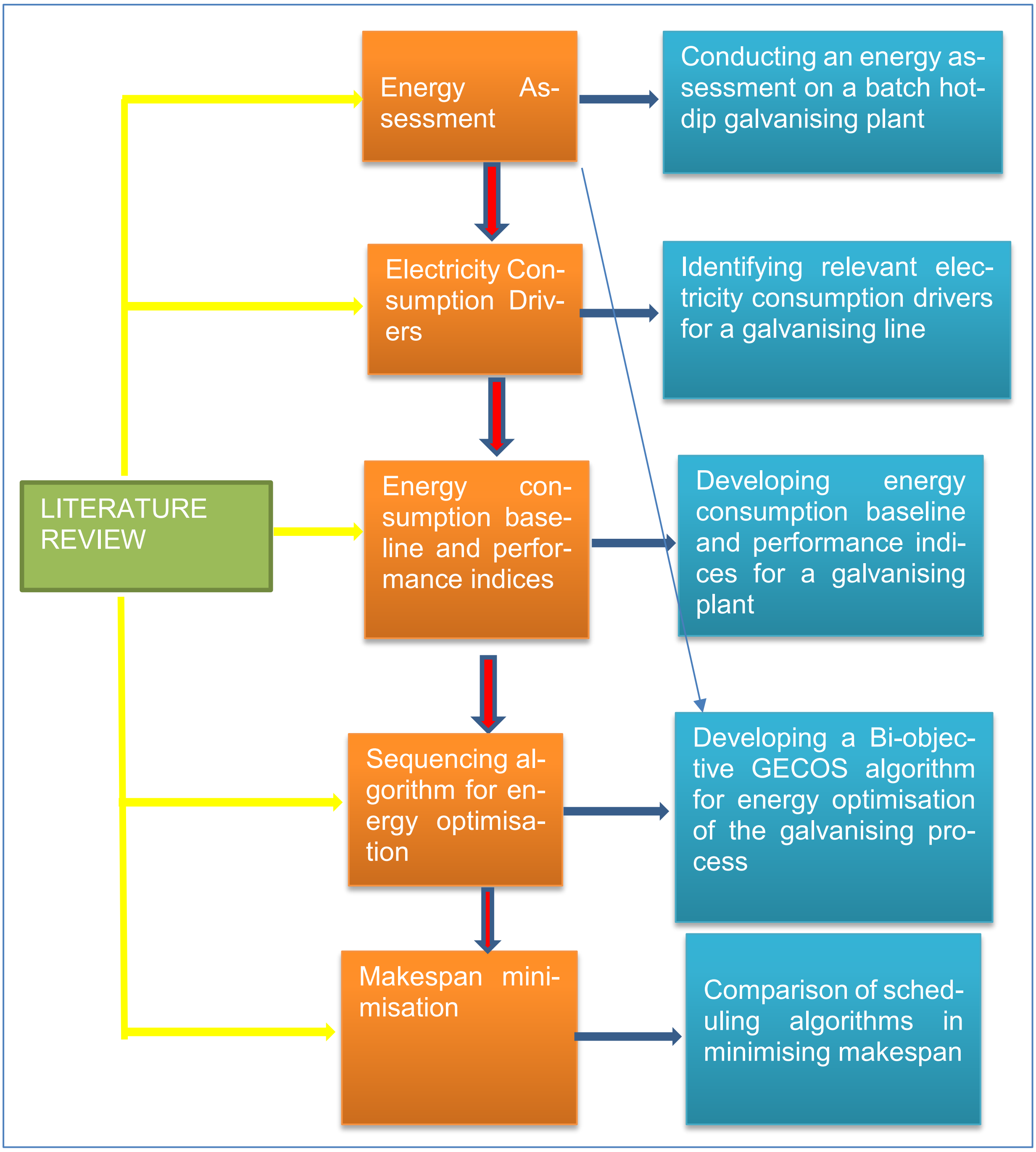

Figure 3.1: Schematic for a research framework

The research framework embraces an energy assessment for batch hot-dip galvanising plants; identification of the relevant electricity consumption drivers for a galvanising process; and energy consumption baseline and performance indices for a galvanising plant. After conducting a comprehensive literature review, prior to the detailed study, a detailed questionnaire on energy management was developed to elicit information from management at the case-in-point galvanising plants.

The definition of the problem (D - in the DMAIC) for the cited galvanising sector was that it was devoid of methodologies for establishing and documenting energy baselines for improving their energy performance for the hot-dip galvanising process. The crux of the research work was the collection and analysis of relevant electricity consumption data, that is measurement and analysis, according to the DMAIC approach. In this case, Measurements (M) were done to identify the relevant electricity consumption drivers for a galvanising process, while Analysis (A) was accomplished to develop energy consumption baseline and performance indices for specified galvanising plants.

The root causes of excessive consumption of electricity during the galvanising process were identified in the analysis phase, after which it was proposed to Improve (I) the process by developing a bi-objective GECOS algorithm for energy optimisation of the galvanising process. As a means of Control (C), four approaches that include McNaughton's algorithm, GECOS algorithm, Shortest Processing Time Algorithm, and Integer Linear Programming algorithm were used for use as means of control in minimising makespan for a galvanising plant.

3.3 Ethical Considerations in Scientific Research

The level of attention on ethical conduct (the actions that are professional and personal when conducting a research activity) has both amplified and widened in response to expectations for greater accountability and reducing research misconduct by society (Fleming and Zegwaard 2018). Research misconduct can be described as any research behaviour, whether deliberate or not, that fails to conscientiously respect high ethical and scientific standards. The issues concerning research misconduct include falsification or fabrication of data, plagiarism, failure to obtain ethical approval from the Research Ethics Committee, problematic data presentation or analysis, failure to obtain the subject's informed consent, undisclosed conflict of interest, inappropriate claims of authorship and duplicate publication (National Academies of Sciences and Medicine 2017).

Since the research was conducted under the auspices of Durban University of Technology (DUT), the DUT's research ethics policy and guidelines were used to ensure that the researcher identified and acceptably addressed ethical issues. In line with DUT policy, the study was considered as Category 1, straightforward research without ethical problems to humans, animals and the environment and thus, was exempted from ethics and biosafety research committee review.

The rationale for the decision was that the research did not have any potential of harm to the participants, the wider community, the researcher and the institution. The harm would range from physical, time and other resource loss, emotional, and reputational harm. It was also vital to ensure that the identity of the four participating organisations was protected and the names of the participating individuals remained anonymous. The four participating organisations were identified as Plant 1, Plant 2, Plant 3 and Plant 4 to ensure that the identity of these organisations was protected.

The detection of plagiarism used to be a challenge in the past, however, the application of web-based software makes it is easier to detect plagiarism. Appendix 1 shows a Turnitin report for plagiarism, and the similarity index is less than 20%, which is considered to be acceptable according to DUT standards. The researcher engaged only in work that is aligned to the area of expertise and appropriate research methods, statistical methods, and sample sizes were selected to avoid misleading results. It was vital to demonstrate honesty and truthfulness to ensure research integrity. The researcher avoided fabrication of data, falsification of results, or omission of relevant data. The research findings were fully reported, underlying assumptions were disclosed and research bias was also avoided.

3.4 Methods for Objective 1

The first objective of the study was to conduct an energy assessment and evaluation of a batch hot-dip galvanising process to identify potential opportunities for the reduction and more efficient use of electrical energy. The research approach that was adopted commenced with an evaluation of an organisation in terms of its awareness of energy management and commitment to improving energy efficiency. Appendix 2 shows a questionnaire for the assessment of how the four organisations or galvanisers were managing energy for their galvanising plants. The following questions were used to elicit information from management at the case-in-point galvanising plants:

- Does the top management know that significant energy cost savings can be achieved by simple low-cost measures without necessitating financial assessment?
- Is the top management committed to energy cost reduction and is there an approved energy policy in place?
- Have roles, responsibilities and authority been identified for all persons influencing significant energy use and is this documented?
- Have significant energy uses been quantified and documented?
- Has a baseline of energy performance been established against which progress can be measured?
- Have indicator(s) or metrics been identified to use in measuring progress against your baseline?
- Have the organisation's energy objectives and targets been identified and documented?
- Have energy action plans been established?
- Is the energy management system evaluated at least once a year and are improvements made based on the results of the evaluation?

The research approach also entailed compiling a detailed electrical energy balance and identifying the most significant energy users of electricity. Average monthly production and monthly electricity consumption data were collected for the four case-in-point plants. Pareto Analysis was used to reveal that tanks highly contributed to monthly electrical energy usage for the four case plants. Pareto Analysis is a formal statistical technique in decision-making used to select a limited number of scenarios or jobs that produce a significant overall effect and is vital where many possible courses of action are competing for attention (Montgomery 2020).

An Excel-based heat loss calculator was then developed for evaluating energy-saving initiatives for the significant energy users after which recommendations were made for reducing the energy consumption of the galvanisers.

3.5 Methods for Objective 2

The first objective of the study was to identify the relevant electricity consumption drivers for a galvanising process. Figure 3.2 shows the boundaries, energy sources, and relevant variables for the ideal facility.

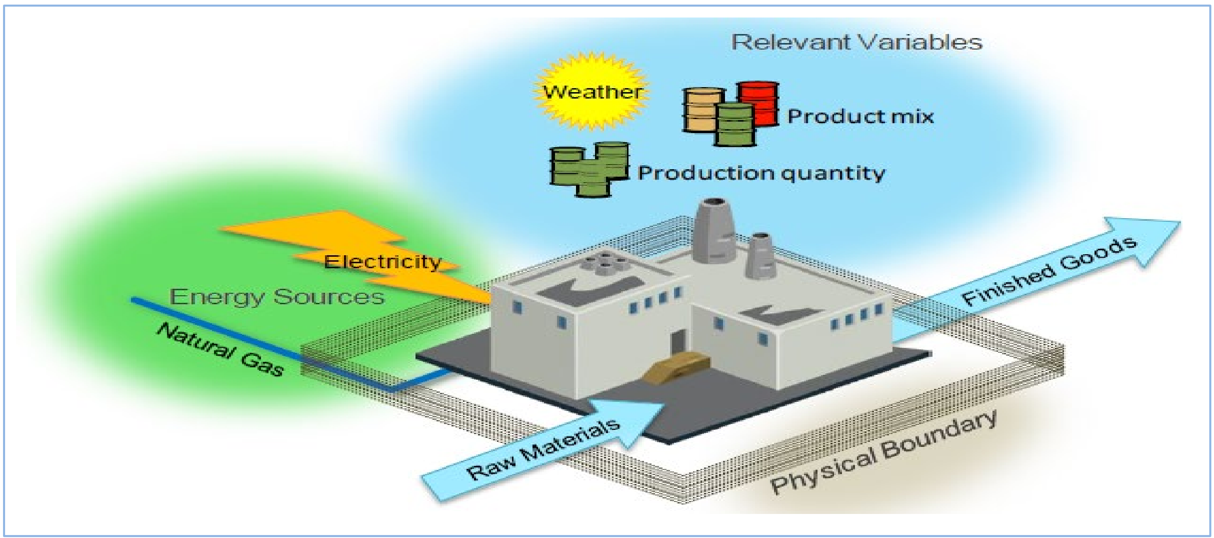

Figure 3.2: Boundaries, energy sources, and relevant variables for a facility

Source: (ENS 2013)

The research approach which was adopted to identify the relevant electricity consumption drivers entails defining the boundaries, identifying energy sources, outlining the baseline period and definition of relevant consumption drivers. The first step in the research approach was defining the boundaries. The galvaniser's energy management plan should outline the operations and facilities within the boundaries and it is crucial to note that baseline results would be undermined if the boundary conditions are not properly outlined. Physical, system-related, and organizational are the three primary boundary types that characterise many organisations. Physical is the most common boundary type which pertains to a facility fence-line or building within which the energy study is based on. System-related boundaries are whereby an organization focuses on a particular single system that constitutes a significant portion of a facility's energy consumption and the performance of that particular system is seen as a proxy for the facility's performance (Hohne, Kusakana and Numbi 2020). System-related boundaries can be required if metering or other data are limited. In this case, physical and organisational-type boundaries are the same and were used in the study.

The second step in the research approach was identifying the energy sources whereby all energy flowing across the defined boundaries were identified, categorized, measured, and collected. Energy sources vary from electricity to on-site renewable generation sources such as solar or wind, as well as from systems. In this case, electrical energy that comes from Eskom, an electric generator was used and the electricity is measured in kilowatt-hours. The process of creating an energy map of the facility that shows its boundary and the energy flows across the boundary is generally used for identifying energy sources and associated EnPIs (Lyubchikov 2016). Coal, petroleum products, natural gas, and biomass are the potential fuel sources that exist, but in this case, the focus was placed on the electricity from Eskom since it is the key energy source for the galvaniser.

The third step for identifying the relevant electricity consumption drivers addressed the measurement and collection of energy consumption data. Meters and utility billing records were used to identify the quantity of electrical energy consumed over the billing period. Knowledge of the billing period is vital for facilitating the pairing of energy consumption with other baseline calculation factors. Shorter time intervals are generally considered to be desirable since they enable better analysis and assure a reasonable degree of confidence.

The fourth step in the research approach was defining the baseline period duration and the specific historical time frame since these two factors generally affect the tracking results of performance improvement. A duration of less than one year for the EnB can be appropriate in operations where energy consumption is steady throughout the year. Short baseline durations may also be necessary for situations with insufficient reliable or available historical data, or when changes occur to the company's culture, policies, or processes. The one-year EnB duration is common since it aligns with the business's energy management objectives such as reducing energy consumption from a previous year. Availability of data can often limit the baseline period and in this case, twelve months were selected.

Three potential EnB time frames that characterize the baseline time frame include immediately preceding the prior event and fixed time frame. The immediately preceding timeframe is used by facilities already making changes that will improve energy performance since it would ease identification and quantification of improvements. Tying up the time frame of an EnB to a prior event would be appropriate for companies that are undergoing a significant change such as a facility enlargement or major acquisition. When demonstrating improvements across a group such as for multi-site corporations, industry organizations, or government programs, using a fixed reference year for the EnB time frame becomes more applicable. Given the case-in-point scenario where no major changes on the facility were implemented, the best option was the immediately preceding timeframe.

The fifth step for identifying the relevant electricity consumption drivers was the definition of the relevant variables. The relevant variables are typically quantifiable factors such as production, weather conditions, and hours of operation, which would influence a plant’s energy consumption. In this case, production data on the number of dips per month, amount of zinc used and product tonnage was collected from the case study organisations’ databases. It was envisaged that the galvaniser’s energy consumption could be influenced by temperature, of which the monthly temperature data was retrieved from an online database. Statistical analysis can be used to establish if the relevant variables would influence energy consumption. Regression analysis was used to determine the relevant variables and to validate the strength of statistical relationships between the variables. Scatter plots were also used to exhibit the relationship between electricity consumption and the relevant variables.

3.6 Methods for Objective 3

The third objective of the study was to develop energy performance indicators for a galvanising plant. The research approach embraced determining and calculating energy performance indicators. The EnPIs was crucial for providing the relevant information on energy performance that would enable the galvaniser to appreciate its energy performance and develop interventions to save energy. Using a precise EnPI is crucial for one to accurately connect operational improvements to energy performance improvements, and in this case, four EnPIs which include Actual versus expected consumption, Energy Intensity Index, CUSUM; and Specific energy consumption are adopted.

Concerning CUSUM, the baseline relationship was used to compute the expected energy consumption for a specified production level and the difference between the expected energy consumption and the actual value is critical for CUSUM analysis. The regression equation was used to compute a predicted consumption for each month by substituting the production for that month in the formula. The actual consumption was then subtracted from the predicted consumption for each month to derive the difference. The difference was then added up for all the months to derive the CUSUM.

The second step in the development process for energy performance indicators was ascertaining if there was a need for baseline adjustments. Changes are common in many organisations and these could include energy source changes, operational change, business change, energy management system change (changes to calculation research approach or improvements to data collection by an organisation). Although there was no need to address baseline adjustments, the galvaniser needed to define intervals at which it would review the key characteristics of its operations that determine energy performance, regardless of whether there were changes to the operations.

3.7 Methods for Objective 4

The results of the first, second, and third objectives were used as input to identify parameters that could be deployed to develop an optimal scheduling algorithm for energy optimisation of the galvanising process. The approach for developing a scheduling algorithm comprises optimisation problem formulation, objective and fitness function, and constraint identification, encoding, selection, crossover, mutation and termination. The GA problem was then set, a control random number generator was adopted, using strong pseudo-random number generator Mersenne Twister, and lower bound, upper bound, population size, number of iterations, distribution index for crossover, distribution index for mutation, crossover probability and mutation probability, were set. The selection of an encoding scheme is also strikingly crucial for the computational performance of the algorithm, with a poor encoding yielding lengthy running searches. The basic flow diagram of the GA is described as shown in Figure 3.3.

The first step in applying a genetic algorithm to a scheduling problem was to represent it as a chromosome. A sequence of tasks and the start times of these tasks concerning each other was defined to represent a scheduling chromosome. Each task and its respective start time would represent a gene. A single chromosome in the population is represented by a specific sequence of tasks, and start times (genes).

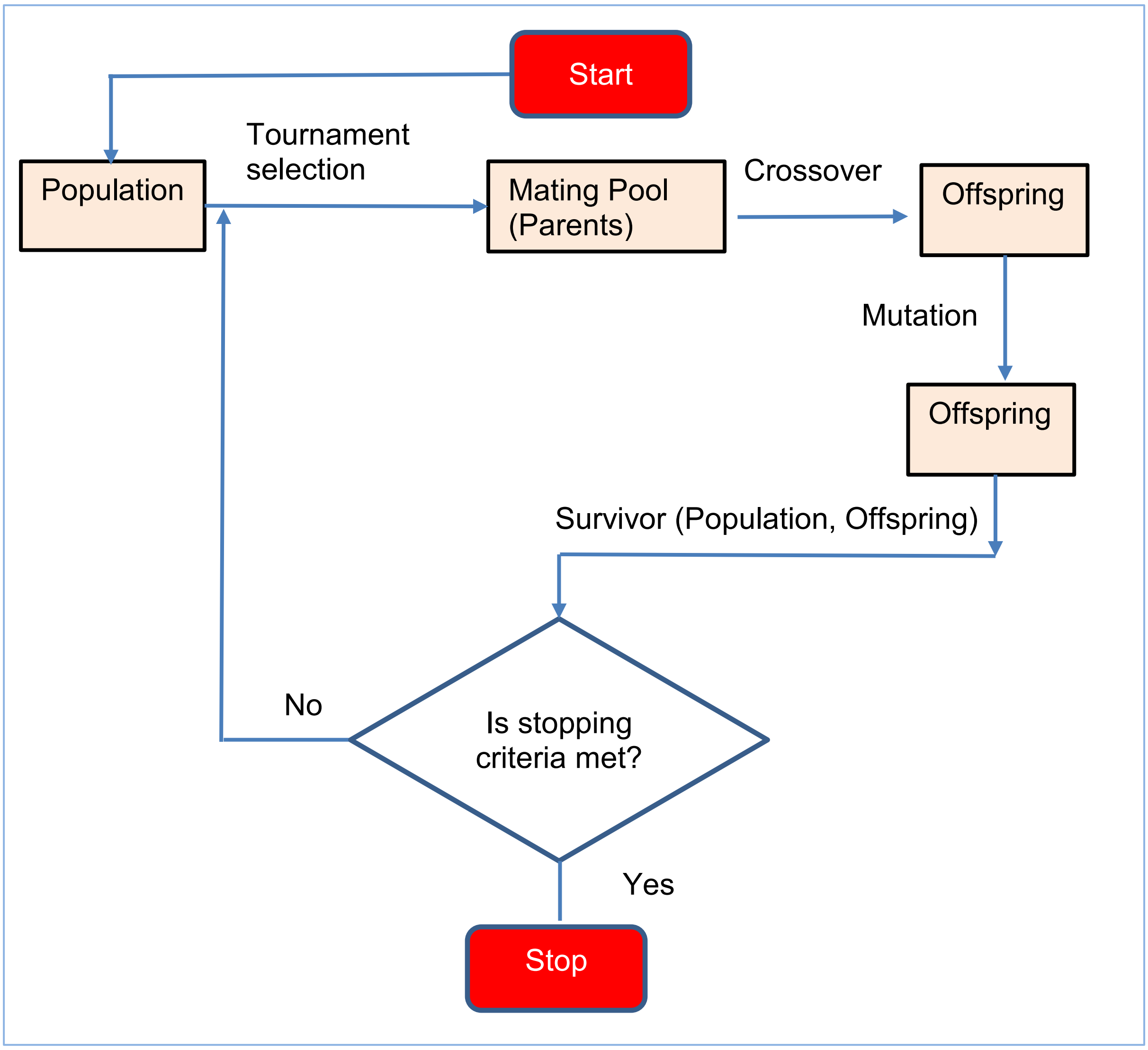

Figure 3.3: Basic flow diagram for the real-coded GA

A chromosome should obey the precedence constraints to ensure that a feasible solution is derived. An initial population was generated using random start times within the precedence constraints and the respective energy consumption values were computed.

The fitness function of optimisation in scheduling was set to minimise energy consumption and makespan for the four key energy-consuming steps which include degreasing, acid pickling, fluxing and zinc bathing. The study adopted binary tournament selection, whereby two chromosomes are considered for analysis, and according to their fitness function, the better chromosome is chosen to participate in the mating pool while the weaker one is discarded.

It was also noted that an improvement in one objective of a non-dominated solution requires a decrease in the other objective for the bi-objective optimisation problem. The following procedure was utilised to derive a set of non-dominated solutions:

Step 1: Generate random values to compute PREP, WE, PE and extract makespan values from fitness values of the Genetic Algorithm;

Step 2: Solve the bi-objective GECOS problem;

Step 3: Add the solution to the set of non-dominated solutions;

Step 4: If the stopping criterion is not satisfied, go to Step 1.

The stopping criterion was per a predetermined number of non-dominated solutions, and after the set of non-dominated solutions was derived, one would then determine the best solution or scheduling plan for implementation.

3.8 Conclusion

The research proposed a unique DMAIC research approach for the provision of a structured and rigorous problem-solving process for improving energy efficiency in a galvanising process. The research framework embraced an energy assessment for batch hot-dip galvanising plants; identification of the relevant electricity consumption drivers for a galvanising process; and energy consumption baseline and performance indices for a galvanising plant; and developing an optimal scheduling algorithm for energy optimisation of the galvanising process. The issues concerning research mis-conduct, plagiarism, ethical approval of the study, and data presentation or analysis were also cited as ethical considerations in scientific research. The research approach for the first objective of the study, which was to conduct an energy assessment and evaluation of a batch hot-dip galvanising process, was presented in this chapter. The research approach commenced with an evaluation of an organisation in terms of its awareness of energy management and commitment to improving energy efficiency. The research approach also entailed compiling a detailed electrical energy balance and identifying the most significant energy users of electricity using Pareto Analysis. A heat loss calculator was then developed for evaluating energy-saving initiatives for the significant energy users after which recommendations were made for reducing the energy consumption of the galvanisers.

The research approach for the second objective of the study, which was to identify the relevant electricity consumption drivers for a galvanising line, was presented in this chapter. The research approach which was adopted for identifying the relevant electricity consumption drivers entailed defining the boundaries, identifying energy sources, outlining the baseline period and definition of relevant consumption drivers. Multiple regression analysis was used to determine the relevant variables and to validate the strength of statistical relationships between the variables. The research approach for objective 3 embraced determining and calculating energy performance indicators. Four EnPIs that include Actual versus expected consumption, Energy Intensity Index, CUSUM and Specific energy consumption, were adopted for the study.

The study adopted a bi-objective optimisation scheduling approach which considers two criteria, that is to minimise the electrical energy consumption and makespan simultaneously. The research approach for developing the bi-objective scheduling algorithm comprises optimisation problem formulation, objective and fitness function and constraint identification, encoding, selection, crossover, mutation and termination. The first step of the research approach comprised the development of a mathematical model for energy consumption optimisation scheduling. The total energy consumption of the hot-dip galvanising process was computed through summation of energy for ready-open-close, waiting for energy consumption and processing energy consumption.

The research approach of the study adopted binary tournament selection, whereby two chromosomes are considered for analysis, and according to their fitness function. SBX operator was adopted for crossover since it can restrict offspring solutions to any arbitrary closeness to the parent solutions. The polynomial mutation was adopted since that enables thorough exploration of the design space for an optimisation problem allowing exploitation of any promising solutions. The bi-objective optimisation scheduling algorithm was simulated and the results were compared against McNaughton's algorithm, Shortest Processing Time, an Integer Linear Programming algorithm on a TORSCHE platform in terms of minimising makespan for a galvanising plant.

CHAPTER 4 : ENERGY ASSESSMENT

4.1 Introduction

The previous chapter focused on the research design and research approach that was adopted for the study, commencing with a research framework that was used as a guide for the focus of the study. Ethical considerations in scientific research and methodologies that were adopted to achieve the four research objectives were also discussed. This chapter focuses on the results on energy assessment and the results focus on the potential opportunities that would characterise a batch hot-dip galvanising process concerning the reduction of the use of electrical energy, considering the galvaniser’s energy management and consumption data. Subsequently, the study discusses the results on the relevant electricity consumption drivers for a galvanising line, considering the number of dips per day, amount of zinc used, galvanised product tonnage, and the ambient temperature conditions. Results are also discussed about energy performance indicators for a galvanising plant concerning the comparison of actual consumption and expected consumption, Energy Intensity Index, Cumulative Sum, and Specific energy consumption.

4.2 Evaluation of Electrical Energy Consumption

The first research question is concerned with identifying potential opportunities that would characterise a batch hot-dip galvanising plant concerning the reduction of the use of electrical energy. The first case-in-point galvaniser provides hot dip galvanising solutions to a wide range of products using a functional jobbing production mode. The plant has a maximum capacity of 100 tonnes per metre and the bath size for degreasing, pickling, fluxing and galvanising tanks is 14m x 1.3m x 2.5m, with cranes having a lifting weight capacity of 4 tonnes. Figure 4.1 shows the flow diagram for the hot-dip galvanising process at the galvaniser.

The final surface preparation step in the galvanising process is fluxing, where a zinc ammonium chloride solution is used to remove any remaining oxides and deposits a protective layer on the steel to prevent any further oxides from forming on the surface before immersion in the molten zinc. The dimensions of the tank are 14 m x 1.3 m x 2.5 m and this 30 000-litre tank has no insulation on the sidewalls and no covers at the top. The galvanising kettle is powered by 24 rows of chromium heating elements sectioned into 4 zones and furnace temperature is generally set at 600^{0}C.

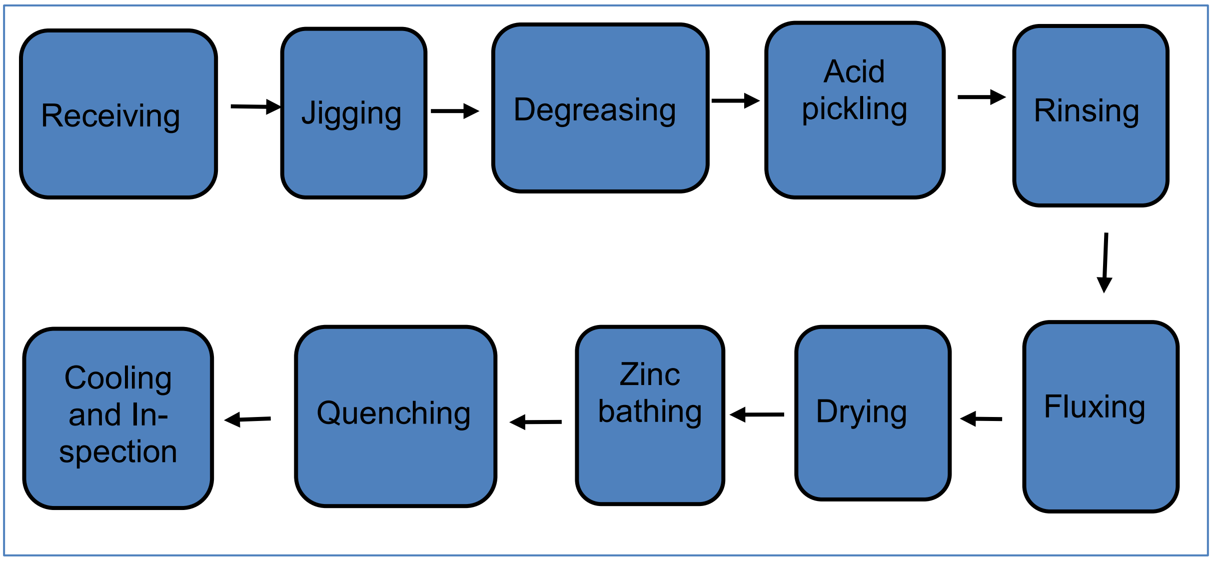

Figure 4.1: Flow diagram for hot-dip galvanising process

The second case-in-point galvaniser boasts a zinc bath that is 9.5m long, 1.3m wide and 3m deep allowing items weighing up to 5 tons to be galvanised in a single dip. The third plant has a maximum capacity of 40 tonnes per day and the bath size for degreasing, pickling, fluxing and galvanising tanks is 5 m x 1.2m x 2.5m, with cranes having a lifting weight capacity of 5 tonnes. The fourth plant is the smallest which has a maximum capacity of 40 tonnes per metre and the bath size for degreasing, pickling, fluxing and galvanising tanks is 9m x 1.2m x 3.0m, with cranes having a lifting weight capacity of 2 tonnes.

4.2.1 Assessment of Galvanisers’ Energy Management

The assessment of the galvanisers’ energy management was characterised by organisational capacity for energy management with regards to key functions which include organisational structure for energy management; policy and planning; knowledge and skills of employees; energy information management; sponsoring of energy management initiatives. At the organisational level, a commitment by the senior management of the organisation and provision of adequate resourcing including the identification of energy specialists and general employee development are crucial facets for energy management.

An initial evaluation of the four organisations' energy performance was conducted. Figure 4.2 shows the results for assessment of organization 1 in terms of its awareness of energy management and commitment to improving its energy efficiency. Although there was no energy policy in place, top management was committed to energy cost reduction. However, management was also generally unaware that significant energy cost savings could be achieved by simple low-cost measures without huge financial investment.

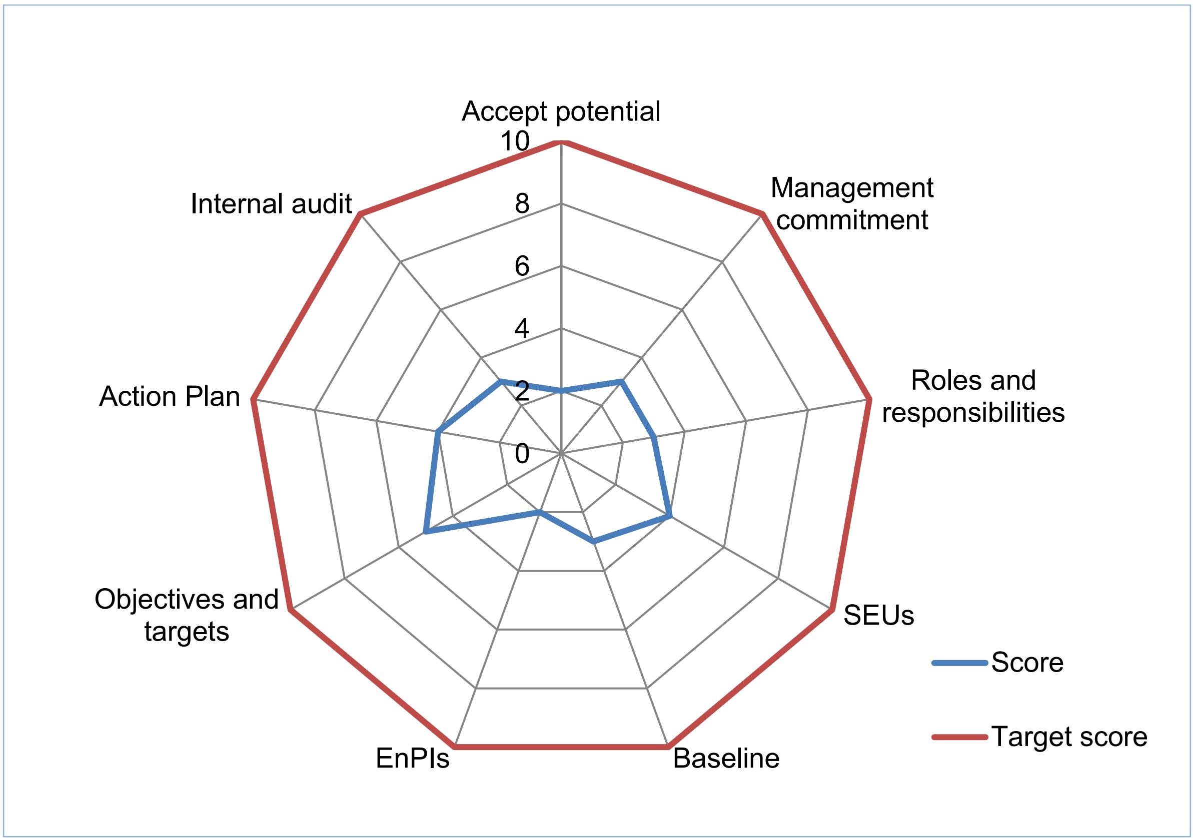

Figure 4.2: Assessment chart for management commitment for plant 1

There was no documentation of the roles, responsibilities and authority for all persons who could influence significant energy users (SEUs) and the significant energy uses have not been quantified and documented. No baselines of energy performance indicators (EnPIs) had been established against which progress can be measured and there were no metrics for measuring progress against baselines. The organisation's energy objectives and targets were neither identified nor documented and there were no energy action plans.

As opposed to organisation 1, as shown in Figure 4.3, the plant for the second organisation exhibited that there was some management commitment, documentation of the roles, and the organisation's energy objectives and targets were identified and documented. However, there were no concrete energy action plans responsibility and authority for all persons who could influence SEUs and the significant energy uses were not adequately been quantified and documented. No proper baselines of EnPIs had been established against which progress can be measured and there were no metrics for measuring progress against baselines.

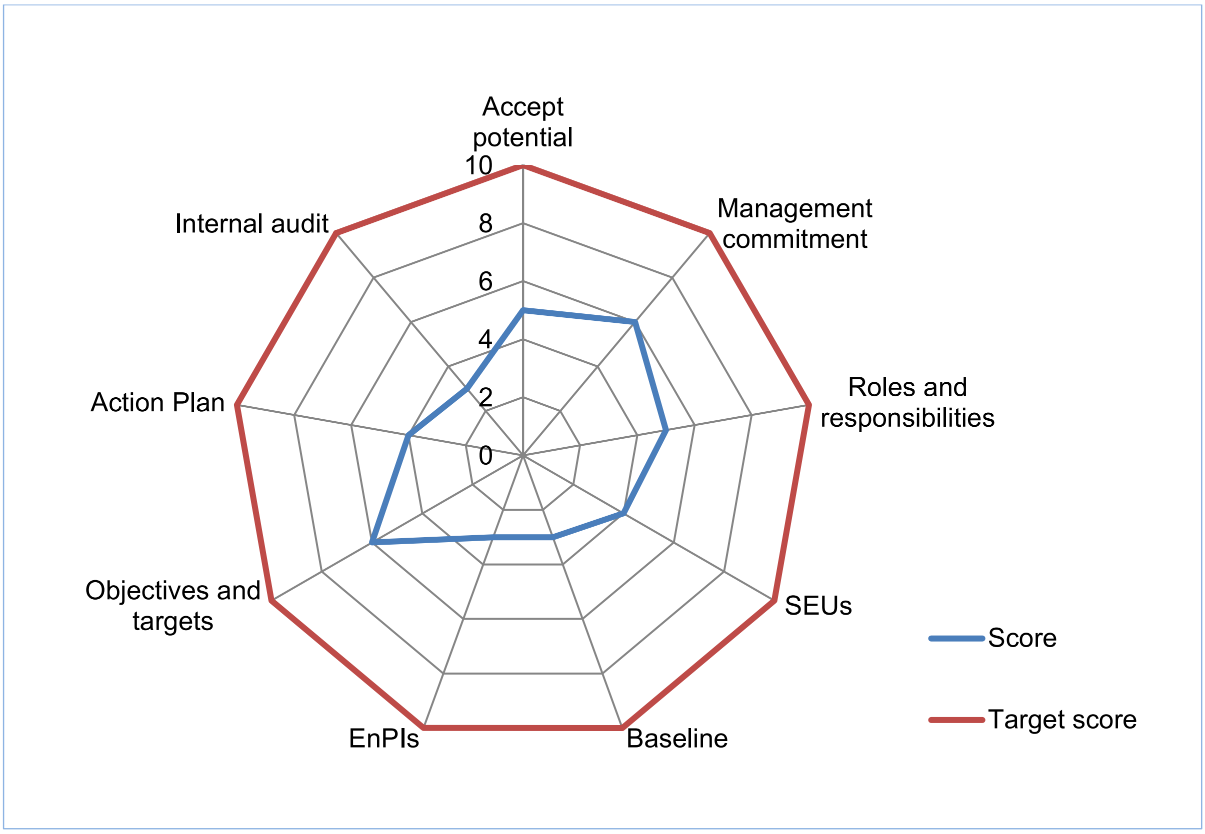

Figure 4.3: Assessment chart for management commitment for plant 2

As opposed to plant 1 and 2 for organisations 1 and 2, Figure 4.4 shows an assessment chart for plant 3 that is characterised by a very low top management commitment and a high operational management commitment. This was due to the involvement of low-level management in training sessions offered by external stakeholders, which did not involve top management. This led to different management levels operating in functional silos, resulting in a lack of buy-in from top management on issues concerning the energy efficiency of galvanising plants.

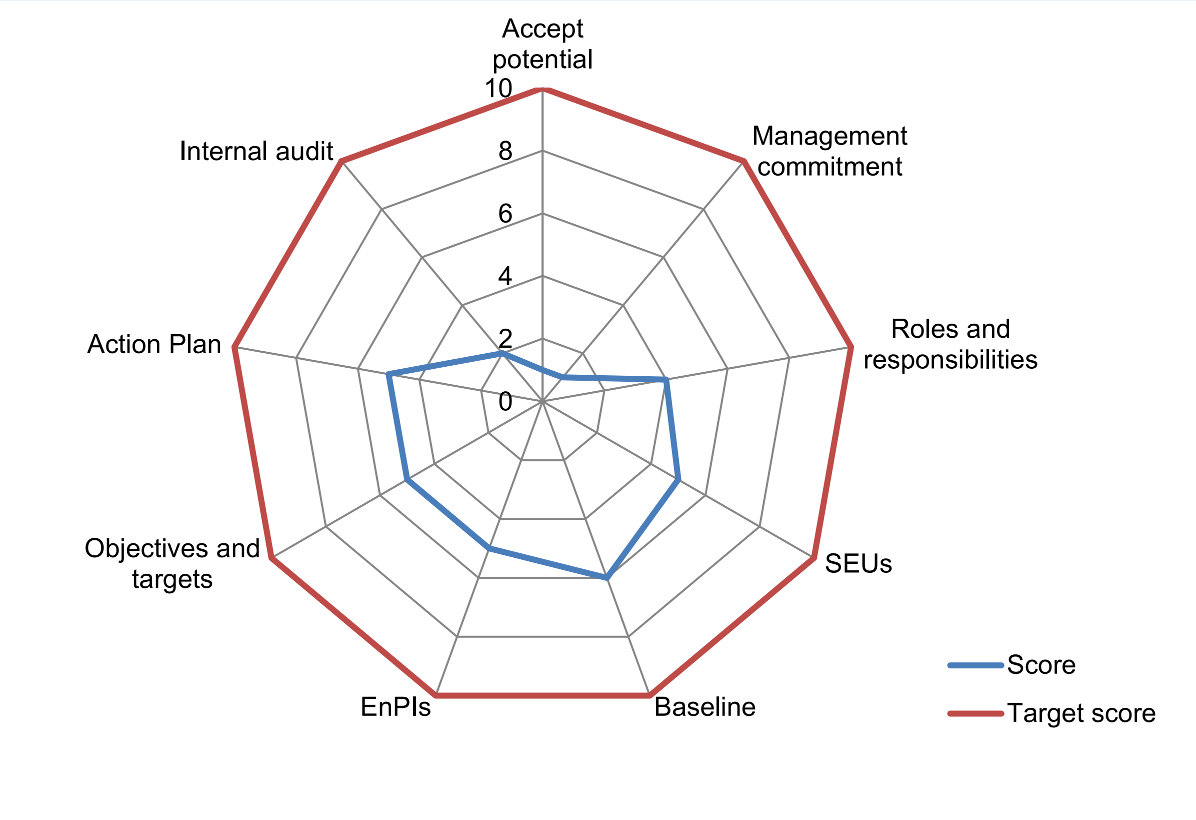

Figure 4.4: Assessment chart for management commitment for plant 3

Figure 4.5 shows an assessment chart for management commitment for plant 4, which is characterised by a very low top management commitment and a very operational management commitment. This was due to the non-involvement of both low-level management and top management in training sessions that could be offered by external stakeholders.

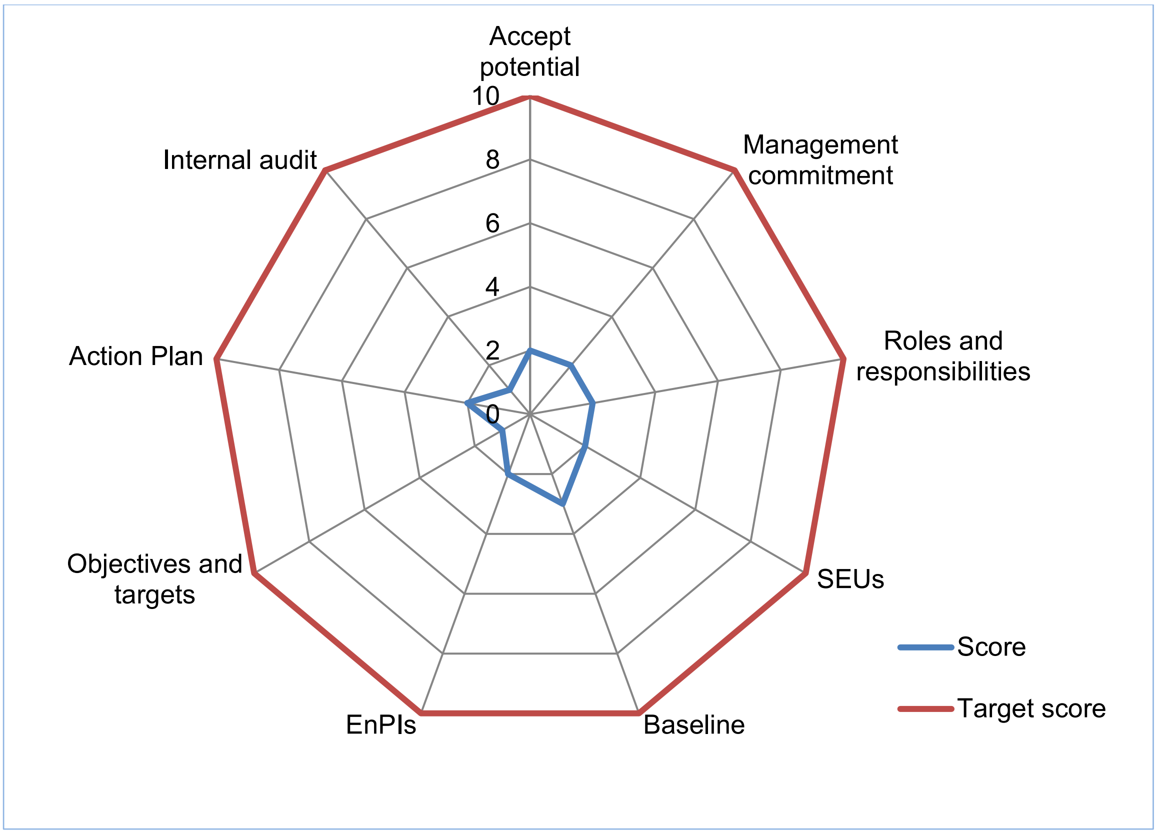

Figure 4.5: Assessment chart for management commitment for plant 4

4.2.2 Assessment of Consumption Data

Appendix 3 shows a sample of the first galvaniser's monthly production data, an average of 33 tonnes of metal was galvanised per day from an average of 45 dips. Total monthly tonnage sat at around 627 921 tonnes of steel material using about 49 757 tonnes of zinc. Average monthly electricity consumption sat at 270 779 kWh and charged at an average rate of R1.49/kWh but higher figures were noted for June (R3.00/kWh), July (R2.95/kWh) and August (R2.95/kWh). The average rate of R1.49/kWh was computed as a mean of the energy standard, energy peak, and energy off-peak as derived from the municipality's monthly bills.

Active energy data for standard usage time, peak usage time and off-peak time is shown in Figure 4.6. The galvaniser utilised a high percentage of both standard time and off-peak times and lower amounts of peak time. It was noted that plant loading during peak periods was lower than for off-peak periods, sitting at around 50 000 kWh per month. A key recommendation would be to further schedule as much production as is feasible during off-peak times or standard times as energy usage for peak times is billed at a rate of almost double that of off-peak time usage.

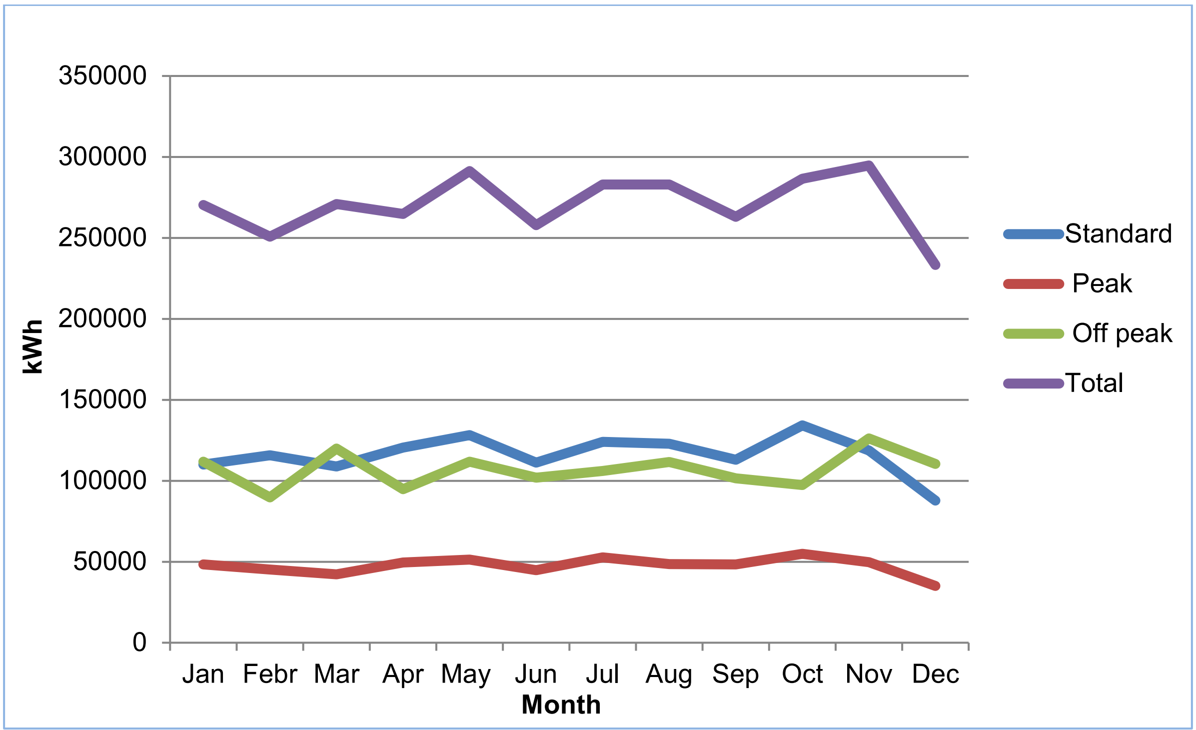

Figure 4.6: Electricity consumption profile

Peak, off-peak and standard energy usage were fairly constant over the year, albeit that a few peaks could be noted as production and factory usage fluctuated in some months. As shown in Figure 4.7, it was also noted that the notified maximum demand is far greater than the average monthly network demand consumption by the company.

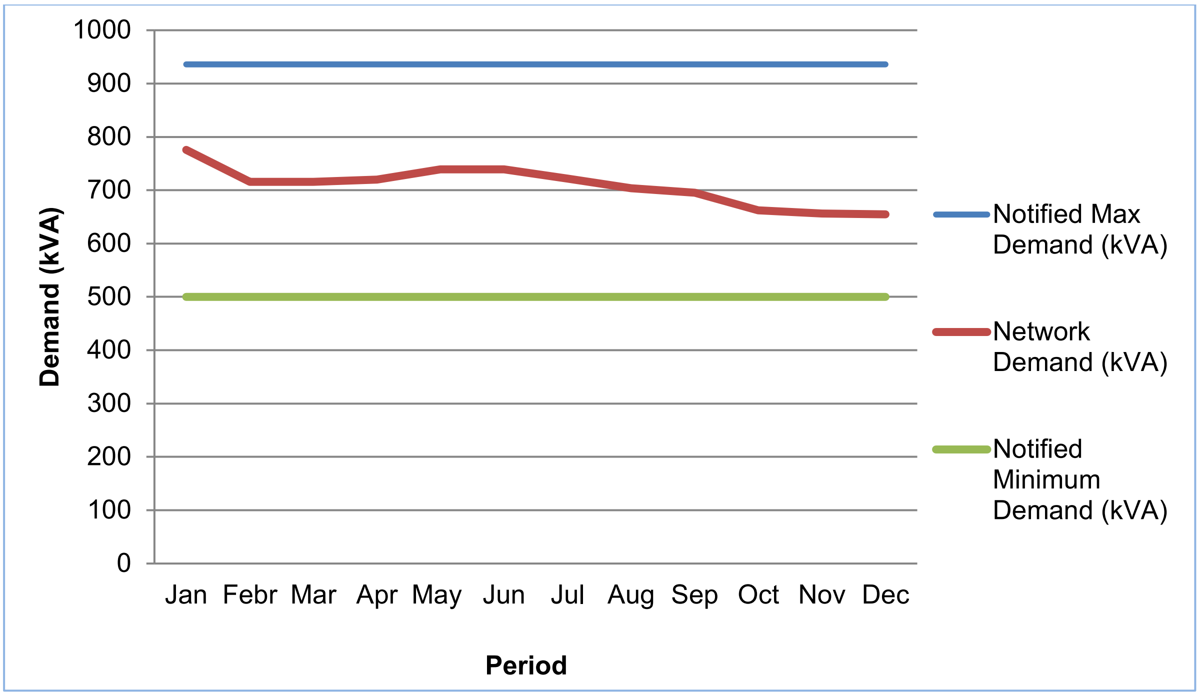

Figure 4.7: Monthly network demand versus notified demand for plant 1

Figure 4.8 shows the percentage contributions of the appliances for the consumption of electrical energy. It was revealed that the galvanising tank consumes the bulk of the energy, followed by the flux and degreasing tanks.

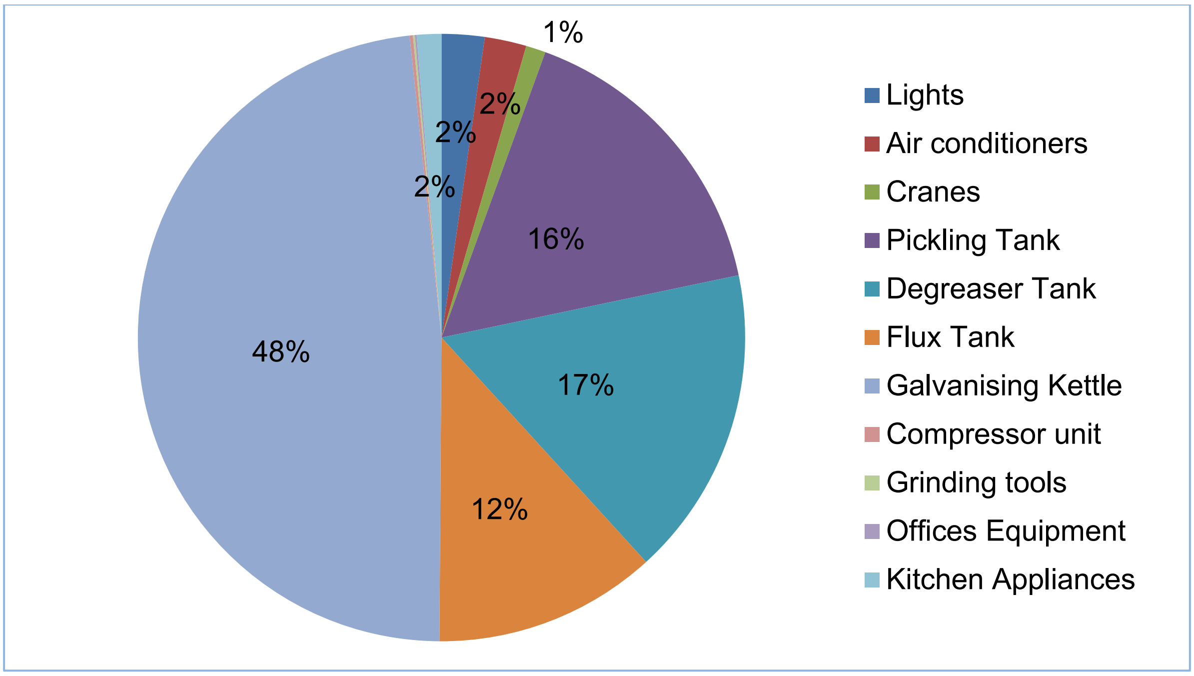

Figure 4.8: Pie chart for electrical energy consumption for plant 1

The results of the measurement phase are depicted in Figure 4.9 where the Pareto chart revealed that galvanising tanks highly contribute to monthly electrical energy usage for plant 1. Thus, the first significant energy users (SEUs) are the galvanising kettles, followed by degreasing and pickling tanks. The flux tanks consume slightly less energy followed by the cranes which are the fifth SEUs. The average total monthly electricity consumption for the plant is about 270 770 kWh.

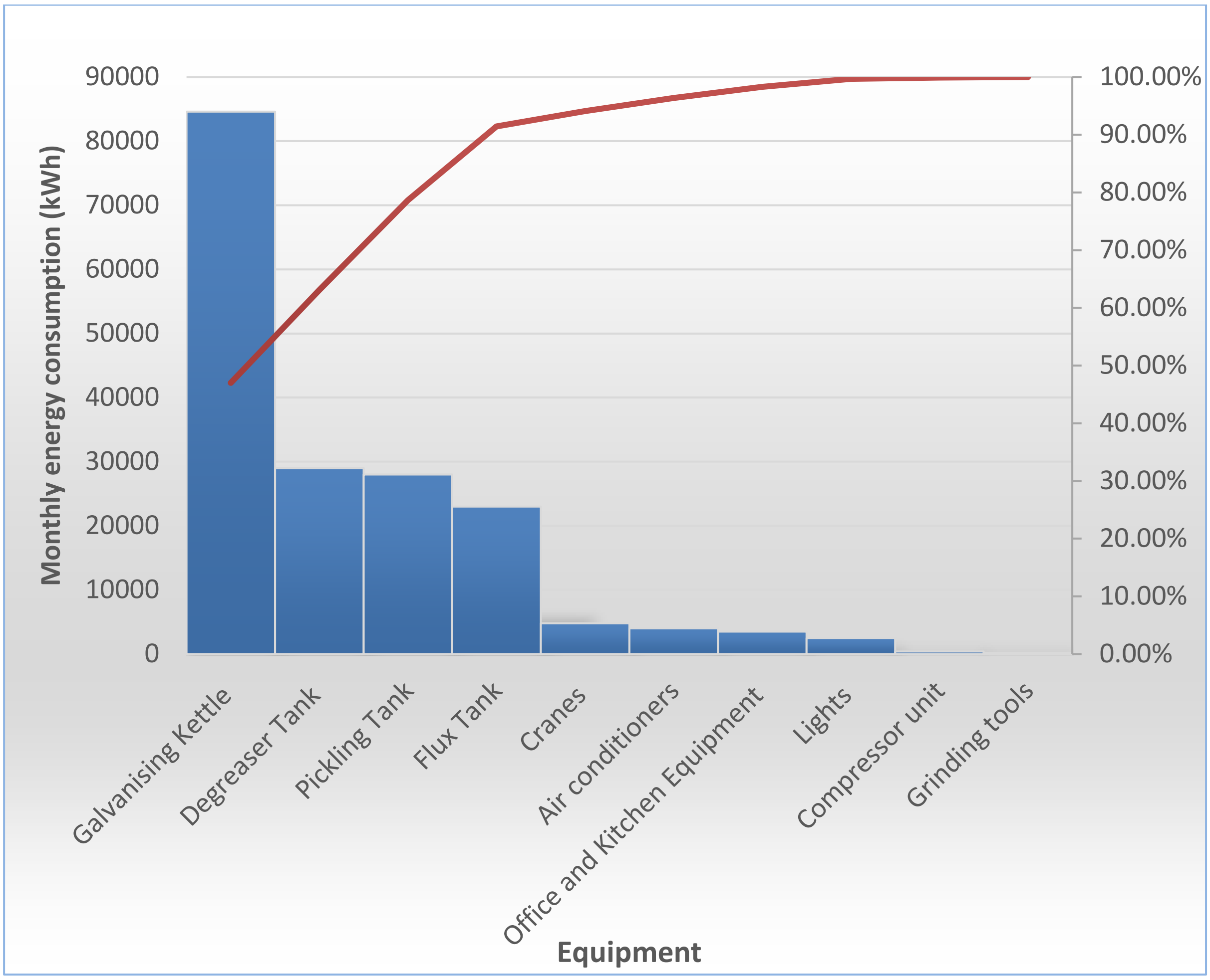

Figure 4.9: Pareto analysis for monthly electrical energy usage for Plant 1

Figure 4.10 shows the average current drawn by each of the heating zones and the spot temperature of the galvanising fluid surface. It is worth mentioning that only the side walls of the tank can be heated, not the bottom. The heat was lost from the tanks primarily through convection and evaporation from the surface of the liquid.

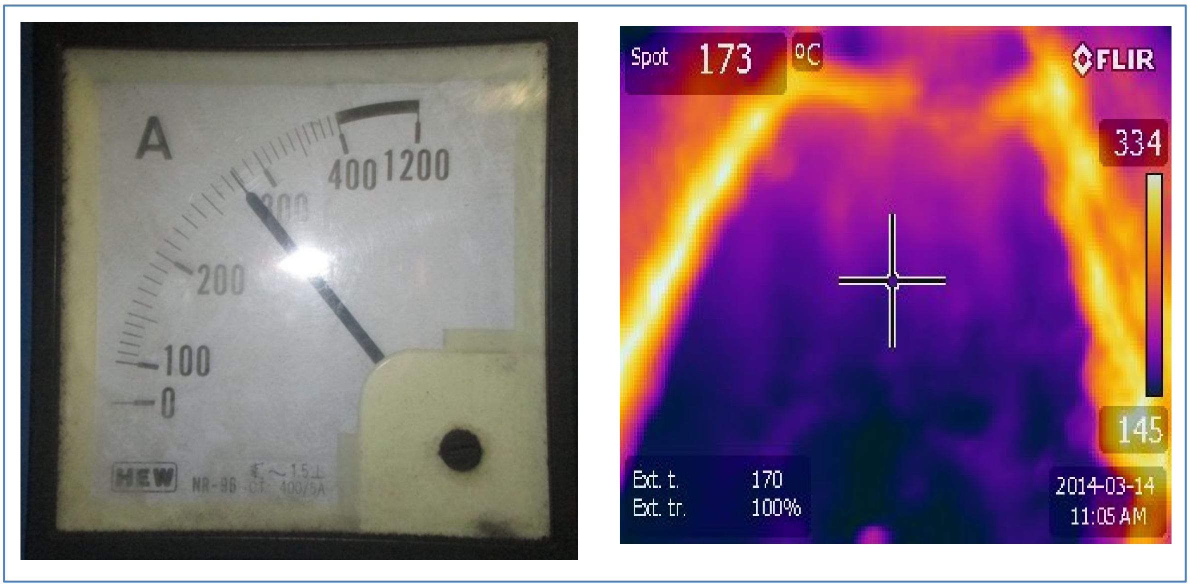

Figure 4.10: Current drawn by heating zones and the spot temperature

The spot temperature at the molten zinc surface was slightly less than the galvanising temperature since dross formation at the top acts as a partially insulating blanket because of its lower thermal conductivity. Since the tank was not covered at the top, the heat was lost over an area of 18.2 m^2 i.e. from 14 m x 1.3 m. This is equivalent to a 14 m horizontal bare pipe with a diameter of 41.3 cm. It was recommended to cover the tank during non-production hours to reduce surface losses. The rate of loss was dependent upon the differential temperature between the zinc fluid and the surface exposed to air movement.

Similar analyses were also conducted for plants 2, 3 and 4, and Figure 4.11 shows a Pareto analysis for monthly electrical energy usage for Plant 2. The galvanising tanks highly contribute to monthly electrical energy usage followed by degreasing and pickling tanks. The flux tanks consume slightly less energy followed by the cranes which are the fifth SEUs. The average total monthly electricity consumption for the plant is about 248 670 kWh.

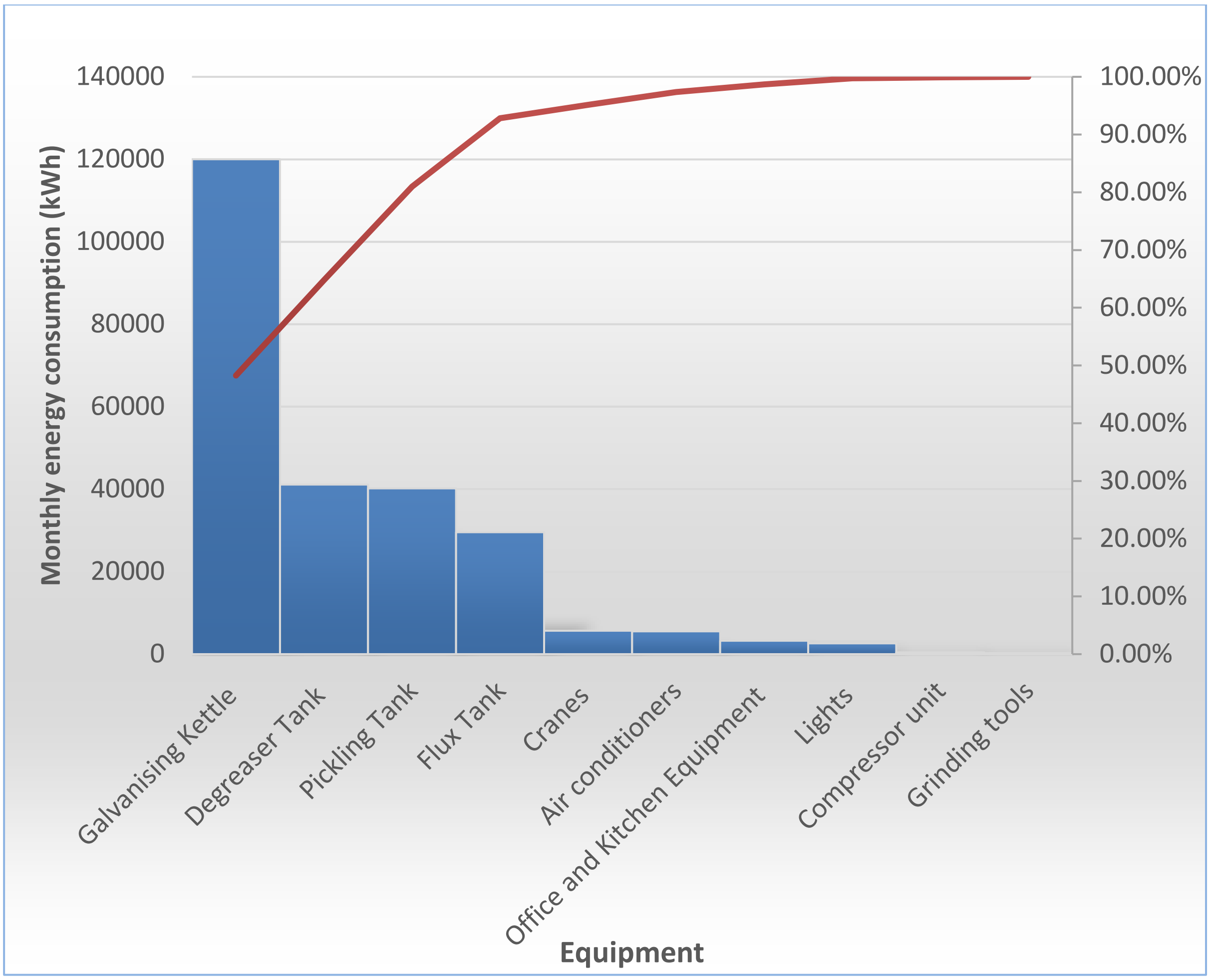

Figure 4.11: Pareto analysis for monthly electrical energy usage for Plant 2

Figure 4.12 shows a Pareto analysis for monthly electrical energy usage for Plant 3. The galvanising tanks highly contribute to monthly electrical energy usage followed by degreasing and pickling tanks. The flux tanks consume slightly less energy followed by the cranes which are the fifth SEUs. The average total monthly electricity consumption for the plant is about 232 350 kWh.

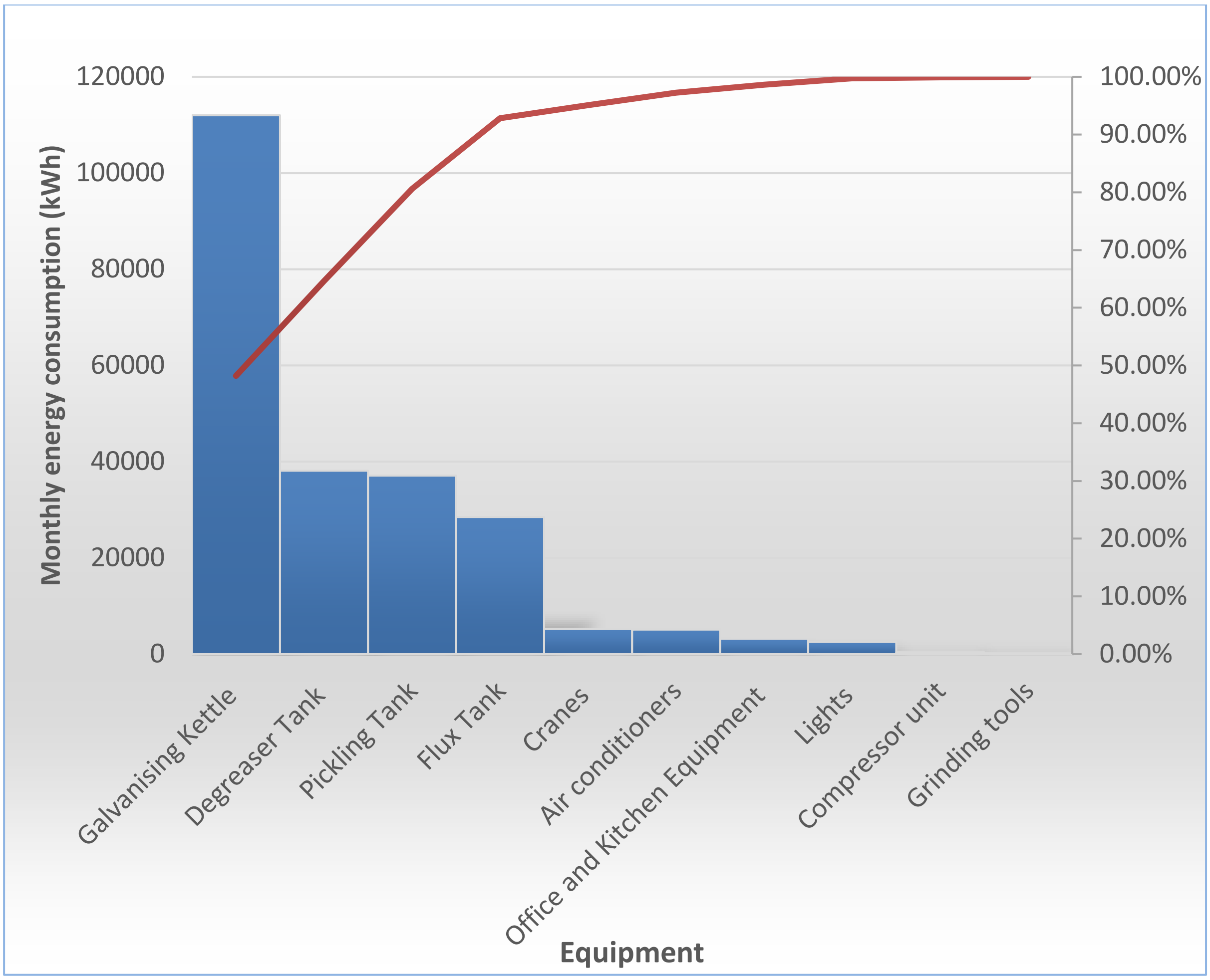

Figure 4.12: Pareto analysis for monthly electrical energy usage for Plant 3

Figure 4.13 shows a Pareto analysis for monthly electrical energy usage for Plant 4, which is the smallest of the four plants. These results also demonstrate that the galvanising tanks are the largest SEU followed by degreasing and pickling tanks. The flux tanks consume slightly less energy followed by the cranes which are the fifth SEUs. The average total monthly electricity consumption for the plant is about 213 370 kWh.

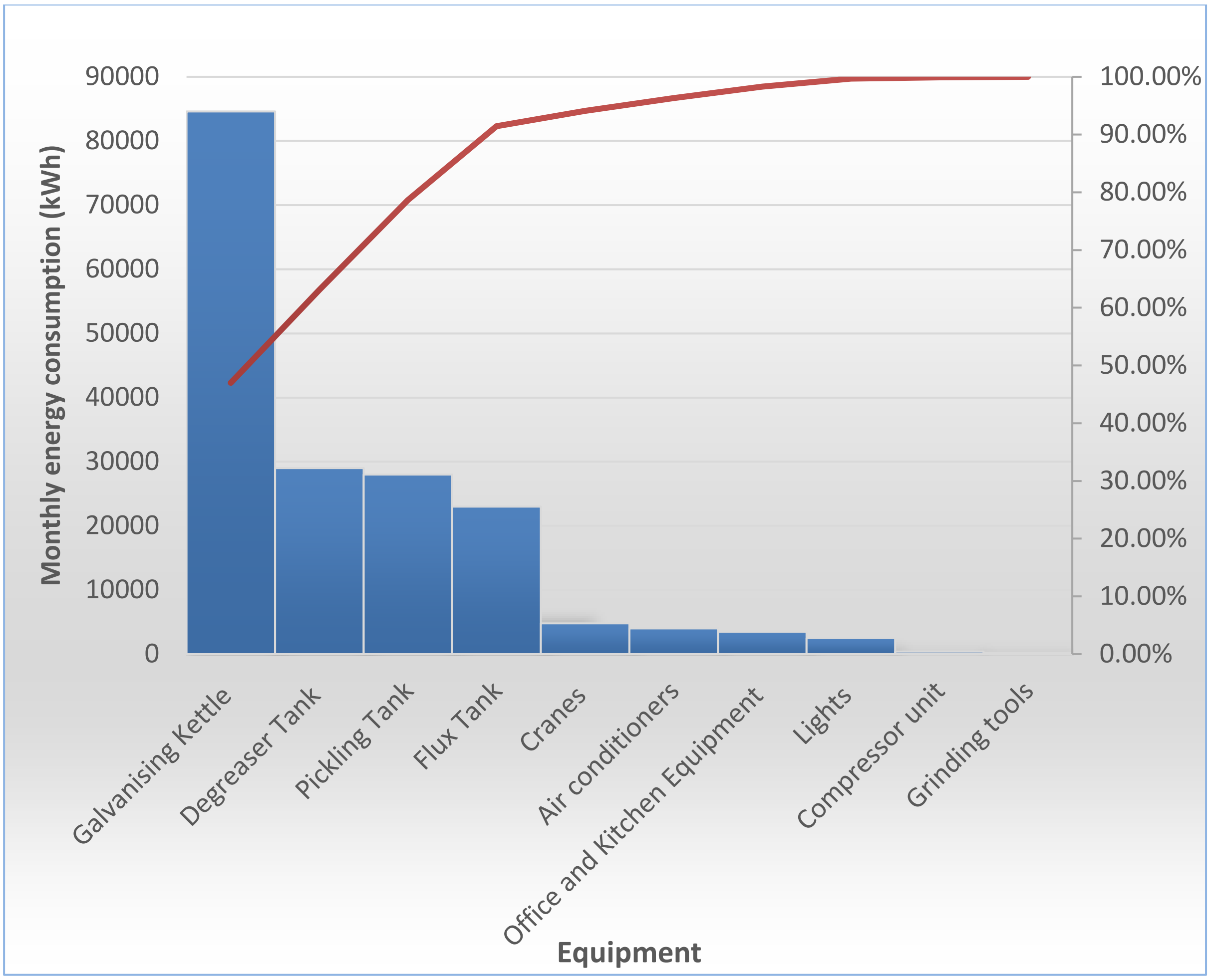

Figure 4.13: Pareto analysis for monthly electrical energy usage for Plant 4

Figure 4.14 shows an overall summary of the distribution of electricity consumption by the case-in-point 4 plants. These results demonstrate that Plant 1 with 29% and 270 770 kWh, is the largest while Plant 4 with 19% and 18000 kWh is the smallest energy consumer.

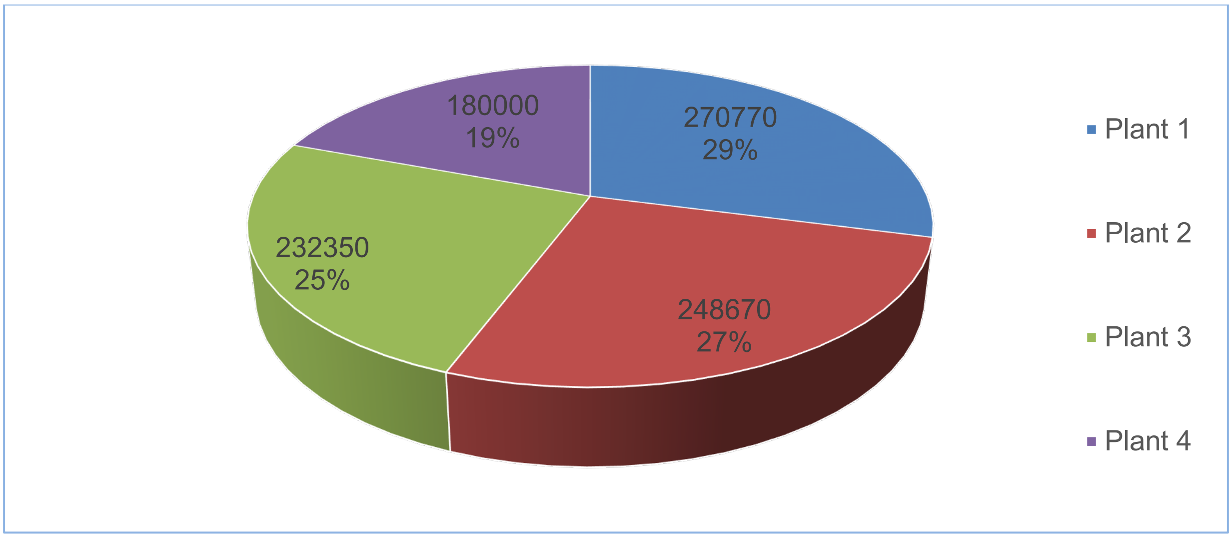

Figure 4.14: Distribution of electricity consumption by four plants

4.2.3 Evaluation of Energy-Saving Initiatives

The assessment results demonstrated that Plant 1 consumed the highest amount of electricity and hence the evaluation of energy-saving initiatives was focused on this plant. It was assumed that since these plants are almost similar in size, the identified energy-saving initiatives would be applicable in all four plants.

4.2.3.1 Galvanising Tank

As highlighted in the review of literature, Newton's law of cooling, Fourier's Law on conductive heat transfer, and the Stefan-Boltzmann Law of 'gray bodies', also characterise the energy losses during the galvanising phase of steel products. The energy lost through the exterior walls of the furnace was assumed to be negligible and is roughly 2 percent of the total consumption ((Wubbenhorst 1956); (Blake and Beck 2004a). An online calculator from CheCalc was used to compute the heat loss from the galvanising tank and estimate the saving that would be derived from insulating it (Checalc 2017). Table 4.1 shows the system parameters that were used to minimise heat loss from a galvanising tank.

Table 4.1: System parameters used to minimise heat loss from galvanising tank

System parameter	Value or description
Process Temperature	173^0C
Ambient Temperature	28^0C
Wind Speed	0.0 km/hr
Fuel Cost	R1.48
Efficiency	90%
Hours Per Year	4224
Nominal Pipe Size	400 mm diameter
Bare Metal	Steel
Bare Surface Emittance	0.8
Outer Jacket Material	All Service Jacket
Outer Surface Emittance	0.9

When large work is immersed into the bath, large temperature gradients would occur and heat must be supplied to the galvanising furnace fast enough. The energy source must be able to supply heat energy to the furnace as soon as it is lost since the steel being dipped into the zinc would initially be at room temperature.

Using the previously stated calculator, the results from Table 4.2 show that covering with a 40 mm thick insulating material will prevent an estimated heat loss of the difference between 12640 kWh/m/yr and 998 kWh/m/yr thus saving R19143.64/m/yr. Given that the tank is 14 m long, and is idle about 50% of the time, 81494 kWh/yr i.e. from (11642 x 14 x 0.5) will be saved annual savings will be about R134 000. About 80.67 tonnes of CO_2 emissions will be avoided, i.e. from (81494 x 0.99/1000).

Table 4.2: Summary of the savings from variable insulation thickness

Variable Insulation Thickness (Sommer, Walton and Cotchen)	Cost (Rand/m/yr)	Heat Loss (kWh/m/yr)	Savings (Rand/m/yr)
Bare	20784.35	12640	
15.0	4274.99	2600	16509.36
25.0	2350.32	1429	18434.03
40.0	1640.71	998	19143.64

4.2.3.2 Flux Tank

Electrical energy is consumed during fluxing, where a zinc ammonium chloride solution is used to remove any remaining oxides and deposits a protective layer on the steel to prevent any further oxides from forming on the surface prior to immersion in the molten zinc. Newton's law of cooling states that the heat flux is a function of a difference of temperatures between the wall and the environment, hence, the flux tanks are characterised by heat loss through convection, conduction and radiation. The dimensions of the tank are 14 m x 1.3 m x 2.5 m and this 30 000-litre tank has no insulation on the side-walls and no covers at the top. Since the tank is not covered at the top and has no insulation on the side-walls, heat is lost over an area of 94.7m^2 i.e. from (2 x 14 x 2.5 + 2 x 1.3 x 2.5 + 14 x 1.3). This is equivalent to a 14 m horizontal, bare pipe with a diameter of 200 cm and Figure 4.15 shows the spot temperature for the side wall of the flux tank.

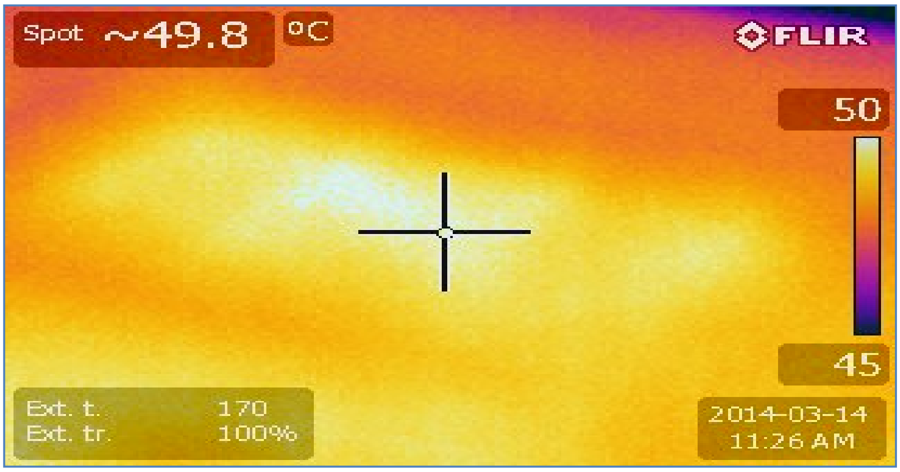

Figure 4.15: Spot temperature for the side-wall of the flux tank

Using the CheCalc calculator, Table 4.3 shows the system parameters that were used to minimise heat loss on the flux tank. Covering with a 40 mm thick insulating material will prevent an estimated heat loss of (2925 - 269) kWh/m/yr to give 2656 kWh/m/yr.

Table 4.3: System parameters used to minimise heat loss on flux tank

System parameter	Value or description
Process Temperature	49.8^{0}C
Ambient Temperature	30^{0}C
Wind Speed	0.0 km/hr
Electricity Cost	R1.48
Efficiency	80%
Hours Per Year	4224
Nominal Pipe Size	2000 mm diameter
Bare Metal	Steel
Bare Surface Emittance	0.8
Outer Jacket Material	All Service Jacket
Outer Surface Emittance	0.9

Given that the tank is 14 m long, and that part of the top will be open, of which its total surface area contributes about 25% of the total surface area, 27888 kWh/yr i.e. from (2656 x 14 x 0.75) will be saved. Annual savings will be about R68 787 and about 27.6 tonnes of CO2 emissions will be avoided, i.e. from (27888 x 0.99/1000). Table 4.4 shows a summary of the savings from the insulation layer, which is 40 mm thick.

Table 4.4: Summary of savings from insulation of 40mm thickness

Variable Insulation Thickness	Cost (Rand/m/yr)	Heat Loss (kWh/m/yr)	Savings (Rand/m/yr)
Bare	5410.93	2925	
Layer 1 (40.0)	497.57	269	4913.36

4.2.3.3 Degreasing Tank

Electrical energy is consumed during the surface preparation of steel when heating caustic soda solution to a temperature of about 80ºC in a degreasing tank. Newton's law of cooling states that the heat flux is a function of a difference of temperatures between the wall and the environment, hence, the degreasing tanks are characterised by heat loss through convection, conduction and radiation. Figure 4.16 shows the spot temperature for the sidewall of the degreasing tank. The dimensions of the tank are 14 m x 1.3 m x 2.5 m and this is equivalent to a 14 m horizontal bare pipe with a diameter of 200 cm.

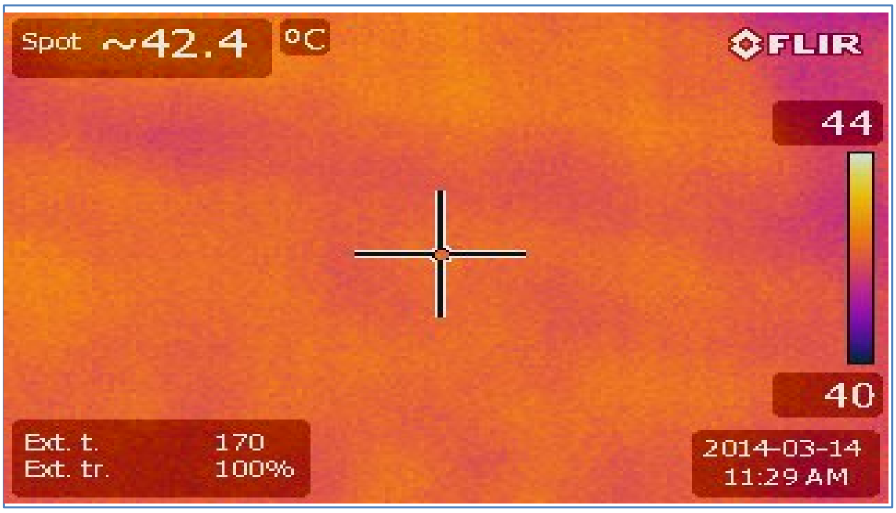

Figure 4.16: Spot temperature for the side-wall of the degreasing tank

Using the previously stated calculator, covering with a 40 mm thick insulating material will prevent an estimated heat loss of (1698-166) kWh/m/yr thus saving R1750.87/m/yr. Given that the tank is 14 m long, and that part of the top will be open, of which its total surface area contributes about 25% of the total surface area, 16086 kWh/yr i.e. from (1532 x 14 x 0.75) will be saved. Annual savings will be about R39 694 and about 15.92 tonnes of CO_2 emissions will be avoided, i.e. from (16086 x 0.99/1000).

4.2.3.4 Geyser

The 200-litre geyser with its current manufacturer's insulation has a standing energy input of 4 kWh over 24 hrs irrespective of use because the hot water is maintained at the setpoint temperature. To calculate the total amount of energy dissipated by the geyser the heat losses in W/m^2 were multiplied by the surface area of the geyser, using the conductivity as 0.055 W/m.K and a surface heat temperature coefficient of 6.3 W/m^2.K. The ambient temperature was considered to be 25°C and the cost of electricity at R1.48 per kWh. This loss could be reduced by adding an external insulating blanket over the geyser. The analysis revealed that the insulating blanket would reduce the heat loss from the geyser by 3.2 kWh/day, resulting in a saving of 292 kWh/yr for the geyser. This cascades to saving R432 per year and avoiding 0.289 tonnes of CO_2 emissions. i.e. from (292 x 0.99/1000). The additional insulation would cost R2 000, and thus simple payback period would be 4.6 years.

Alternately, a better solution will be retrofitting the geyser with an instant water heater. This heater has an in-line water heater utilizing electrically conductive polymer structures for electrodes and varying the area of electrodes that confront one another would yield variable temperatures to which the water is heated. The heat is by the resistance of the water to the electrical current flowing between the electrodes. Their advantages include better energy efficiency, minimised space utilisation and longer life expectancy. The efficiency of tank-less hot water heaters ranges from 85 to 97% as opposed to conventional tank-style hot water heater systems which are characterised by efficiencies of less than 70%.

After observation for a month, the time taken to heat the water from using the 4 kW element was 1 hour. A day heating profile, therefore, consisted of eight 1 hour intervals. One can consider retrofitting the present 4 kW geyser with a 7kW instant water heater with flow rates ranging from 1 to 6 litres per minutes and save ((4 kWh x 8h) – (7 kWh x 3 h), i.e. 11 kWh per day or 2640 kWh per year if we consider 20 working days per month. The resultant saving would be equivalent to R3 900. A 7kW instant water heater costs about R3 000 and installation costs about R2 000 to give R5 000, and a simple payback period would be 1.2 years.

4.2.3.5 Scheduling Production Dips

Scheduling influences the energy consumption behaviour of the whole system, and by integrating energy efficiency criteria into scheduling, a reduction of energy costs may be realised. It was noted that about 50% of the dips utilised about half the full length of the galvanising tank. Figure 4.17 shows a galvanised product coming out of a dip, of which the product uses less than half the size of the galvanising tank. The issue of scheduling of production dips is addressed in the fourth research question, which explores the parameters that must be deployed to develop an optimal scheduling algorithm for energy optimisation of the galvanising process.

Figure 4.17: Galvanised product coming out of a dip

4.2.3.6 Summary of Estimated Energy and Cost Savings for Plant 1

Table 4.5 shows a summary of estimated energy and cost savings from energy minimisation options. It reveals that covering galvanising kettle would yield huge energy savings followed by insulation of the flux tank. Further insulation of the geyser does not realise much energy saving. About 125 760 kWh of electricity at an estimated cost of R242 913 would be saved by implementing the stated four energy minimisation opportunities.

Table 4.5: Summary for estimated energy and cost savings

Energy Minimisation Opportunities	Estimated Savings (kWh/Annum)	Estimated Savings (Rand/ Annum)	Investment (Rands)	Estimated CO_2 emissions avoided (Tons/yr)	Simple Payback Period
Covering galvanising kettle	81 494	134 000	100 000	80.67	0.7
Insulation of flux tank	27 888	68 787	80 000	27.6	1.2
Insulation of degreasing tank	16 086	39 694	80 000	15.92	2.0
Insulation of geyser	292	432	2 000	0.289	4.6
Retrofitting with instant water heater	2640	3900	5000	2.61	1.3
Total	125 760	242913	267000	124	

4.3 Relevant Electricity Consumption Drivers for Galvanising Process

The second research question was to identify the relevant electricity consumption drivers for a galvanising process. The relevant variables are typically quantifiable factors such as production, weather conditions, and hours of operation, which would influence the galvaniser's energy consumption. Production data on the number of dips per month, amount of zinc used and product tonnage was collected from the companies' databases and it was envisaged that the galvaniser's energy consumption could be influenced by temperature, of which the monthly temperature data was retrieved from an online database. Statistical analysis was then used to establish if the relevant variables would influence energy consumption. Multivariate regression analysis was used to determine the relevant variables and to validate the strength of statistical relationships between the variables.

Since it was anticipated that there could be more than one predictor variable for electricity consumption by the galvaniser, multivariate regression was initially adopted for the study. The four relevant variables or energy drivers that were considered include number dips per day, amount of zinc used, galvanised product tonnage, and ambient temperature conditions. These drivers were numbered as follows:

- Driver 1: Number dips per day
- Driver 2: Amount of zinc used
- Driver 3: Galvanised product tonnage
- Driver 4: Ambient temperature conditions

4.3.1 Multivariate Regression Analysis for Plant 1

It was vital to develop a model that estimates the relationship between dependent and independent variables to predict an outcome variable, which is the amount of electricity used by Plant 1 in this case. Four energy drivers that include number dips per day, amount of zinc used, galvanised product tonnage, and the ambient temperature conditions were considered to predict the amount of electricity used by Plant 1. Table 4.6 shows the electricity consumption data as well as the relevant variables or drivers.

Table 4.6: Data for relevant variables and electricity consumption for Plant 1

Month	Dips per month	Zinc used (Tons)	Product tonnage (tons)	Ambient Temperature (°C)	Total Electricity (kWh)
Jan	870	52124	691571	25	270236
Feb	813	47434	691571	25	250718
Mar	932	52259	691571	25	270935
Apr	870	51242	691571	23	264703
May	1045	56523	691571	20	291350
Jun	831	49836	691571	18	257878
July	967	54154	691571	18	282982
Aug	894	54477	691571	19	282981
Sept	907	49757	715047	20	262942
Oct	1114	56880	715047	21	286594
Nov	1284	62021	817006	22	294731
Dec	816	48980	623543	24	233301

It is advisable to develop a scatter plot matrix of the dependent variable and predictors before a regression model is selected, to check if linear regression is appropriate and, if suitable, what model should be adopted. Figure 4.18 shows a scatter plot for electricity consumption and the number of dips per month. A moderate R-squared value of 0.6389 with one outlier was noted, an indication that the regression equation model would be moderately accurate in modelling the linear, positive relationship between electricity consumption and the number of dips per month for the galvanising plant.

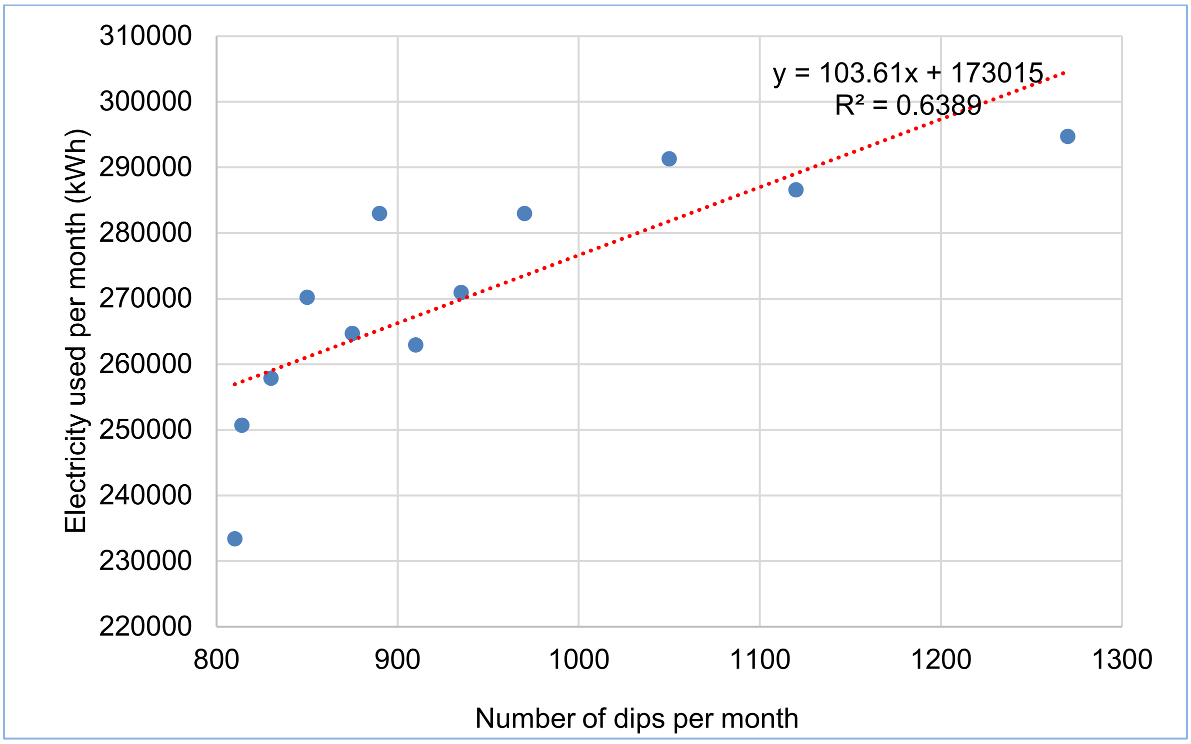

Figure 4.18: Scatter plot for electricity consumption and number of dips

Figure 4.19 shows a scatter plot for electricity consumption and amount of zinc used per month. A high R-squared value of 0.7806 was noted, and the scatter plot shows some strong correlation between the amount of zinc used and the electricity consumption by the galvanising plant.

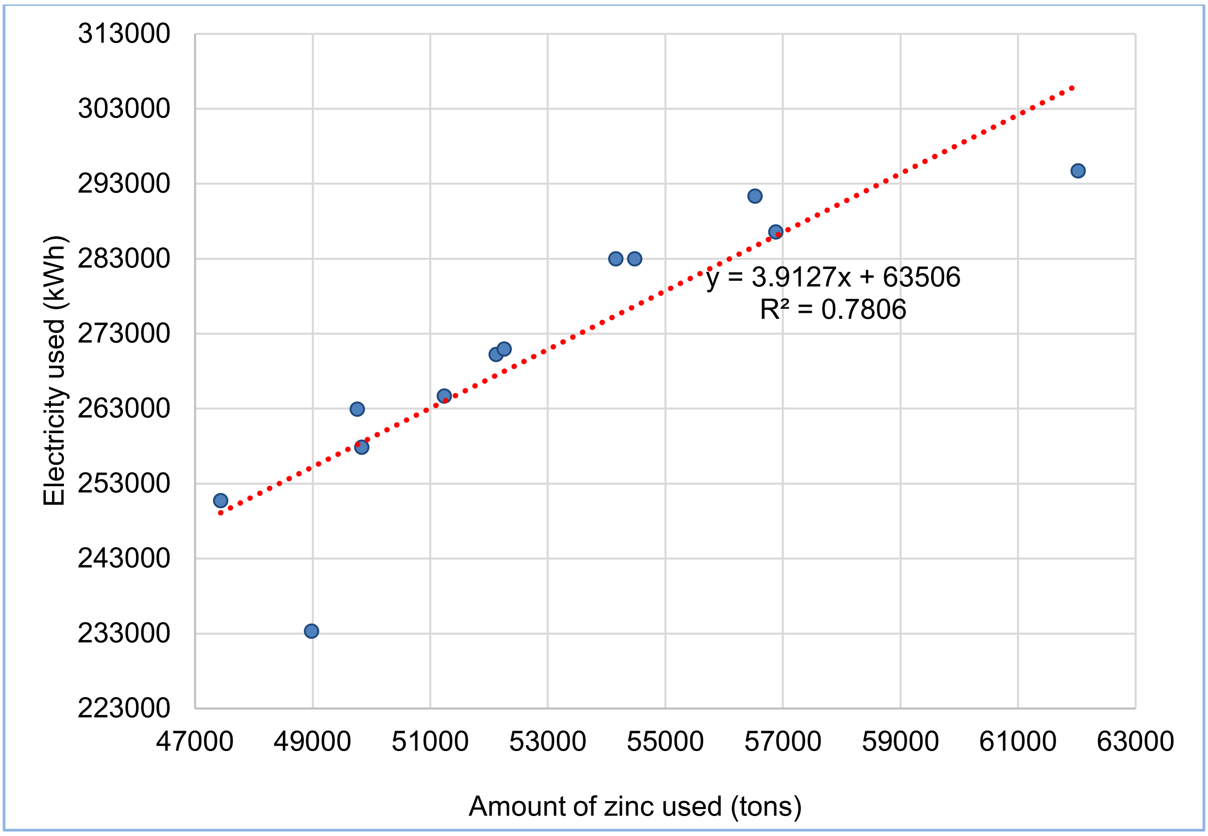

Figure 4.19: Scatter plot for electricity consumption and zinc used

Figure 4.20 shows a scatter plot for electricity consumption and product tonnage. A moderate R-squared value of 0.5367 was noted, an indication that the regression equation model was moderately accurate in modelling the linear, positive relationship between electricity consumption and product tonnage.

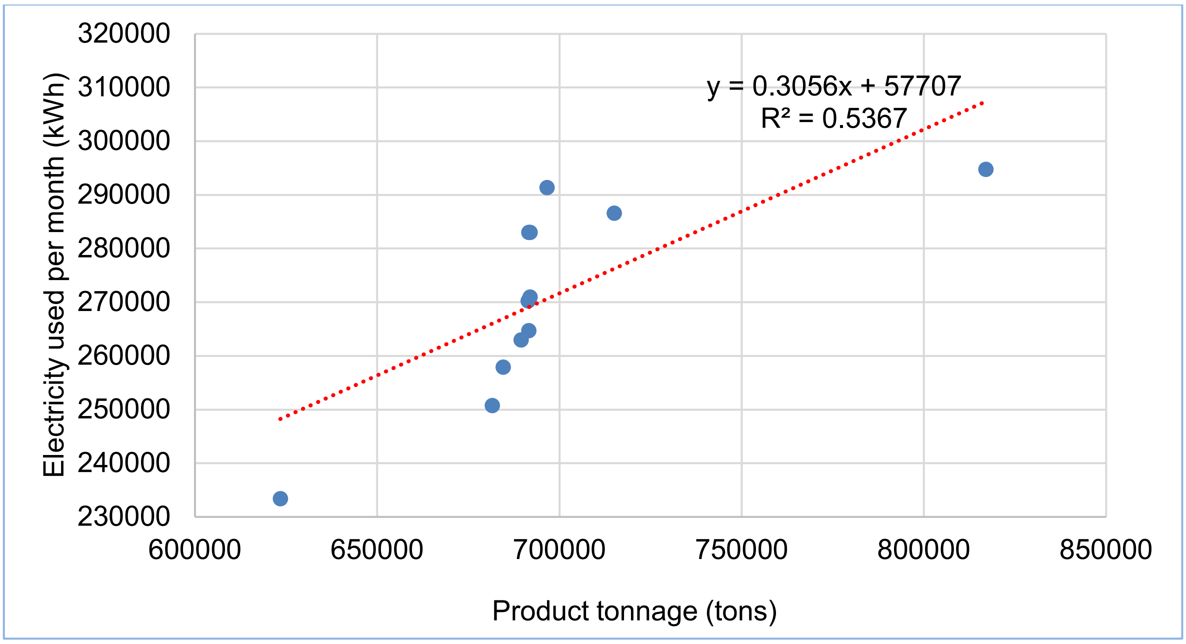

Figure 4.20: Scatter plot for electricity consumption and product tonnage

Figure 4.21 shows a scatter plot for electricity consumption and ambient temperature conditions. A low R-squared value of 0.1172 was noted, an indication that the regression equation model less accurate in modelling the linear, negative relationship between electricity consumption and ambient temperature.

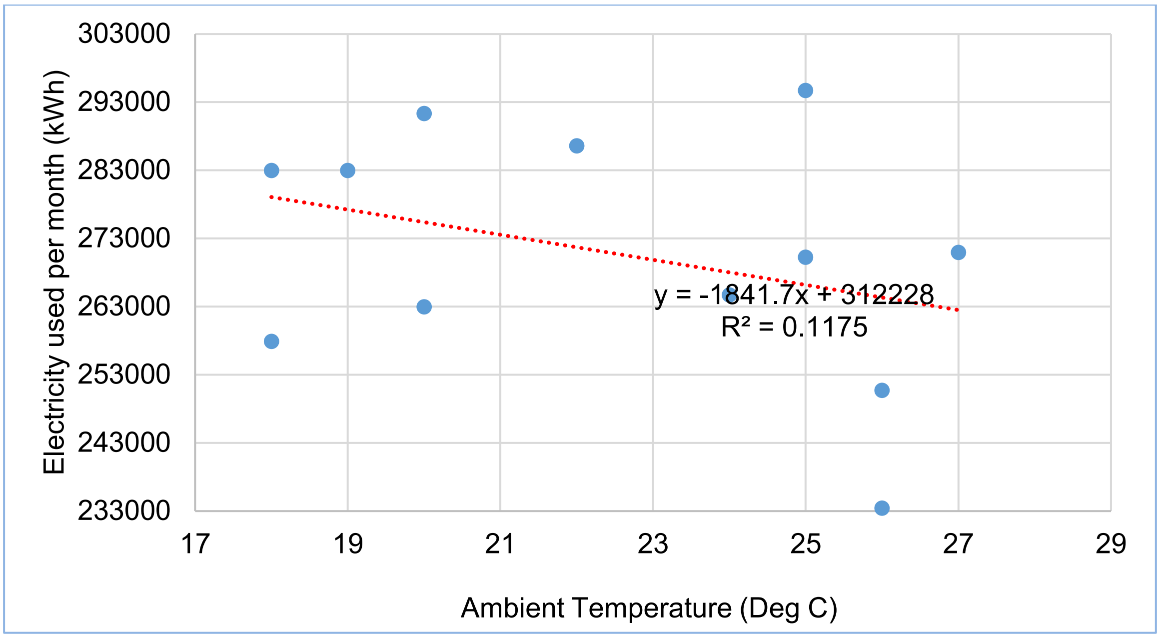

Figure 4.21: Scatter plot for electricity consumption and ambient temperature

The initial regression analysis yielded a good R^2 value but the p-values (probability that the dependent and independent variables are not related) were greater than 0.05 at a 95% confidence level, as shown in Table 4.7.

Table 4.7: Regression Statistics and ANOVA for 4 drivers for Plant 1

Regression Statistics						
Multiple R	R Square	Adjusted R Square	Standard Error	Observations		
0,921548	0,84925	0,763108	8825,768	12		
ANOVA						
	df	SS	MS	F	Significance F	
Regression	4	3,07E+09	7,68E+08	9,858651	0,005284	
Residual	7	5,45E+08	77894178			
Total	11	3,62E+09				
	Coeffi-cients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	84337,76	70307,43	1,199557	0,269333	-81912,9	250588,4
Dips per month	-23,368	58,94876	-0,39641	0,703607	-162,76	116,0236
Zinc used	1,897754	3,134276	0,605484	0,563965	-5,51363	9,309138
Product ton-nage	0,189619	0,157043	1,20743	0,266476	-0,18173	0,560968
Ambient Tem-perature	-1081,65	1042,061	-1,03799	0,333793	-3545,74	1382,429

Further analysis was then executed using different combinations using 3 relevant variables, then subsequently combinations for 2 relevant variables and the results for R^2 were improving but the p- values were yet above 0.05. One would have expected temperature variation to have an influence on electricity consumption by the galvaniser, but the effect could be negligible given that the significant energy user, which is the galvanising kettle operates at around 400°C, yet maximum ambient temperature has a range of 18°c to 25°C, which is smaller than 10% of the operating temperature of the kettle.

Table 4.8 shows the regression statistics, significance, and P-values for relevant variables that were considered as drivers for electricity consumption by the galvaniser. The best results were noted from using only one variable, and these results show that zinc used (production) is the main driver for electricity consumption, with an R^2 value of 0,780634, Significance F of 0,000171, and p-value of 0.0021. R-squared is a statistical measure of how closely the data are to the fitted regression line and a high R^2, which was noted for the zinc used shows that the model will fit the data much better.

Table 4.8: Regression Statistics for driver 2 for Plant 1

Regression Statistics					
Multiple R	0.878271				
R Square	0.7806				
Adjusted R Square	0.748496				
Standard Error	9083.174				
Observations	12				
ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.78E+09	2.78E+09	33.73687	0.000171
Residual	10	8.25E+08	82504043		
Total	11	3.61E+09			
	Coefficients	*Standard Error*	*t Stat*	*P-value*	
Intercept	65514.63	35438.53	1.848684	0.094248	
X Variable 1	3.880942	0.668167	5.808345	0.0021	

At 95% confidence level, Significance F for the amount of zinc used is statistically significant, meaning that the results did not likely happen by chance. The p-value is determined by the F statistic and is the probability that the results could have happened by chance. A small p-value (typically ≤ 0.05) indicates strong evidence against the null hypothesis, so we reject the null hypothesis and accept the alternative that the results could not have happened by chance. The above satisfactory results were then used to develop a regression model.

The stated satisfactory results from Table 4.8 were then used to develop a regression model, of which the equation is shown in Figure 4.22. The scatter plot shows a strong correlation between the amount of zinc used and the electricity consumption by the galvanising plant.

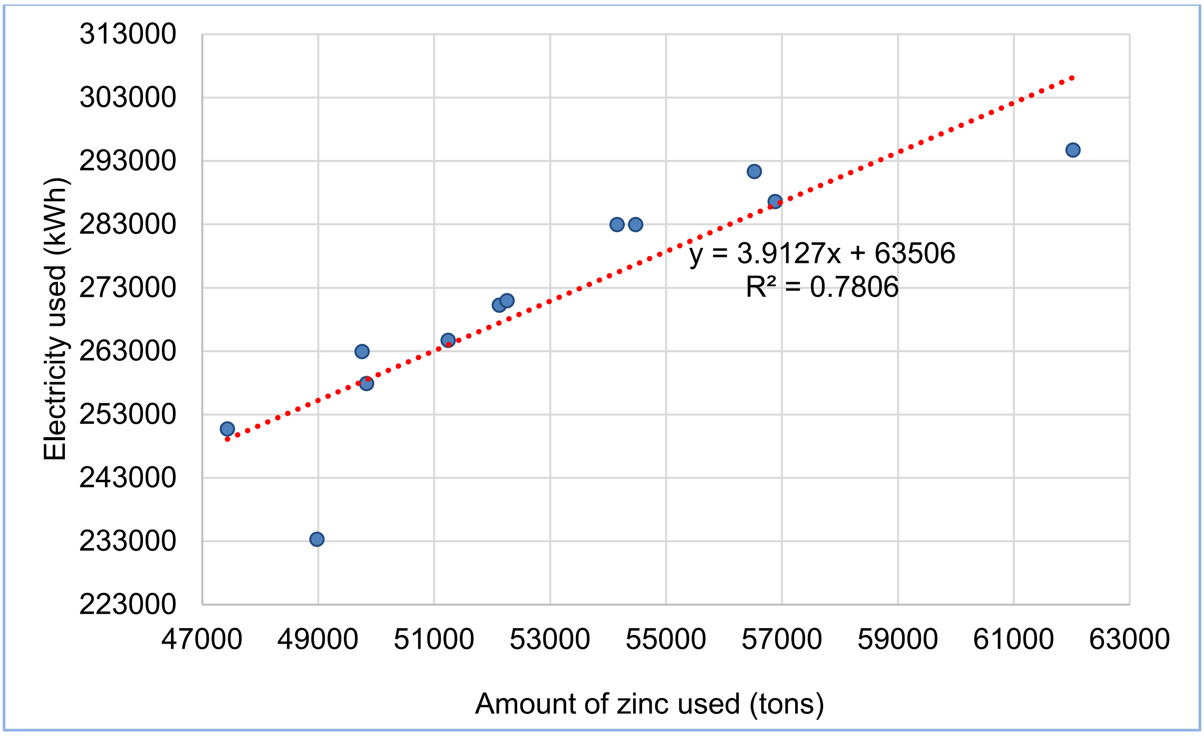

Figure 4.22: Schematic for regression model for Plant 1

The dotted line shows the baseline equation. It is worth mentioning that when one is investigating wasted energy, a good starting point is scrutiny of the base loads. In theory, one would expect low base loads of below 10% from a plant since the facility is not in use, energy should only be required for items such as security lighting and equipment such as refrigerators that need to operate continuously. However, in this case, the galvanising plant has a substantially higher baseload of 63506 kWh, which is equivalent to 23% of the average monthly consumption of electricity. This is largely attributed to the fact the zinc in the galvanising furnace has to be kept molten even during non-working hours and over the weekend.

4.3.2 Multivariate Regression Analysis for Plant 2

It was vital to develop a model that estimates the relationship between dependent and independent variables to predict an outcome variable, which is the amount of electricity used by Plant 2. Four relevant variables which include number dips per day, amount of zinc used, galvanised product tonnage, and the ambient temperature conditions were considered to predict the amount of electricity used by Plant 2. Table 4.9 shows the preliminary data for relevant variables and electricity consumption for Plant 2.

Table 4.9: Data for relevant variables and electricity consumption for Plant 2

Month	Dips per month	Zinc used (Tons)	Product tonnage (tons)	Ambient Temperature (Deg C)	Electricity used (kWh)
Jan	617	43440	516938	25	248000
Feb	590	39461	681573	26	230060
Mar	685	43595	691971	27	248642
Apr	635	42633	691571	24	242920
May	760	47015	696571	20	267376
Jun	600	45040	684571	18	256640
July	710	44876	691931	18	259650
Aug	650	45397	691571	19	259670
Sept	663	49760	689507	20	241250
Oct	816	56878	715047	22	244750
Nov	926	62025	817006	25	257200
Dec	590	48970	561074	26	222460
Average					248218

The initial regression analysis yielded a good R^2 value of 0.788 but the p-values were less than 0.05 for dips per month, zinc used and ambient temperature at 95% confidence level, as shown in Table 4.10. These results were found to be statistically significant given that the significance F (0.016402) value is less than 0.05.

Table 4.10: Regression Statistics and ANOVA for 4 drivers for Plant 2

Regression Statistics						
Multiple R	0.887879					
R Square	0.78833					
Adjusted R Square	0.667375					
Standard Error	7504.703					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	4	1.47E+09	3.67E+08	6.517574	0.016402	
Residual	7	3.94E+08	56320573			
Total	11	1.86E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	293975.2	31182.28	9.427635	3.15E-05	220240.8	367709.6
Dips per month	166.7335	51.69228	3.225501	0.014542	44.50066	288.9663
Zinc used	-1.76486	0.675039	-2.61445	0.034688	-3.36107	-0.16864
Product tonnage	-0.03374	0.045942	-0.73446	0.486535	-0.14238	0.074893
Ambient Temperature	-2388.26	699.3396	-3.41502	0.011211	-4041.93	-734.581

Further analysis was also executed using different combinations using 3 relevant variables, then subsequently combinations for 2 relevant variables and the results for R^2 were improving but the p- values were yet above 0.05. Table 4.11 shows the regression statistics and ANOVA for Plant 2 drivers which include the number of dips per month, amount of zinc used and product tonnage. The results demonstrate that only drivers 1 and 2 were statistically significant at a 95% confidence interval at significance F (0.003974).

Table 4.11: Regression Statistics and ANOVA for drivers 1, 2 and 3 for Plant 2

Regression Statistics						
Multiple R	0.891623					
R Square	0.794992					
Adjusted R Square	0.718113					
Standard Error	9627.516					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	3	2.88E+09	9.58E+08	10.34093	0.003974	
Residual	8	7.42E+08	92689064			
Total	11	3.62E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	205978.6	30143.24	6.833326	0.000133	136468.2	275489
Dips per month	264.321	65.73323	4.021117	0.003835	112.7399	415.9021
Zinc used	-2.13718	0.865675	-2.4688	0.038783	-4.13343	-0.14093
Product tonnage	-0.02276	0.056643	-0.40175	0.698386	-0.15338	0.107863

Table 4.12 also shows the regression statistics and ANOVA for drivers 1, 2 and 4 for Plant 2 that were considered as the relevant variables for electricity consumption by the galvaniser. The best results were noted from using the number of dips per month, amount of zinc used and ambient temperature as the relevant variables, with an R^2 value of 0.882925, Significance F of 0.00044, and p- values of 0.000269, 0.014079 and 0.03647.

Table 4.12: Regression Statistics and ANOVA for drivers 1, 2 and 4 for Plant 2

Regression Statistics						
Multiple R	0.939641					
R Square	0.882925					
Adjusted R Square	0.839022					
Standard Error	7275.452					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	3	3.19E+09	1.06E+09	20.11081	0.00044	
Residual	8	4.23E+08	52932196			
Total	11	3.62E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	234790.2	22238.98	10.55759	5.65E-06	183507	286073.3
Dips per month	243.2022	39.43559	6.167073	0.000269	152.2635	334.1408
Zinc used	-1.98848	0.635906	-3.127	0.014079	-3.45488	-0.52208
Ambient Temperature	-1634.33	651.5797	-2.50826	0.03647	-3136.88	-131.784

Table 4.13 shows the regression statistics and ANOVA for drivers 1 and 2 for Plant 2 and it is evident that the p-values became larger and the R^2 value decreased when compared to using drivers 1, 2 and 4.

Table 4.13: Regression Statistics and ANOVA for drivers 1 and 2 for Plant 2

Regression Statistics						
Multiple R	0.889301					
R Square	0.790855					
Adjusted R Square	0.744379					
Standard Error	9168.017					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	2	2.86E+09	1.43E+09	17.01622	0.000875	
Residual	9	7.56E+08	84052541			
Total	11	3.62E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	197689.6	20926.81	9.446714	5.73E-06	150349.9	245029.3
Dips per month	248.2276	49.62981	5.001584	0.000737	135.9572	360.498
Zinc used	-2.05435	0.800641	-2.56589	0.030392	-3.86553	-0.24318

The stated satisfactory results from Table 4.12 were then used to develop a regression model. Hence the number of dips per month, amount of zinc used and ambient temperature conditions were considered as the relevant variables for Plant 2 to derive the relationship that is shown in equation 4.1.

$$Electricity\ used = 243.2x_1 - 1.99x_2 - 1634.3x_3 + 197690 \qquad (4.1)$$

Where x_1 is the number of dips per month, x_2 is the amount of zinc used and x_3 is ambient temperature. It was also imperative to consider residual patterns for the various model options. Residuals are described as the difference between the values predicted from the model for a specific month and the actual electricity usage measured for that month.

4.3.3 Multivariate Regression Analysis for Plant 3

It was also vital to develop a model that estimates the relationship between dependent and independent variables to predict the amount of electricity used by Plant 3. The number of dips per day, amount of zinc used, galvanised product tonnage, and the ambient temperature conditions are the four energy drivers that were considered to determine the amount of electricity used by Plant 3. Table 4.14 shows the preliminary data for relevant variables and electricity consumption for Plant 3.

Table 4.14: Data for relevant variables and electricity consumption for Plant 3

Month	Dips per month	Zinc used (Tons)	Product tonnage (tons)	Ambient Temperature (Deg C)	Electricity used (kWh)
Jan	605	37868	449868	27	231750
Feb	582	32683	681573	28	201980
Mar	676	38067	691971	29	232592
Apr	630	37211	691571	26	226870
May	700	41302	696571	22	251326
Jun	590	39471	684571	20	240652
July	705	41193	691931	20	253750
Aug	640	39208	691571	21	240740
Sept	653	38034	689507	22	225160
Oct	806	40166	715047	24	228740
Nov	860	49900	817006	27	254150
Dec	560	36809	414377	29	196405
Average					232010

The initial regression analysis yielded a good R^2 value but the p-values (probability that the dependent and independent variables are not related) were greater than 0.05 at a 95% confidence level, as shown in Table 4.15.

Table 4.15: Regression Statistics and ANOVA for 4 drivers for Plant 3

Regression Statistics						
Multiple R	0.881142					
R Square	0.776412					
Adjusted R Square	0.648647					
Standard Error	10930.9					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	4	2.9E+09	7.26E+08	6.07689	0.019648	
Residual	7	8.36E+08	1.19E+08			
Total	11	3.74E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	152152.1	58217.72	2.613502	0.034736	14489.07	289815.1
Dips per month	-29.4165	83.50462	-0.35227	0.735001	-226.874	168.0406
Zinc used	3.299953	1.752345	1.883163	0.101692	-0.84369	7.443591
Product tonnage	0.029717	0.045678	0.650584	0.536077	-0.07829	0.137729
Ambient Temperature	-2024.19	1161.326	-1.743	0.124861	-4770.29	721.9069

Further analysis was then executed using different combinations using 3 relevant variables, then subsequently combinations for 2 relevant variables. Table 4.16 shows the regression statistics and ANOVA for drivers 1, 2 and 3 for Plant 3 and the results for R^2 were not improving and the p- values were yet above 0.05.

Table 4.16: Regression Statistics and ANOVA for drivers 1, 2 and 3 for Plant 3

Regression Statistics						
Multiple R	0.80367					
R Square	0.645885					
Adjusted R Square	0.513092					
Standard Error	12867.9					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	3	2.42E+09	8.05E+08	4.863845	0.032735	
Residual	8	1.32E+09	1.66E+08			
Total	11	3.74E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	86236.32	38858.64	2.219232	0.057251	-3371.86	175844.5
Dips per month	-67.348	86.65255	-0.77722	0.459393	-267.169	132.4731
Zinc used	3.82839	1.674872	2.28578	0.051604	-0.03387	7.690652
Product tonnage	0.060884	0.046063	1.321737	0.2228	-0.04534	0.167106

Table 4.17 shows the regression statistics and ANOVA for drivers 1, 2 and 4 for Plant 3, with an R^2 value of 0.7638, Significance F of 0.006893, and p-values were above 0.05 except ambient temperature which had a p-value of 0.03.

Table 4.17: Regression Statistics and ANOVA for drivers 1, 2 and 4 for Plant 3

Regression Statistics						
Multiple R	0.873976					
R Square	0.763833					
Adjusted R Square	0.675271					
Standard Error	10508.6					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	3	2.86E+09	9.52E+08	8.624799	0.006893	
Residual	8	8.83E+08	1.1E+08			
Total	11	3.74E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	173552.3	43162.99	4.02086	0.003837	74018.3	273086.4
Dips per month	12.07436	61.40246	0.196643	0.849011	-129.52	153.6687
Zinc used	2.79156	1.3957	2.000114	0.080502	-0.42693	6.01005
Ambient Temperature	-2415.51	939.1751	-2.57195	0.033027	-4581.25	-249.767

Table 4.18 shows the regression statistics and ANOVA for drivers 1 and 2 for Plant 3 and it is evident that the p-values became larger and the R2 value decreased when compared to using drivers 1, 2 and 4.

Table 4.18: Regression Statistics and ANOVA for drivers 1 and 2 for Plant 3

Regression Statistics						
Multiple R	0.754026					
R Square	0.568556					
Adjusted R Square	0.472679					
Standard Error	13391.27					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	2	2.13E+09	1.06E+09	5.930084	0.022759	
Residual	9	1.61E+09	1.79E+08			
Total	11	3.74E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	96542.18	39616.64	2.43691	0.037555	6923.107	186161.3
Dips per month	-8.90416	77.55264	-0.11481	0.911113	-184.34	166.5321
Zinc used	3.595818	1.733347	2.074494	0.067868	-0.32529	7.516923

Table 4.19 shows the regression statistics and ANOVA for drivers 2 and 4 for Plant 3. The best results were noted from using these two variables, with an R^2 value of 0,6627, Significance F of 0,0075, and p-values were less than 0.05. The stated satisfactory results from Table 4.19 were then used to develop a regression model. Hence, the amount of zinc used and ambient temperature conditions were considered as the relevant variables for Plant 3 to derive the relationship that is shown in equation 4.2.

$$Electricity\ used = 1.624x_1 - 2037.24x_2 + 234459 \qquad (4.2)$$

where;

x_1 is the amount of zinc used and x_2 is ambient temperature.

Table 4.19: Regression Statistics and ANOVA for drivers 2 and 4 for Plant 3

Regression Statistics						
Multiple R	0.8140915					
R Square	0.662745					
Adjusted R Square	0.5877994					
Standard Error	8354.3085					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	2	1.23E+09	6.17E+08	8.8430	0.007513	
Residual	9	6.28E+08	6979447			
Total	11	1.86E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	234459.63	33848.88	6.926659	6.86E-05	157888.2	311031
Zinc used	1.6233734	0.635464	2.554625	0.03095	0.185853	3.06089
Ambient Temper-ature	-2037.2478	740.0248	-2.75295	0.02236	-3711.3	-363.195

4.3.4 Multivariate Regression Analysis for Plant 4

A model that estimates the relationship between dependent and independent variables to predict an outcome variable, which is the amount of electricity used was developed for Plant 4. Four energy drivers which include number dips per day, amount of zinc used, galvanised product tonnage, and the ambient temperature conditions were considered to determine the amount of electricity used by Plant 4. Table 4.20 shows the preliminary data for relevant variables and electricity consumption for Plant 4.

Table 4.20: Data for relevant variables and electricity consumption for Plant 4

Month	Dips per month	Zinc used (Tons)	Product tonnage (tons)	Ambient Temperature (Deg C)	Electricity used (kWh)
Jan	480	28563	338184	30	179660
Feb	462	23619	681573	29	149980
Mar	555	28741	691971	28	180492
Apr	510	27918	691571	27	174960
May	578	31866	696571	23	199326
Jun	471	30103	684571	21	188652
July	583	31863	691931	21	201695
Aug	522	29895	691571	22	188640
Sept	533	28433	689507	24	173160
Oct	560	30195	715047	27	176640
Nov	638	38340	817006	29	202050
Dec	422	26406	297068	30	144705
Average					179997

Similarly, as with other previous plants, the initial regression analysis yielded a good R^2 value but the p-values (probability that the dependent and independent variable are not related) were greater than 0.05 at a 95% confidence level, as shown in Table 4.21.

Table 4.21: Regression Statistics and ANOVA for 4 drivers for Plant 4

Regression Statistics						
Multiple R	0.881142					
R Square	0.776412					
Adjusted R Square	0.648647					
Standard Error	10930.9					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	4	2.9E+09	7.26E+08	6.07689	0.019648	
Residual	7	8.36E+08	1.19E+08			
Total	11	3.74E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	152152.1	58217.72	2.613502	0.034736	14489.07	289815.1
Dips per month	-29.4165	83.50462	-0.35227	0.735001	-226.874	168.0406
Zinc used	3.299953	1.752345	1.883163	0.101692	-0.84369	7.443591
Product tonnage	0.029717	0.045678	0.650584	0.536077	-0.07829	0.137729
Ambient Temperature	-2024.19	1161.326	-1.743	0.124861	-4770.29	721.9069

Further analysis was then executed using different combinations using 3 relevant variables, then subsequently combinations for 2 relevant variables and the results for R^2 were improving but the p-values were yet above 0.05.

Table 4.22: Regression Statistics and ANOVA for drivers 1, 2 and 3 for Plant 4

Regression Statistics						
Multiple R	0.856301					
R Square	0.733252					
Adjusted R Square	0.633221					
Standard Error	11123.22					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	3	2.72E+09	9.07E+08	7.330277	0.011046	
Residual	8	9.9E+08	1.24E+08			
Total	11	3.71E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	45290.1	30931.61	1.464201	0.181296	-26038.3	116618.5
Dips per month	62.60872	127.6903	0.490317	0.637074	-231.846	357.0631
Zinc used	3.143053	1.753521	1.792424	0.110829	-0.90057	7.186679
Product tonnage	0.013325	0.031833	0.418571	0.686541	-0.06008	0.086733

Table 4.23 shows the regression statistics and ANOVA for drivers 1, 2 and 4 for Plant 3, with an R^2 value of 0.8721, Significance F of 0.0006, and p-values were below 0.05 except for dips per month, which had a p-value of 0.273.

Table 4.23: Regression Statistics and ANOVA for drivers 1, 2 and 4 for Plant 4

Regression Statistics						
Multiple R	0.933865					
R Square	0.872104					
Adjusted R Square	0.824143					
Standard Error	7702.093					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	3	3.24E+09	1.08E+09	18.18357	0.000624	
Residual	8	4.75E+08	59322241			
Total	11	3.71E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	110668.2	30828.59	3.58979	0.007087	39577.32	181759.1
Dips per month	79.97516	68.0375	1.175457	0.273607	-76.9196	236.8699
Zinc used	2.713744	1.163717	2.331963	0.048014	0.030208	5.397279
Ambient Temperature	-2054.53	682.9228	-3.00844	0.016854	-3629.35	-479.708

Table 4.24 shows the regression statistics and ANOVA for drivers 1 and 2 for Plant 4 and it is evident that the p-values became larger and the R^2 value decreased when compared to using drivers 1, 2 and 4.

Table 4.24: Regression Statistics and ANOVA for drivers 1 and 2 for Plant 4

Regression Statistics						
Multiple R	0.852883					
R Square	0.72741					
Adjusted R Square	0.666834					
Standard Error	10601.29					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	2	2.7E+09	1.35E+09	12.00831	0.002883	
Residual	9	1.01E+09	1.12E+08			
Total	11	3.71E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	42119.68	28582.67	1.473609	0.174681	-22538.8	106778.2
Dips per month	96.91153	93.3268	1.03841	0.326171	-114.208	308.0314
Zinc used	2.929191	1.598723	1.832207	0.100144	-0.68737	6.545753

Table 4.25 shows the regression statistics and ANOVA for drivers 2 and 4 for Plant 4. The best results were noted from using these two variables, with an R^2 value of 0.85, Significance F of 0.000196, and p-values were less than 0.05. The stated satisfactory results from Table 4.25 were then used to develop a regression model. Hence, the amount of zinc used and ambient temperature conditions were considered as the relevant variables for Plant 4 to derive the relationship that is shown in equation 4.3.

$$Electricity\ used = 3.83x_1 - 2121x_2 + 121292 \qquad (4.3)$$

where x_1 is the amount of zinc used and x_2 is ambient temperature.

Table 4.25: Regression Statistics and ANOVA for drivers 2 and 4 for Plant 4

Regression Statistics						
Multiple R	0.9219623					
R Square	0.8500145					
Adjusted R Square	0.8166843					
Standard Error	7863.7242					
Observations	12					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	2	3.15E+09	1.58E+09	25.5029	0.000196	
Residual	9	5.57E+08	6183815			
Total	11	3.71E+09				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	121291.65	30092.61	4.030613	0.0029	53217.45	189365
Zinc used	3.8322900	0.683926	5.603371	0.0003	2.285142	5.37943
Ambient Temperature	-2120.9525	694.8632	-3.05233	0.0137	-3692.84	-549.063

4.4 Development of Energy Performance Indicators for a Galvanising Plant

The results of the second objective were input to answering the third research question that characterised the development of energy consumption baseline and performance indices for a galvanising plant. The EnPIs was crucial for providing the relevant information on energy performance that would enable the galvaniser to appreciate its energy performance and develop interventions to save energy. The research question is as follows: "What are the energy performance indicators for a galvanising plant with regards to the comparison of actual consumption and expected consumption, Energy Intensity Index, Cumulative Sum, and Specific energy consumption"? Energy consumption benchmarking was also done as analyses energy performance data of comparable activities to evaluate and compare performance between the four galvanising plants.

4.4.1 Actual Versus Expected Consumption during the Baseline Period

4.4.1.1 Actual Versus Expected Consumption for Plant 1

Bottom-up energy efficiency and saving calculations can be used to derive the energy savings that could be achieved by the galvaniser after the implementation of energy efficiency measures. Baseline energy consumption is the consumption that occurs before any energy-saving interventions are implemented and Figure 4.23 shows a comparison of actual consumption and expected consumption during the reporting period. The energy efficiency interventions that were made at the beginning of the ensuing year did not yield any decreased electricity consumption relative to the expected or baseline energy consumption that would have occurred in the absence of the interventions. The energy savings were calculated as the difference between the baseline energy consumption and the actual energy consumption, and in this case, no energy savings were realised for Plant 1.

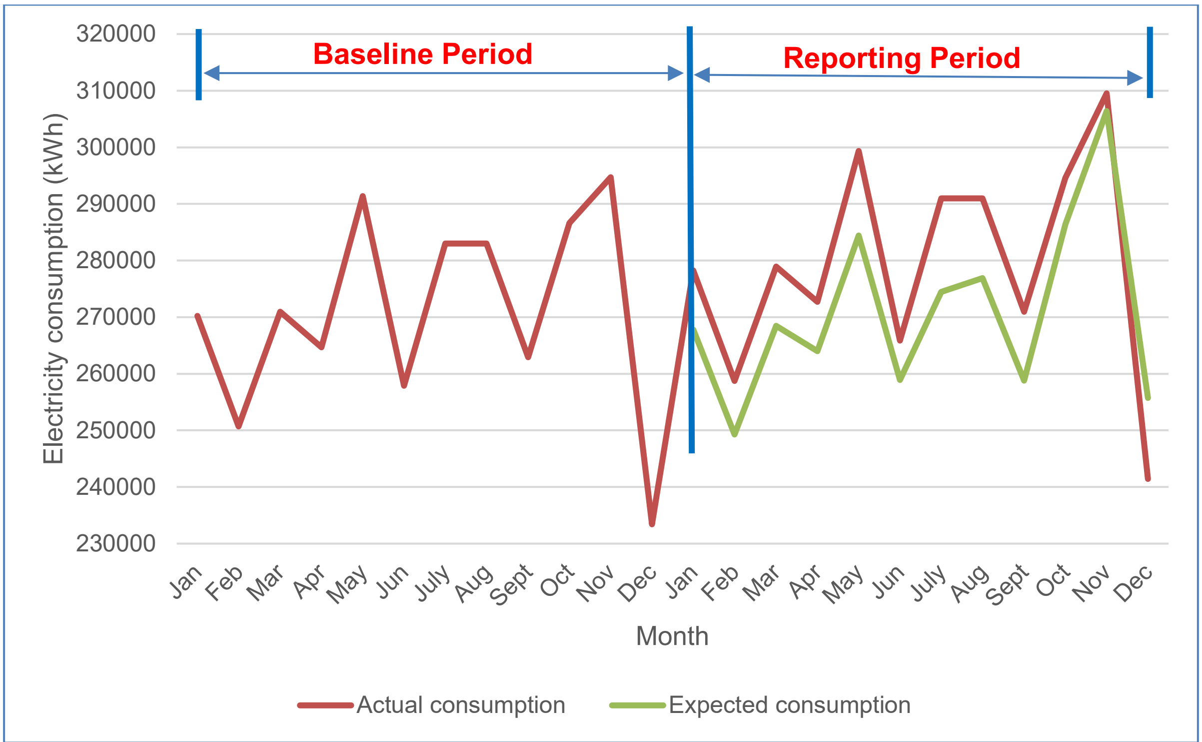

Figure 4.23: Actual vs expected consumption for reporting period for Plant 1

4.4.1.2 Actual versus Expected Consumption for Plant 2

Figure 4.24 shows a comparison of actual consumption and expected consumption during the reporting period. Despite an increase in average production from the base-line period (monthly average: 47424 tonnes of zinc) to reporting period (monthly aver-age:47530 tonnes of zinc), the energy efficiency interventions made in the ensuing year led to a decrease in electricity consumption relative to the expected or baseline energy consumption that would have occurred in the absence of the interventions. The energy savings are calculated as the difference between the baseline energy con-sumption and the actual energy consumption, hence there were substantial energy savings that were realised for Plant 2.

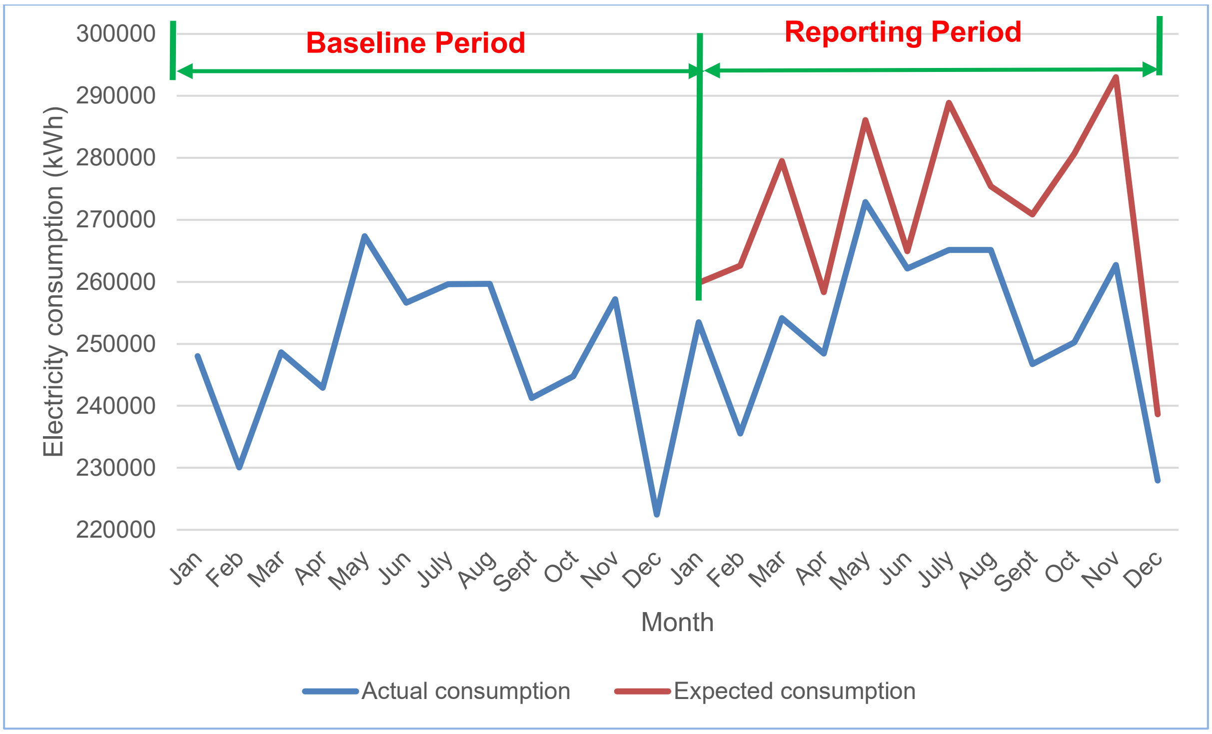

Figure 4.24: Actual vs expected consumption for reporting period for Plant 2

4.4.1.3 Actual versus Expected Consumption for Plant 3

Figure 4.25 shows a comparison of actual consumption and expected consumption during the reporting period.

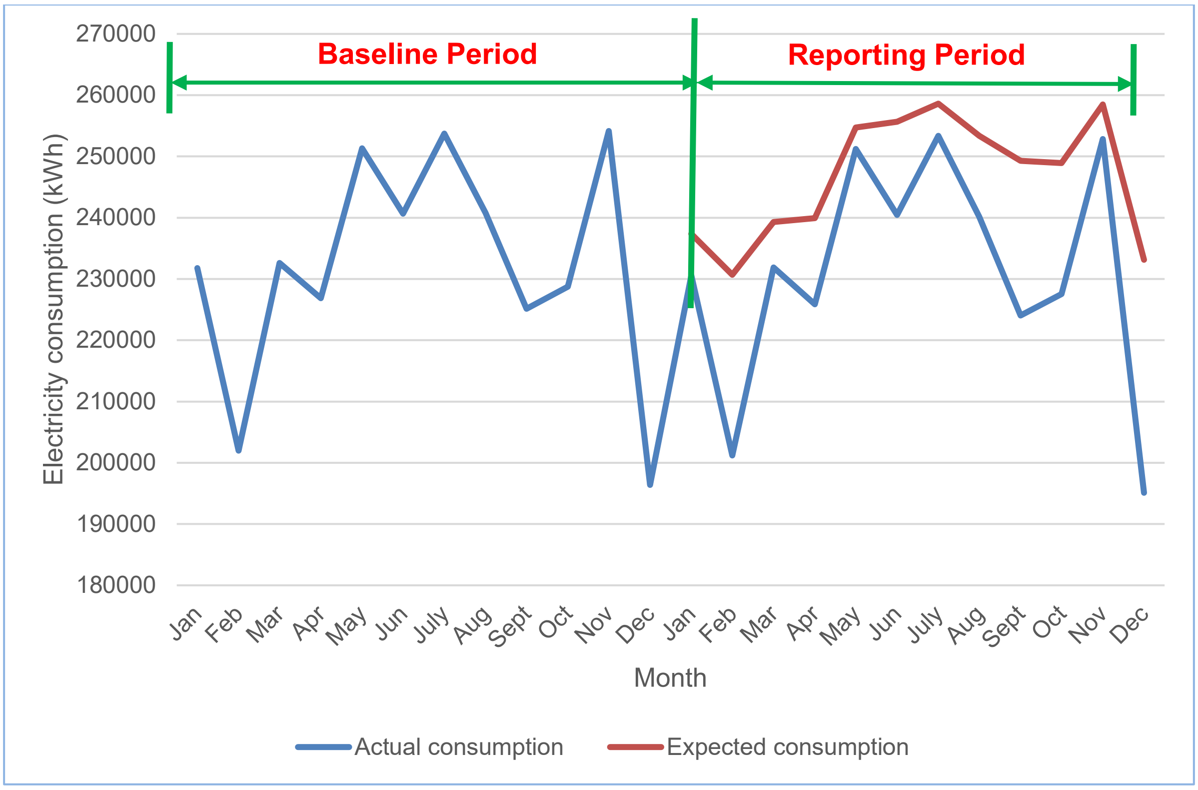

Figure 4.25: Actual vs expected consumption for reporting period for Plant 3

An increase in average production was noted from the baseline period (monthly average: 39326 tonnes of zinc) to reporting period (monthly average: 39387 tonnes of zinc). A decrease in electricity consumption was realised due to energy efficiency interventions were made in the ensuing year by covering process tanks with a 40 mm thick insulating material that prevented heat loss.

4.4.1.4 Actual versus Expected Consumption for Plant 4

Figure 4.26 shows a comparison of actual consumption and expected consumption during the reporting period.

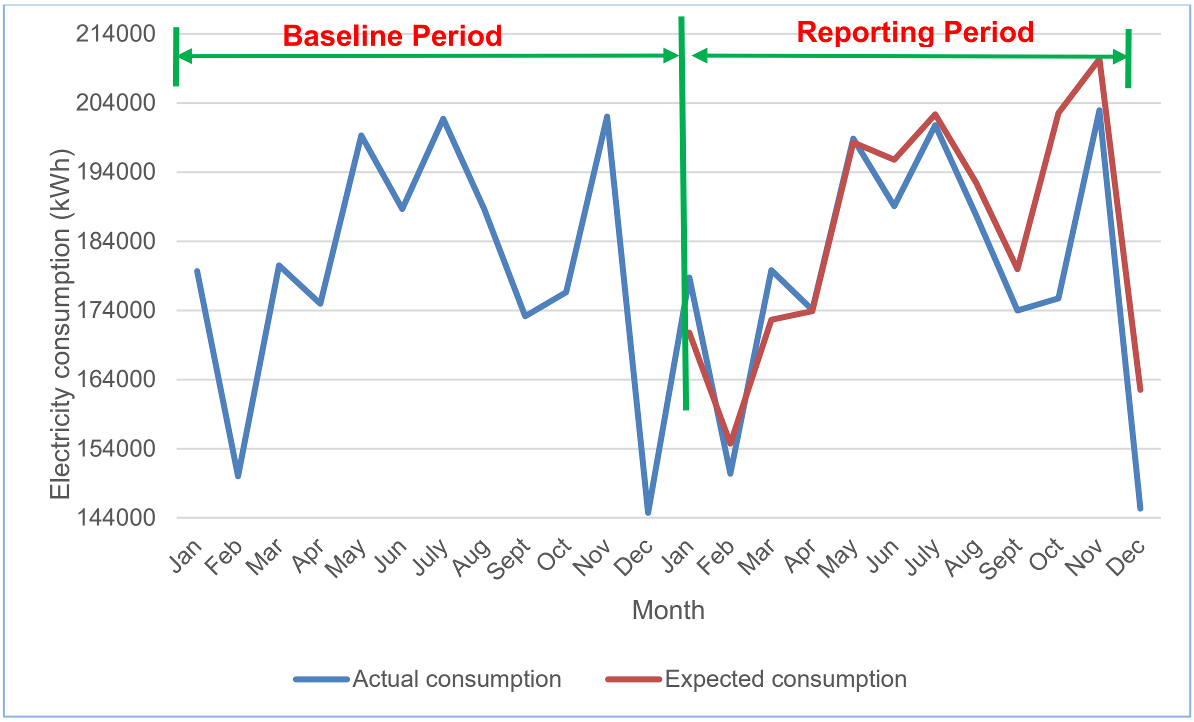

Figure 4.26: Actual vs expected consumption for reporting period for Plant 4

The plant experienced a notable increase in average production from the baseline period (monthly average: 29662 tonnes of zinc used) to reporting period (monthly average: 30334 tonnes of zinc used). The energy efficiency interventions made in the ensuing year, except in March, led to a decrease in electricity consumption relative to the expected or baseline energy consumption that would have occurred in the absence of the interventions. The energy savings are calculated as the difference between the baseline energy consumption and the actual energy consumption; hence, there were substantial energy savings that were realised for Plant 4, especially during the second half of the year.

4.4.2 Energy Intensity Index

Energy intensity index is the ratio of actual energy consumed to what would have been expected in the absence of any energy efficiency initiatives. Energy Intensity is measured by the quantity of energy required per unit output or activity so that using less energy to produce a product reduces the intensity. EII is essential for monitoring the process to establish the existing pattern of energy consumption, and hence, targeting to identify energy consumption level which is appropriate as a management goal to strive for energy efficiency.

4.4.2.1 Energy Intensity Index for Plant 1

Figure 4.27 shows the Energy Intensity Index for the galvaniser. The energy performance of galvaniser was poor for the months January, February, March, May, July and August, average in April and June, and good in November and December where there was less production due to annual shutdown and festive season holiday.

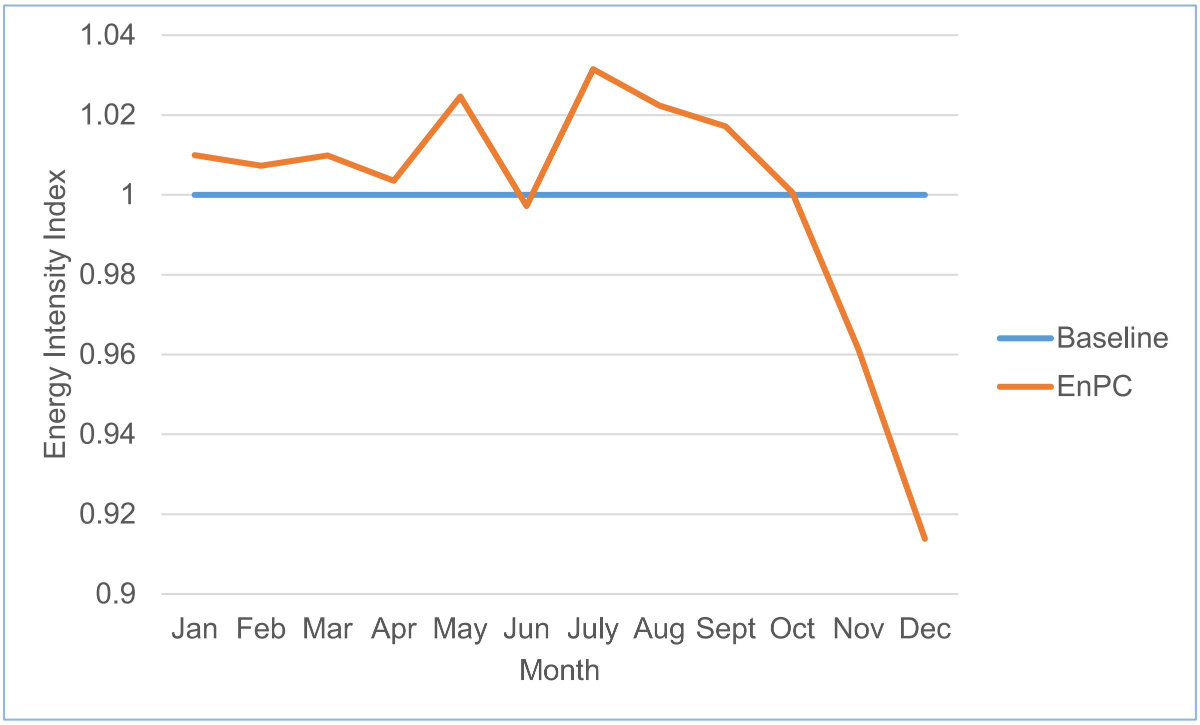

Figure 4.27: Energy Intensity Index for Plant 1

4.4.2.2 Energy Intensity Index for Plant 2

Figure 4.28 shows the Energy Intensity Index for the galvaniser. The energy performance of the galvaniser was generally good for the reporting period. Energy performance improved from January to February, deteriorated from March to June, improved in July, but decreased in August, before improving up to November.

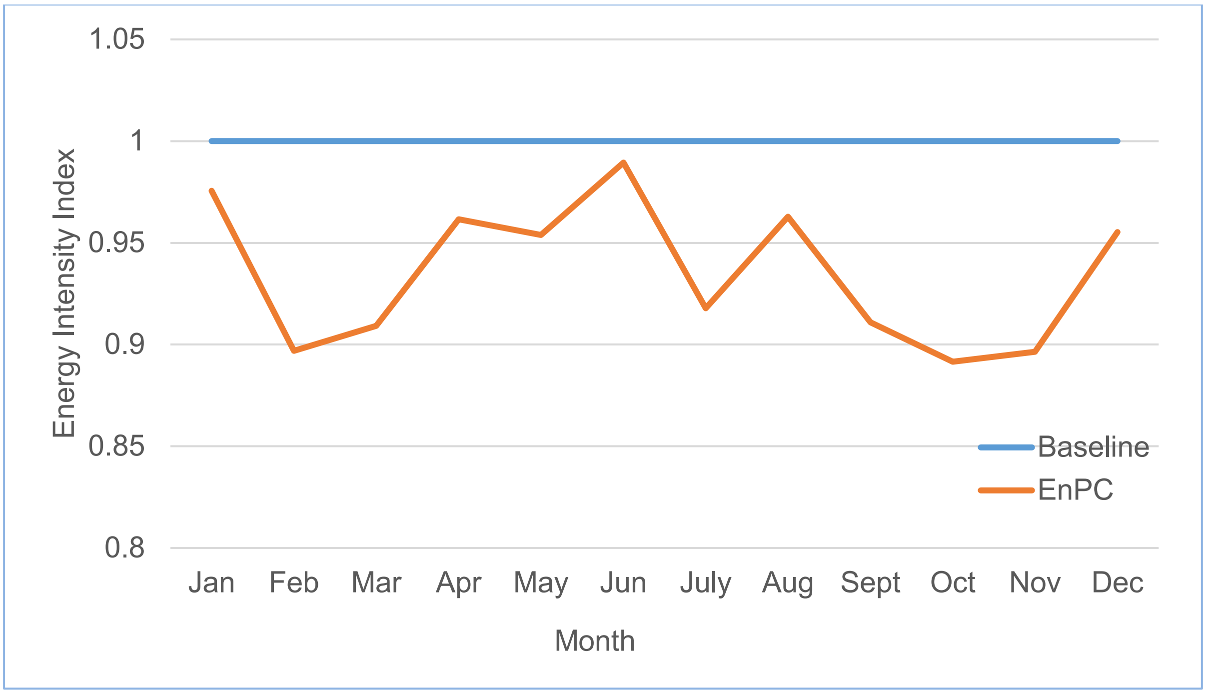

Figure 4.28: Energy Intensity Index for Plant 2

4.4.2.3 Energy Intensity Index for Plant 3

Figure 4.29 shows the Energy Intensity Index for the galvaniser. The energy performance of galvaniser was generally good but inconsistent for the reporting period. Energy performance was cyclical, improved from January to February, deteriorated in March, improved in April, decreased in May, and improved in June. The energy performance was generally good in September and October during the reporting period.

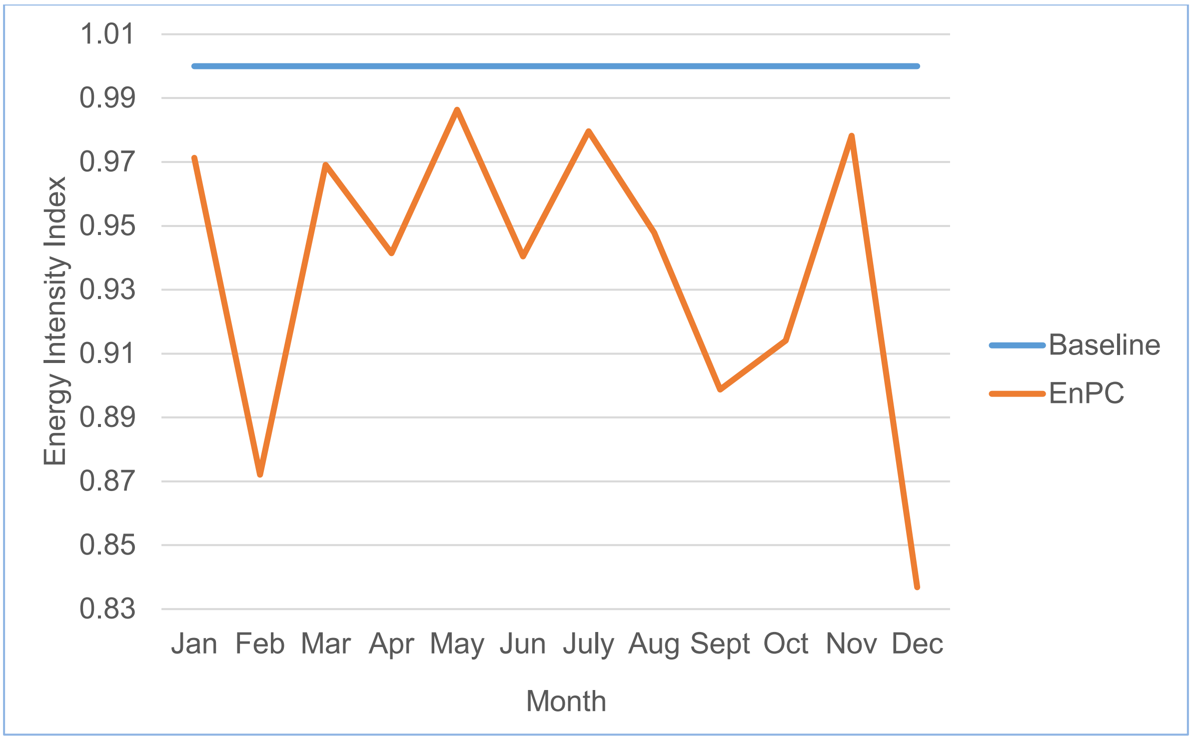

Figure 4.29: Energy Intensity Index for Plant 3

4.4.2.4 Energy Intensity Index for Plant 4

Figure 4.27 shows the Energy Intensity Index for the galvaniser. The energy performance of galvaniser was generally good for all the months except in March during the reporting period. The energy performance for Plant 4 was best in October during the reporting period.

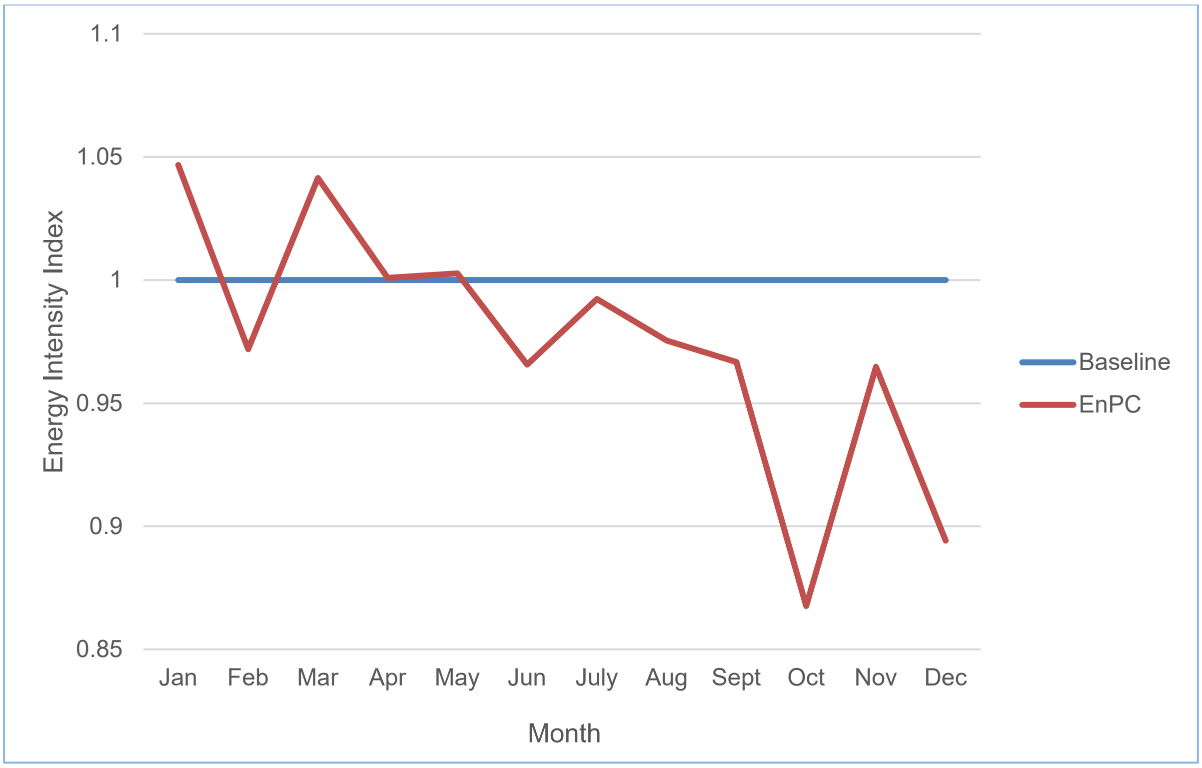

Figure 4.30: Energy Intensity Index for Plant 4

4.4.3 Cumulative Sum

4.4.3.1 Cumulative Sum for Plant 1

It has been noted that Plant 1 failed to sustain the energy efficiency interventions that were made at the beginning of the ensuing year, and thus did not yield any decreased electricity consumption. Table 4.26 shows a summary for EII, CUSUM and targeted savings CUSUM. CUSUM represents the difference between the baseline (expected or standard consumption) and the actual consumption points over the reporting period.

Table 4.26: Summary for EII, CUSUM and targeted savings CUSUM

Month	Expected consumption	EII	Actual savings	CuSum	Targeted consumption (2.5%)	Targeted Savings (Tgt-Exp)	Target Savings CUSUM
Jan	267761	1.04	10475	10475	261067	-6694	-6694
Feb	249274	1.04	9443	19919	243042	-6232	-12926
Mar	268479	1.04	10456	30375	261767	-6712	-19638
Apr	264005	1.03	8698	39073	257405	-6600	-26238
May	284392	1.05	14958	54031	277282	-7110	-33348
Jun	258892	1.03	6986	61017	252419	-6472	-39820
July	274475	1.06	16506	77524	267613	-6862	-46682
Aug	276884	1.05	14097	91620	269962	-6922	-53604
Sept	258801	1.05	12149	103769	252331	-6470	-60074
Oct	286426	1.03	8173	111943	279265	-7161	-67235
Nov	306401	1.01	3129	115072	298741	-7660	-74895
Dec	255735	0.94	-14321	100751	249342	-6393	-81288

The expected energy consumption was calculated basing on the trendline equation shown in Figure 4.22. The difference between actual and calculated electricity consumption was calculated and then CUSUM was computed.

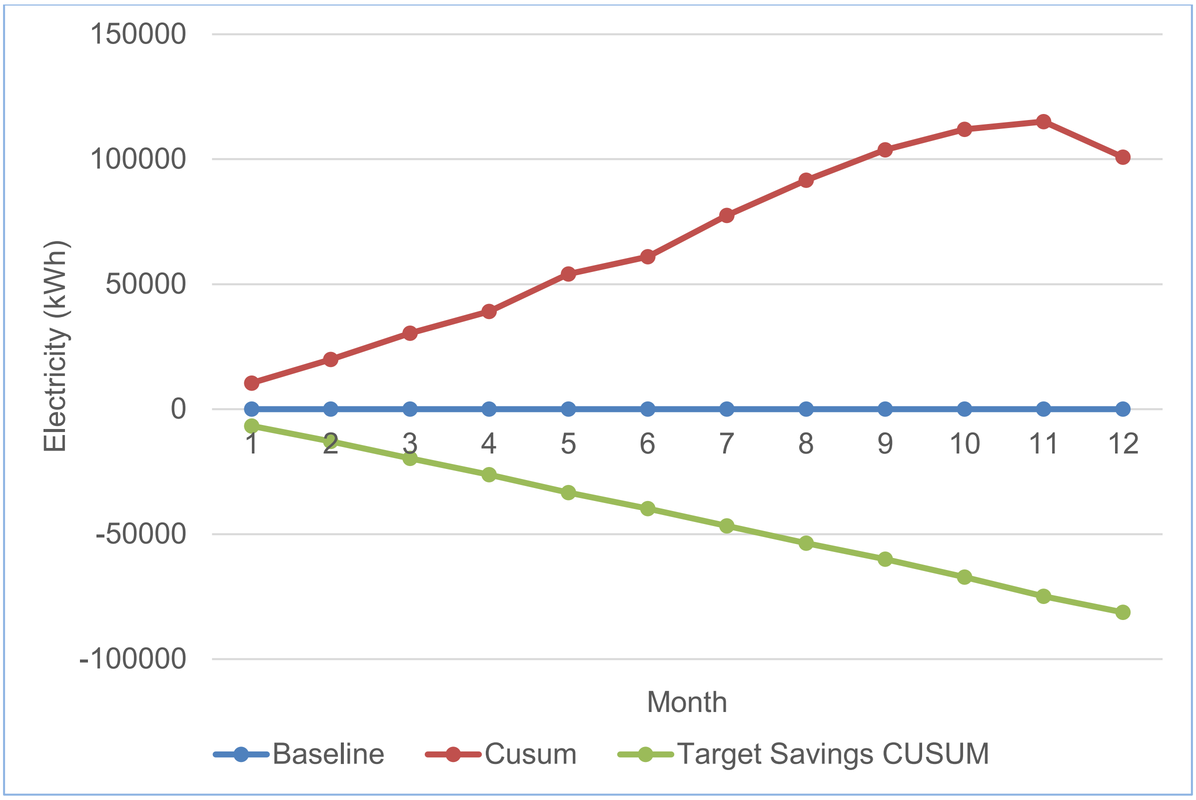

Figure 4.31: CUSUM and targeted savings CUSUM

Figure 4.31 shows that during the reporting period, energy performance is deteriorating at a uniform rate (line going up) from January to April, decrease at a slightly higher rate from April to May, improves slightly from May to June and deteriorates again from June to November, and finally improves in December. It is crucial to note that when analysing a CUSUM graph, the changes in direction of the line point out crucial events that are relevant to the energy consumption pattern. Since it was known that during the baseline period, the case-in-point galvaniser had no changes in the energy system, the poor performance can be attributed to poor housekeeping, poor control, or maintenance. Considering the reporting period under study, a targeted reduction in energy consumption to 97.5% (2.5% savings), would yield cumulative savings shown in Figure 4.31.

4.4.3.2 Cumulative Sum for Plant 2

Plant 2 experienced an increase in average production from the baseline period to reporting period and the energy efficiency interventions made in the ensuing year led to a decrease in electricity consumption relative to the expected energy consumption. Table 4.27 shows a summary for EII, CUSUM and targeted savings CUSUM. CUSUM represents the difference between the baseline (expected or standard consumption) and the actual consumption points over the reporting period.

Table 4.27: Summary for EII, CUSUM and targeted savings CUSUM

Month	Expected consumption	EII	Actual savings	CuSum	Targeted consumption (2.5%)	Targeted Savings (Tgt-Exp)	Target Savings CUSUM
Jan	259852	0.98	-6352	-6352	253356	-6496	-6496
Feb	262612	0.90	-27052	-33405	256047	-6565	-13062
Mar	279511	0.91	-25369	-58774	272523	-6988	-20049
Apr	258330	0.96	-9910	-68683	251871	-6458	-26508
May	286072	0.95	-13196	-81879	278920	-7152	-33659
Jun	264938	0.99	-2798	-84677	258315	-6623	-40283
July	288870	0.92	-23720	-108398	281649	-7222	-47505
Aug	275428	0.96	-10258	-118655	268542	-6886	-54390
Sept	270880	0.91	-24130	-142785	264108	-6772	-61162
Oct	280687	0.89	-30437	-173223	273670	-7017	-68180
Nov	293022	0.90	-30322	-203545	285697	-7326	-75505
Dec	238637	0.96	-10677	-214222	232671	-5966	-81471

Figure 4.32 shows that during the reporting period, energy performance is improving (line going down) from January to May, deteriorates slightly from May to June and improves again to the end of the year. It is crucial to note that when analysing a CUSUM graph, the changes in direction of the line point out crucial events that are relevant to the energy consumption pattern. Since it was known that the case-in-point galvaniser made some changes in terms of energy management of the process tanks, the change in performance can be attributed to covering process tanks with a 40 mm thick insulating material that prevented heat loss. Considering the reporting period under study, a targeted reduction in energy consumption to 97.5 % (2.5% savings), would yield cumulative savings shown in Table 4.27.

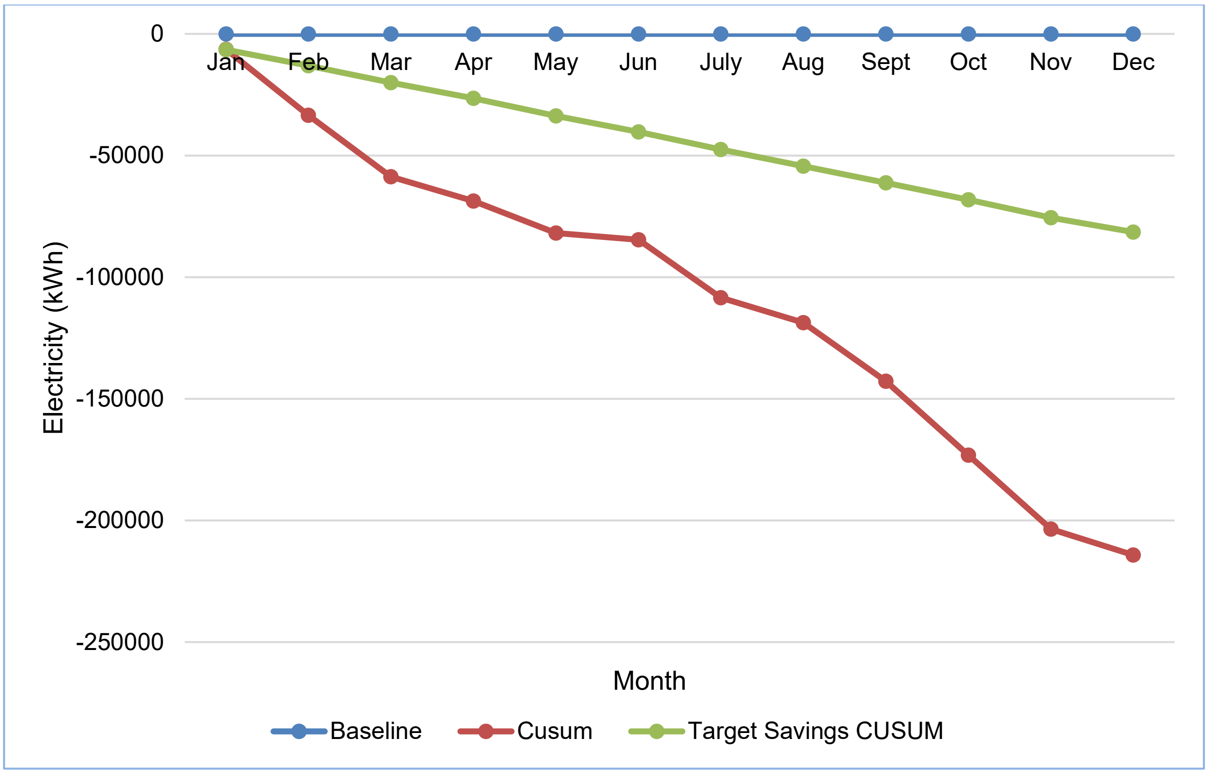

Figure 4.32: CUSUM and targeted savings CUSUM

4.4.3.3 Cumulative Sum for Plant 3

It has been established that an increase in average production was noted from the baseline period to reporting period and a decrease in electricity consumption was realised when energy efficiency interventions were made in the ensuing year. Table 4.28 shows a summary for EII, CUSUM and targeted savings CUSUM. CUSUM represents the difference between the baseline (expected or standard consumption) and the actual consumption points over the reporting period.

Table 4.28: Summary for EII, CUSUM and targeted savings CUSUM

Month	Expected consumption	EII	Actual savings	CuSum	Targeted consumption (2.5%)	Targeted Savings (Tgt-Exp)	Target Savings CUSUM
Jan	237372	0.97	-6822	-6822	231438	-5934	-5934
Feb	230684	0.87	-29504	-36326	224917	-5767	-11701
Mar	239296	0.97	-7404	-43730	233313	-5982	-17684
Apr	239910	0.94	-14040	-57770	233912	-5998	-23682
May	254700	0.99	-3474	-61244	248333	-6368	-30049
Jun	255673	0.94	-15221	-76465	249281	-6392	-36441
July	258614	0.98	-5264	-81730	252149	-6465	-42906
Aug	253339	0.95	-13199	-94928	247005	-6333	-49240
Sept	249297	0.90	-25237	-120166	243065	-6232	-55472
Oct	248928	0.91	-21388	-141554	242705	-6223	-61695
Nov	258471	0.98	-5621	-147175	252009	-6462	-68157
Dec	233146	0.84	-38041	-185216	227317	-5829	-73986

Figure 4.33 shows that during the reporting period when compared to the baseline period, energy performance has improved (line going down) throughout the year. The changes in direction of the line point out crucial events that are relevant to the energy consumption pattern.

Since it was known that the case-in-point galvaniser made some changes in terms of energy management of the process tanks, the change in energy performance can be attributed to covering process tanks with insulating material that prevented heat loss. Considering the reporting period under study, a targeted reduction in energy consumption to 97.5 % (2.5% savings), would yield cumulative savings shown in Table 4.28.

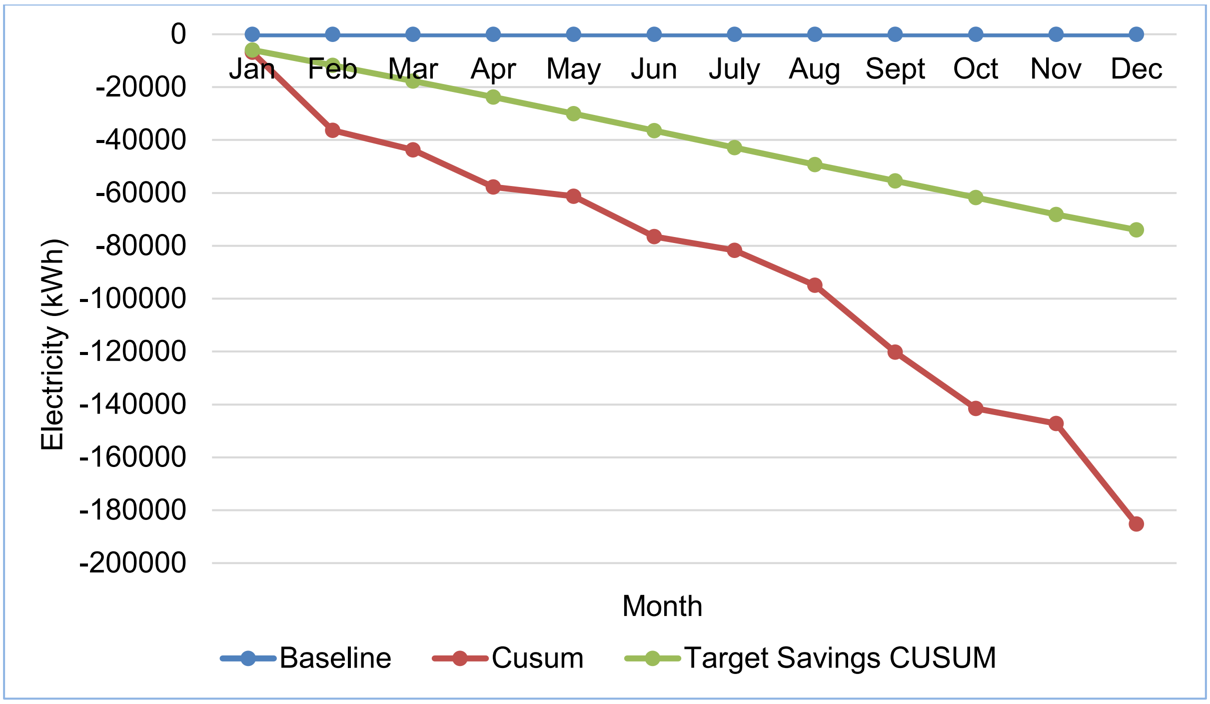

Figure 4.33: CUSUM and targeted savings CUSUM

4.4.3.4 Cumulative Sum for Plant 4

Plant 4 has experienced a notable increase in average production from the baseline period to reporting period and the energy efficiency interventions made in the ensuing year, except in March, led to a decrease in electricity consumption relative to the base-line energy consumption. Table 4.29 shows a summary for EII, CUSUM and targeted savings CUSUM. CUSUM represents the difference between the baseline (expected or standard consumption) and the actual consumption points over the reporting period.

Since it was known that the case-in-point galvaniser made some changes in terms of energy management of the process tanks, the change in performance can be at-tributed to covering process tanks with insulating material that prevented heat loss. Considering the reporting period under study, a targeted reduction in energy consump-tion to 97.5 % (2.5% savings), would yield cumulative savings shown in Table 4.29. The plant managed to achieve substantial energy savings, as shown in Figure 4.34, from November to December of the reporting period, cumulative savings went beyond the target savings CUSUM.

Table 4.29: Summary for EII, CUSUM and targeted savings CUSUM

Month	Expected consumption	EII	Actual savings	CuSum	Targeted consumption (2.5%)	Targeted Savings (Tgt-Exp)	Target Savings CUSUM
Jan	170778	1.05	7982	7982	166508	-4269	-4269
Feb	154719	0.97	-4339	3643	150851	-3868	-8137
Mar	172636	1.04	7156	10799	168320	-4316	-12453
Apr	173904	1.00	156	10955	169557	-4348	-16801
May	198284	1.00	542	11497	193327	-4957	-21758
Jun	195769	0.97	-6717	4779	190875	-4894	-26652
July	202362	0.99	-1567	3213	197303	-5059	-31711
Aug	192469	0.98	-4729	-1517	187657	-4812	-36523
Sept	179942	0.97	-5982	-7499	175444	-4499	-41022
Oct	202557	0.87	-26817	-34316	197493	-5064	-46086
Nov	210367	0.96	-7417	-41732	205107	-5259	-51345
Dec	162512	0.89	-17207	-58940	158450	-4063	-55407

Figure 4.34 shows that energy performance during the reporting period is improved (line going down) from January to February, deteriorated from February to March, was fairly constant between March and May, improved gradually between May and September, and improved more rapidly up to the end of the year. It is crucial to note that when analysing a CUSUM graph, the changes in direction of the line point out crucial events that are relevant to the energy consumption pattern.

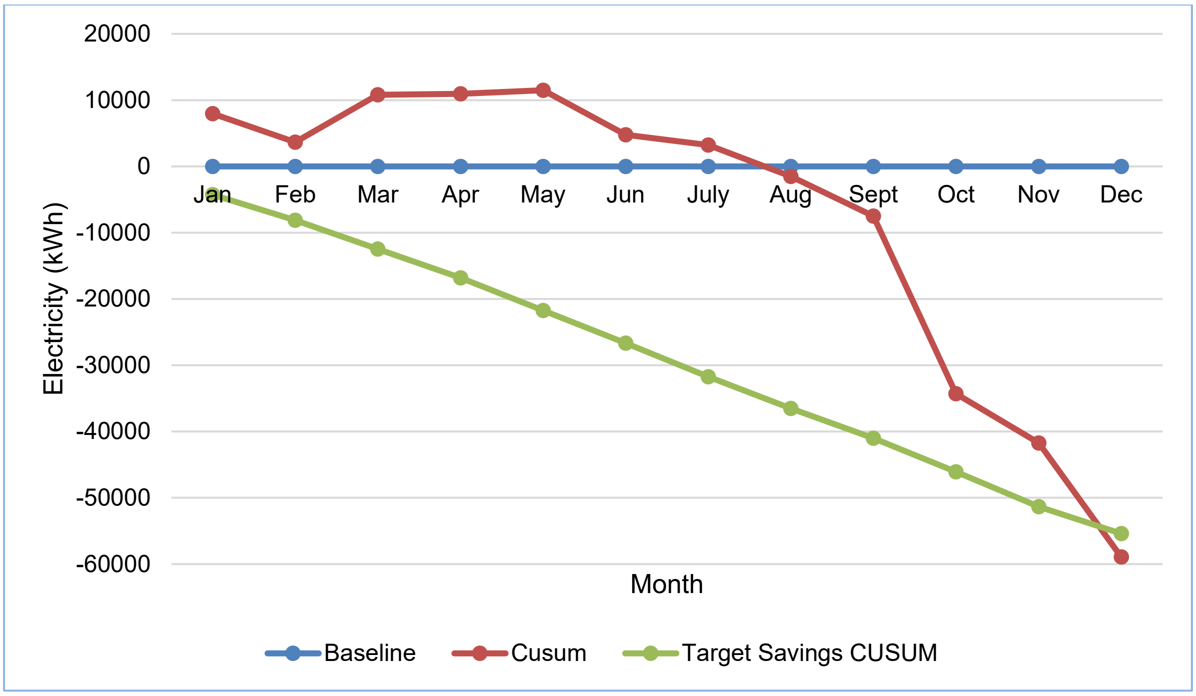

Figure 4.34: CUSUM and targeted savings CUSUM

4.4.4 Specific Energy Consumption

4.4.4.1 Specific energy Consumption for Plant 1

Figure 4.35 shows a comparative schematic for specific energy consumption per tonne of zinc used for the baseline and reporting periods. Concerning the baseline period, the galvaniser has been failing to achieve a set target of 5 kWh per tonne for the months from January to October, but it achieved in November and December where there was less production due to annual shutdown and festive season holiday.

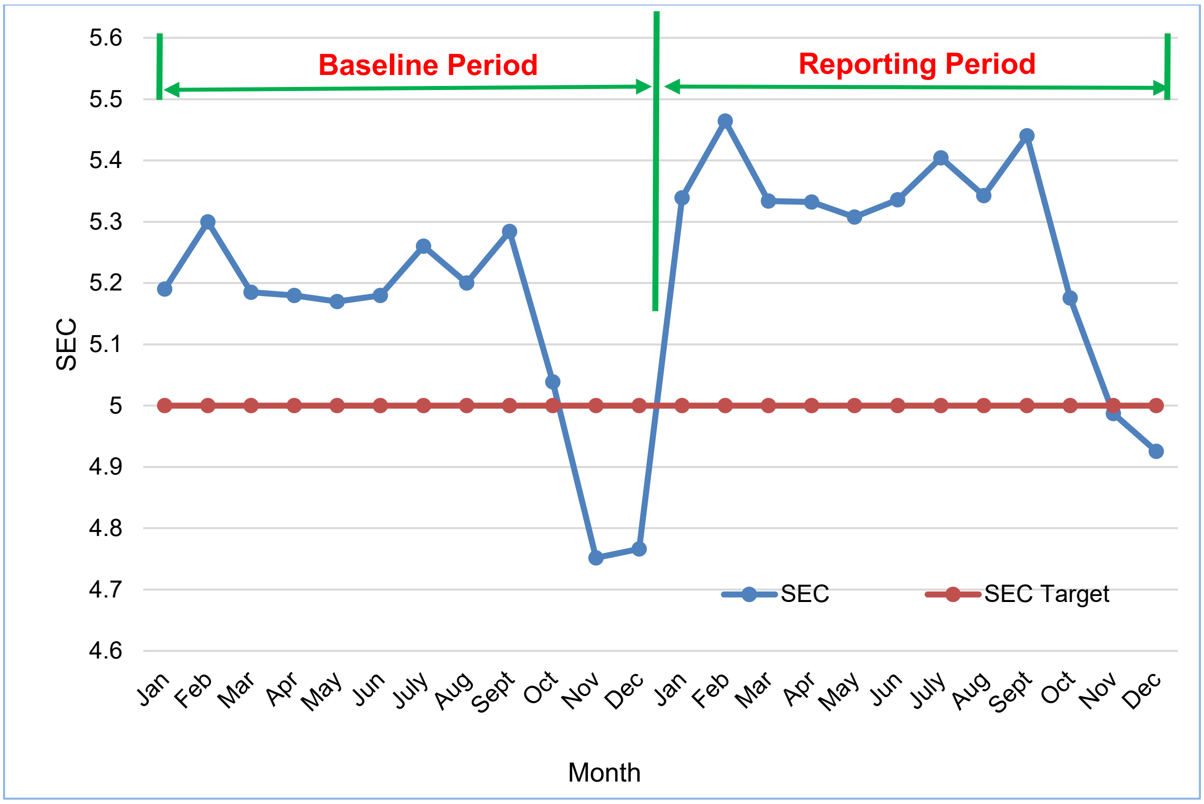

Figure 4.35: Monthly SEC per tonne of zinc used for Plant 1

Figure 4.35 also reveals that the specific energy consumption per tonne of zinc used for the reporting period has generally increased when compared to the SEC for the baseline period.

It was established that the level of production affects the specific energy consumption. The addition of production data to the SEC chart would therefore aid to explain the trends on the SEC chart. For instance, a very low SEC would be anticipated if the level of production is low as a result of baseload or fixed energy consumption (energy consumption that happens regardless of production levels).

Figure 4.36 illustrates the relationship between SEC and the amount of zinc used (Production). There was generally no substantial increase in the amount of zinc used between the baseline and reporting period. Since the data fit between SEC and the amount of zinc used is poor, yet there should be a relationship, the scenario of Plant 1 indicates a poor level of control and hence greater potential for energy savings.

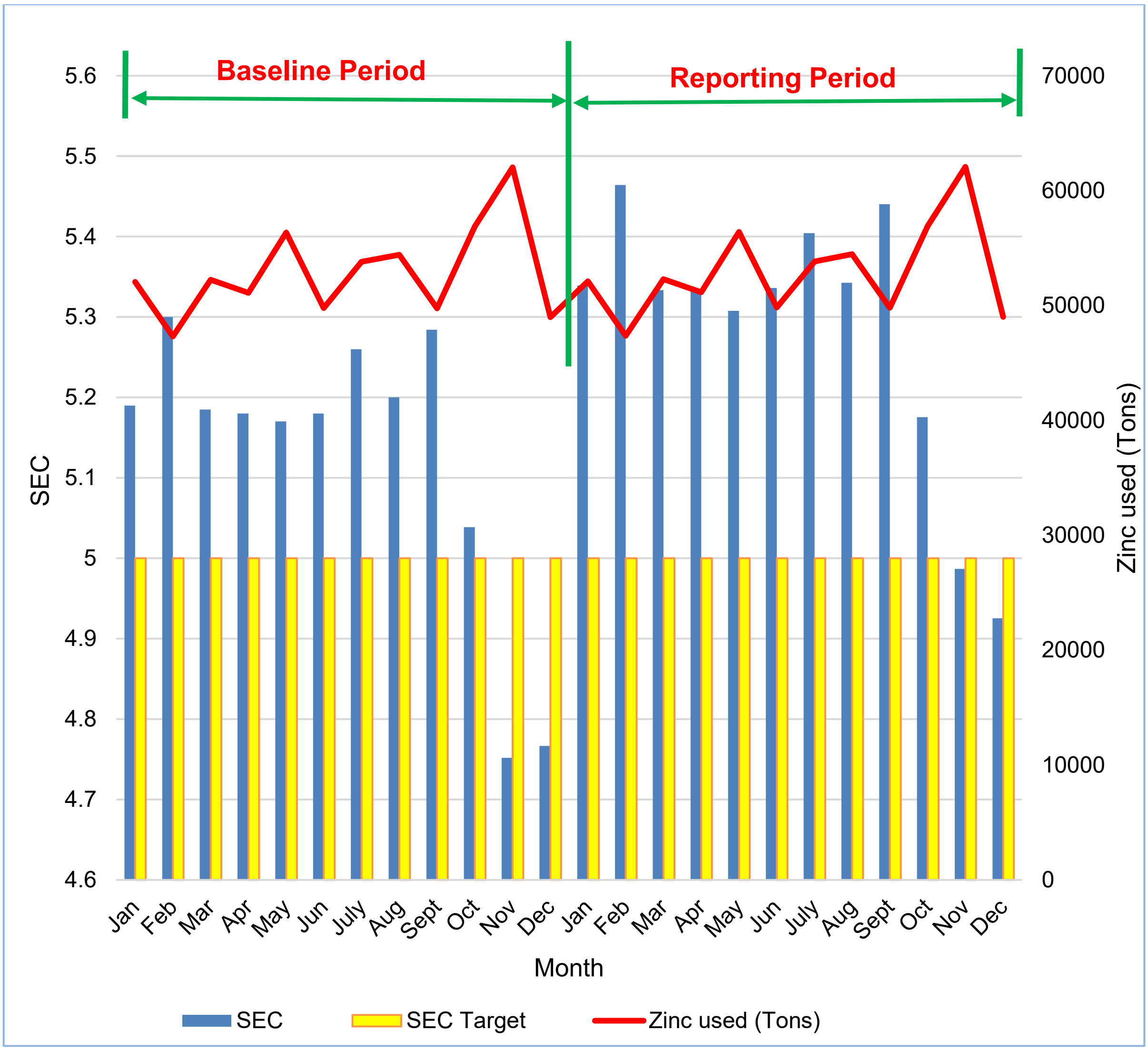

Figure 4.36: SEC with Production (Zinc used) for Plant 1

4.4.4.2 Specific Energy Consumption for Plant 2

Figure 4.37 shows a comparative schematic for specific energy consumption per tonne of zinc used for the baseline and reporting periods for Plant 2. The baseline and reporting periods were benchmarked against a set target of 5 kWh. The galvaniser failed to achieve the target for the months from January to October during the baseline period, but it achieved in November and December. On the other hand, the galvaniser failed to achieve the target for the months from January to August during the reporting period but achieved from September to December.

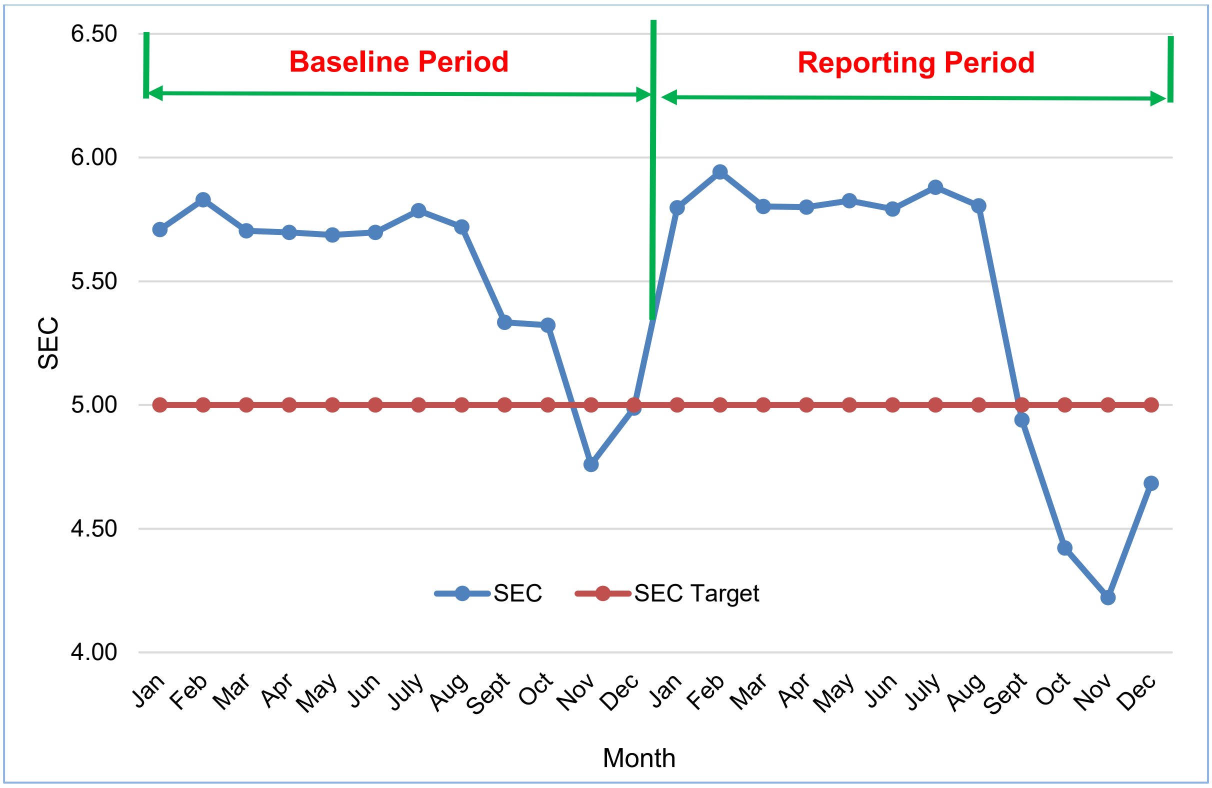

Figure 4.37: Monthly SEC per tonne of zinc used for Plant 2

Figure 4.37 also reveals that the specific energy consumption per tonne of zinc used for the reporting period has generally increased when compared to the SEC for the baseline period. This is attributed to a poor level of control such as attending to reworks on cracks, damaged areas, and dross removal which is conducted on a timed basis, yet drossing frequency should be dependent upon tonnage galvanised.

The addition of production data to the SEC chart would aid to explain the trends on the graph since it was established that the level of production affects the specific energy consumption. It was revealed from Figure 4.38 that as the level of production increased the SEC generally decreased, as noted especially in November for both the baseline and reporting periods for Plant 2.

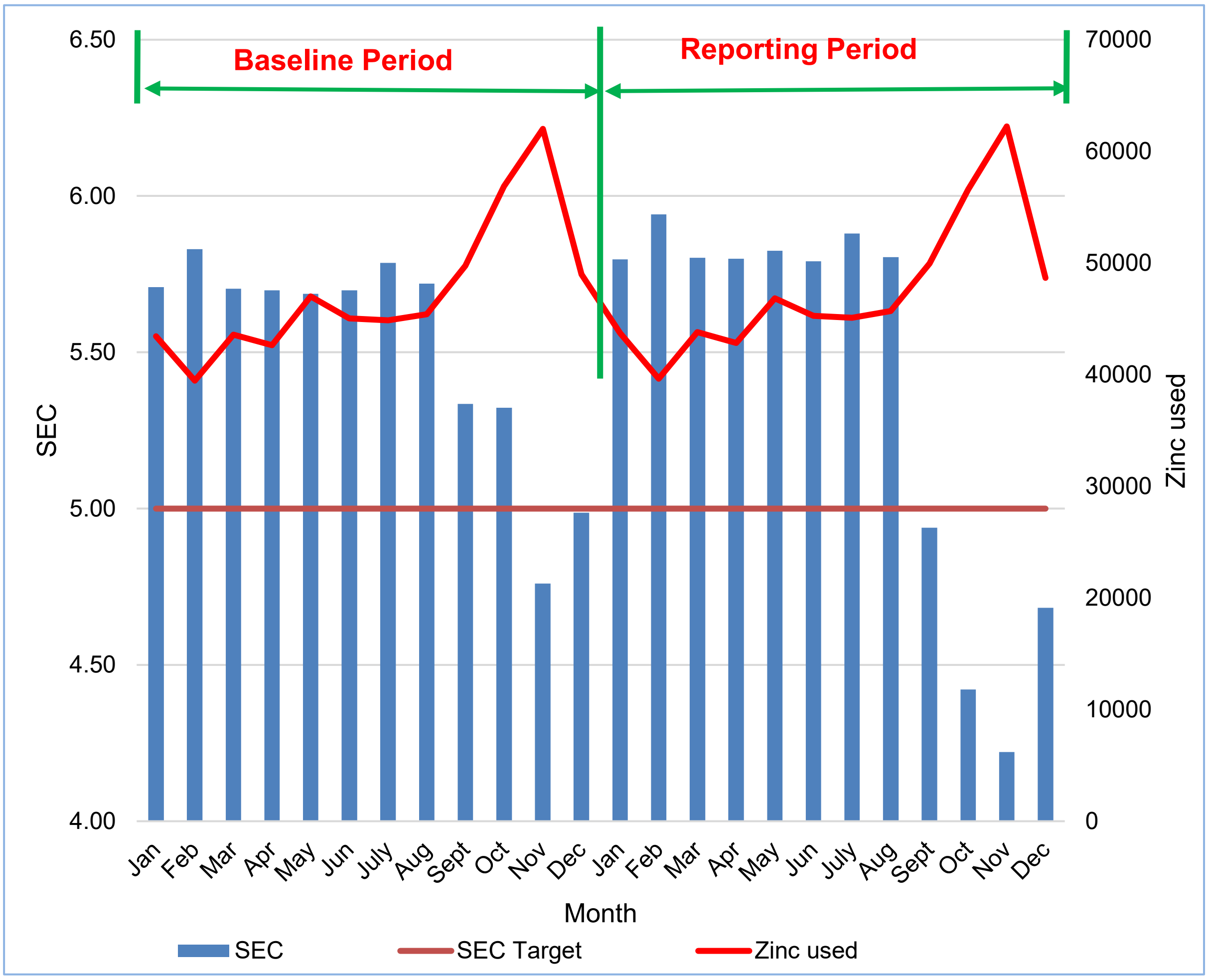

Figure 4.38: SEC with Production (Zinc used) for Plant 2

4.4.4.3 Specific Energy Consumption for Plant 3

The use of SEC is simple and is one of the basic approaches for calculating energy usage per unit of a product since the average energy consumed, the quantity of energy-consuming devices, and the quantity produced during the period of interest are used for the calculation of SEC (Palamutçu 2015). Figure 4.39 shows a comparative schematic for specific energy consumption per tonne of zinc used for the baseline and reporting periods. The baseline and reporting periods were benchmarked against a set target of 5 kWh. The galvaniser failed to achieve the target for all the months during the baseline period. On the other hand, due to energy efficiency interventions during the reporting period, the galvaniser's energy performance improved it managed to achieve the target during the last quarter of the reporting period.

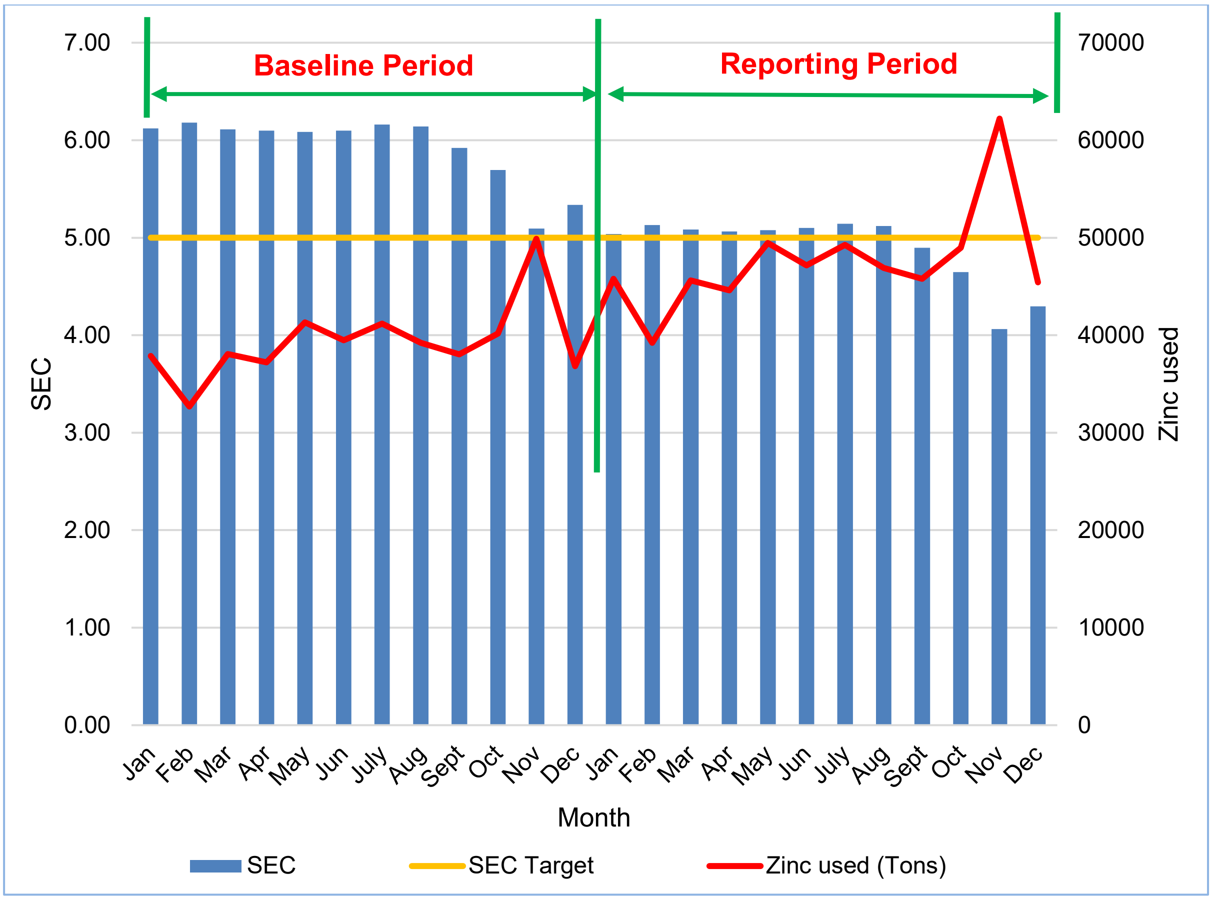

Figure 4.39: SEC with Production (Zinc used) for Plant 3

Since the level of production has an effect on the specific energy consumption, it was imperative to add the production data to the SEC chart and explain the trends on the SEC chart. The results from Figure 4.39 show that the level of production during the reporting period is higher than the production level during the baseline period, while on the other hand, SEC decreased during the reporting period for Plant 3.

4.4.4.4 Specific Energy Consumption for Plant 4

It was established that galvanising tanks are the largest SEU followed by degreasing and pickling tanks, while the flux tanks consume slightly less energy followed by the cranes which are the fifth SEUs for Plant 4. Figure 4.40 shows a comparative schematic for specific energy consumption per tonne of zinc used for the baseline and reporting periods. The baseline and reporting periods were benchmarked against a set target of 5 kWh. Similar to Plant 3, the galvaniser failed to achieve the target for all the months during the baseline period. On the other hand, due to energy efficiency interventions during the reporting period, the galvaniser's energy performance improved it managed to achieve the target from May to December of the reporting period.

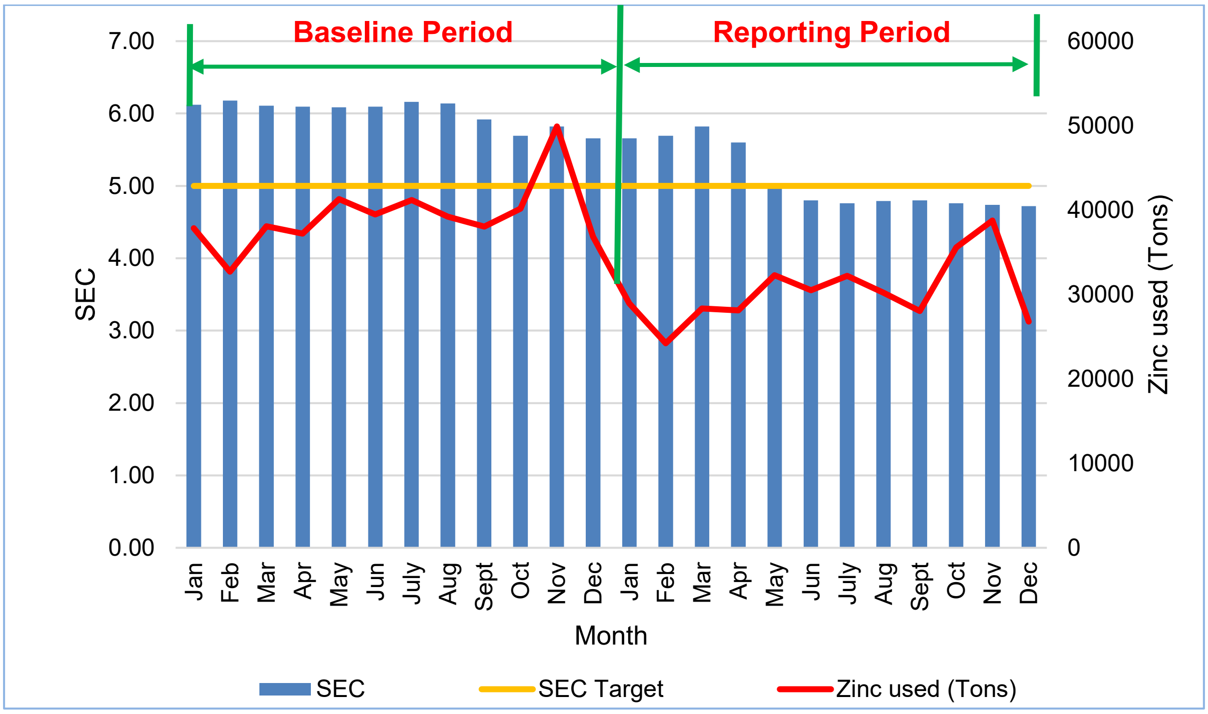

Figure 4.40: SEC with Production (Zinc used) for Plant 4

Production data was added to the SEC chart to establish the effect of the level of production on the specific energy consumption. The results from Figure 4.40 show that the level of production during the reporting period is lower than the production level during the baseline period, and the SEC also decreased during the reporting period.

4.4.4.5 Discussion of Specific Energy Consumption

Energy is consumed during the galvanising process even during idling periods when no parts are being produced by the plant since large quantities of zinc must be maintained in a molten state. Therefore, the SEC is not constant and is dependent on the production rate of the galvaniser. Previous work by Blake and Beck (2004b) had also revealed the production-dependent nature of SEC, outlining that the energy losses from the surface and walls of the furnace or tank during the galvanising process become more influential at low levels of production. The evidence from work measurement revealed that the time spent without insulative covers over the exposed surface of molten zinc was over 60% longer than the time which the furnace spent in production. The energy lost through the exterior walls of the furnace was assumed to be negligible, accounting for about 1.5% of the total consumption. It is against the backdrop that the time spent without insulative covers over the exposed surface of molten zinc was far longer than the time which the furnace spent in production, that it was crucial to develop an optimal scheduling algorithm for energy optimisation.

There was generally no substantial amount of zinc used between the baseline and reporting period, hence the scenario of Plant 1 indicates a poor level of control and hence greater potential for energy savings. On the other hand, for Plant 2, it was revealed that as the level of production increased the SEC generally decreased. The level of production during the reporting period was found to be higher than the production level during the baseline period, while on the other hand, SEC decreased during the reporting period for Plant 3.

On the other hand, for Plant 4, the level of production during the reporting period was found to be lower than the production level during the baseline period, and the SEC also decreased during the reporting period. Hence, given the disparity between the results of SEC for the four plants, it was noted that SEC alone cannot be used as an EnPC since it is not influenced by production only but affected by other variables such as material handling efficiency.

4.4.5 Energy Consumption Benchmarking

Energy consumption benchmarking was also done as analyses energy performance data of comparable activities to evaluate and compare performance between the four galvanising plants. The essence of energy consumption benchmarking was to increase general awareness of energy efficiency among the galvanisers which in turn may affect a behaviour change provides objective, reliable information on energy use and the benefits of improvements. Energy consumption benchmarking would necessitate the identification of best practices that can be replicated within a facility or across facilities. The following measures were used to compare the four galvanising facilities prior to any energy efficiency interventions:

- Electricity/zinc ratio;
- Electricity /dips ratio;
- Product tonnage/zinc used ratio.

Box-and-whisker plots were used as an exploratory graphic to exhibit the distribution of electricity to zinc ratio, electricity to dips ratio and product tonnage to zinc used ratio, explicitly showing the centre, spread and overall range of the distributions.

4.4.5.1 Box and Whiskers Plot for Electricity - Zinc Ratios

Figure 4.41 shows a box and whiskers plot for electricity/zinc ratios for the four plants before energy efficiency interventions. The results for all four plants demonstrate that the median is closer to the top of the box, revealing that the distribution is negatively skewed (skewed left). Some outliers were noted for Plant 1 and Plant 3.

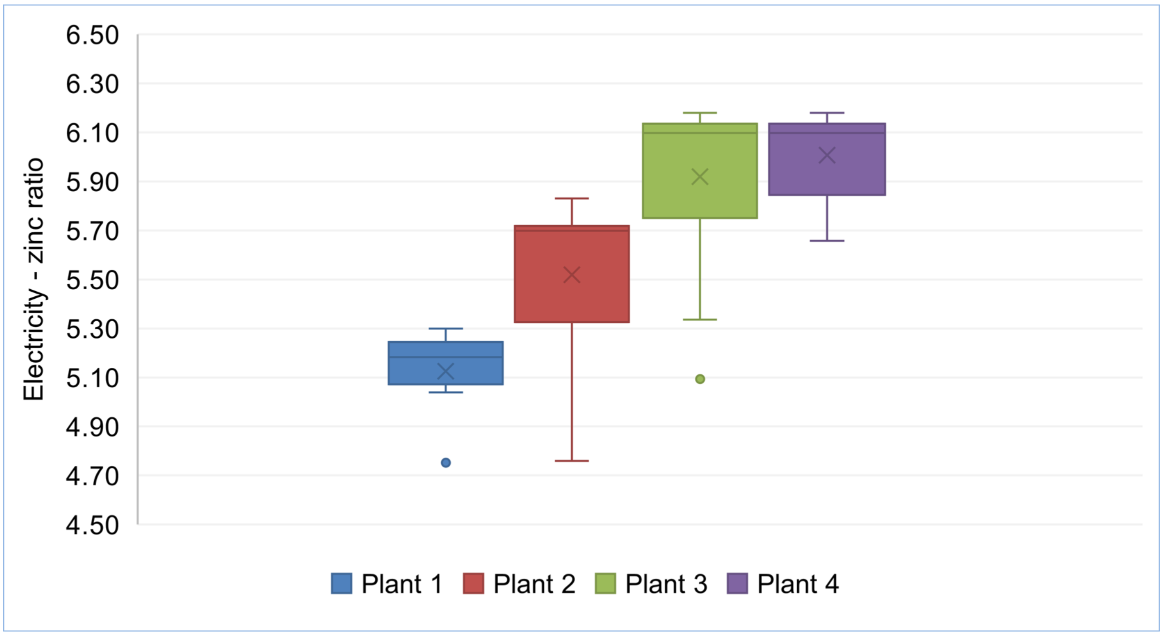

Figure 4.41: Box and whiskers for electricity/zinc ratio before interventions

The comparison of the respective medians of box plots revealed that the median line of a box plot for Plant 1 lies outside of the box of a comparison box plot for Plant 2, an indication that there is likely to be a difference between the two groups. Significant differences were also noted between Plant 2 and Plant 3. However, the comparison of the respective medians of box plots revealed that the median line of a box plot for

Plant 3 lies inside of the box of a comparison box plot for Plant 4, an indication that there is likely to be no difference between the two groups.

Comparison of the interquartile ranges and whiskers of box plots (box lengths) was also done to examine how the data is dispersed between each plant sample data. The results from Figure 4.41 shows longer boxes for Plant 2 and 3, an indication that the data is more dispersed. The data for Plant 1 revealed less dispersion, while the dispersion for Plant 3 was medium.

Figure 4.42 shows the box and whiskers plot for the electricity/zinc ratio after the energy efficiency interventions. The results demonstrate a major improvement in energy performance by Plant 3, a marginal increase for Plant 4, and no improvement for Plant 1 and Plant 2.

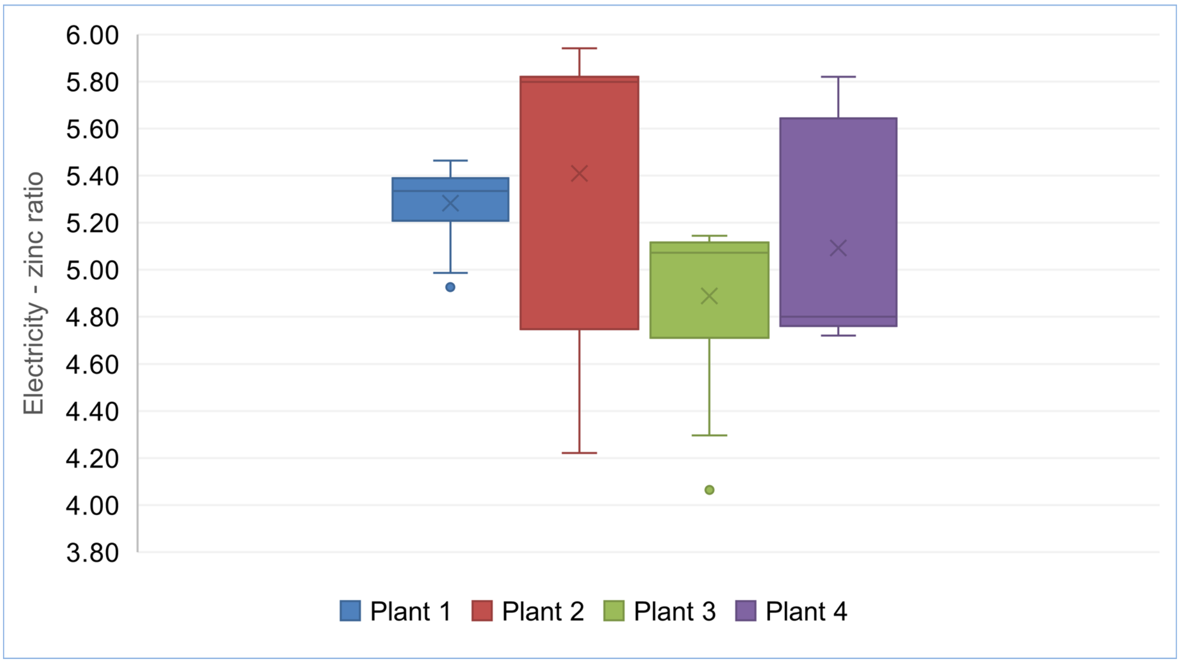

Figure 4.42: Box and whiskers plot for electricity/zinc ratio after interventions

4.4.5.2 Box and Whiskers Plot for Electricity - Dips ratio

It was also vital to investigate the relationship between the amount of electricity used and the number of dips for each of the plants since the number of dips would generally influence the frequency of covering and uncovering the process tanks to abate heat loss. Figure 4.43 shows a box and whiskers plot for electricity/dips ratios for the four plants before energy efficiency interventions. The results for Plant 1 and Plant 4 demonstrate that the median is closer to the centre of the box, revealing that the distribution is symmetrical, while the median for Plant 2 and Plant 3 is closer to the bottom of the box, an indication that the distribution is positively skewed. Some outliers were noted for Plant 2 and Plant 3. The comparison of the respective medians of box plots revealed that the median line of a box plot for Plant 1 lies outside of the box of a comparison box plot for Plant 2, an indication that there is likely to be a difference between the two groups. Significant differences were also noted between Plant 2 and Plant 3 and between Plant 3 and Plant 4.

Comparison of the interquartile ranges and whiskers of box plots was also done to examine how the data is dispersed between each plant sample data. The results from Figure 4.43 shows longer boxes for Plant 2 and 4, an indication that the data is more dispersed. The data for Plant 1 revealed less dispersion, while the dispersion for Plant 3 was medium.

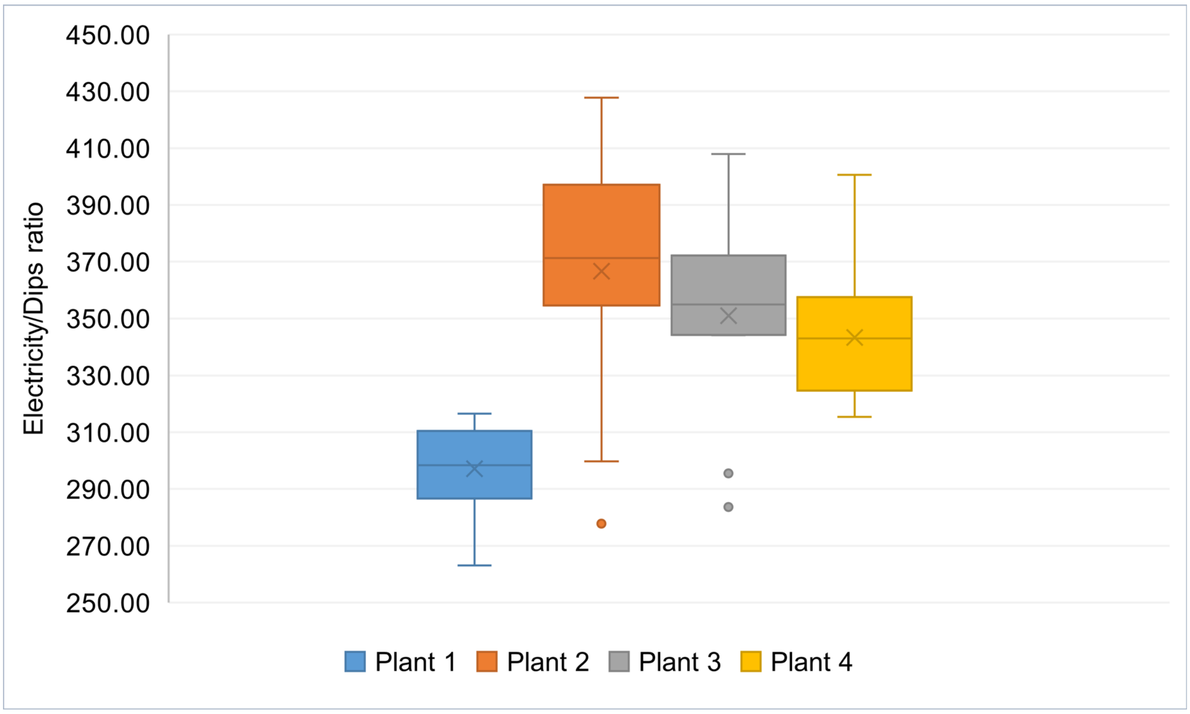

Figure 4.43: Box and whiskers plot for Electricity/Dips ratio

4.4.5.3 Box and Whiskers Plot for Electricity - Product Tonnage Ratio

It was also vital to investigate the relationship between the amount of electricity used and the product tonnage for each of the plants since it is long-standing galvanising industry practice to charge hot-dip galvanised products based on ‘white weight’, which is the weight of the steel after it has been galvanised. The material in hot-dip galvanising is moved throughout the facility by overhead cranes and lowered into the surface preparation and galvanising baths. Considering the case-in-point galvanisers, hot-dip galvanised products are usually priced in rands per tonne of galvanised steel.

Figure 4.44 shows a box and whiskers plot for electricity/product tonnage ratios (kWh/tonne) for the four plants before energy efficiency interventions. The results for Plant 3 and Plant 4 demonstrate that the median is closer to the centre of the box, revealing that the distribution is symmetrical, while the median for Plant 1 is closer to the bottom of the box, an indication that the distribution is positively skewed.

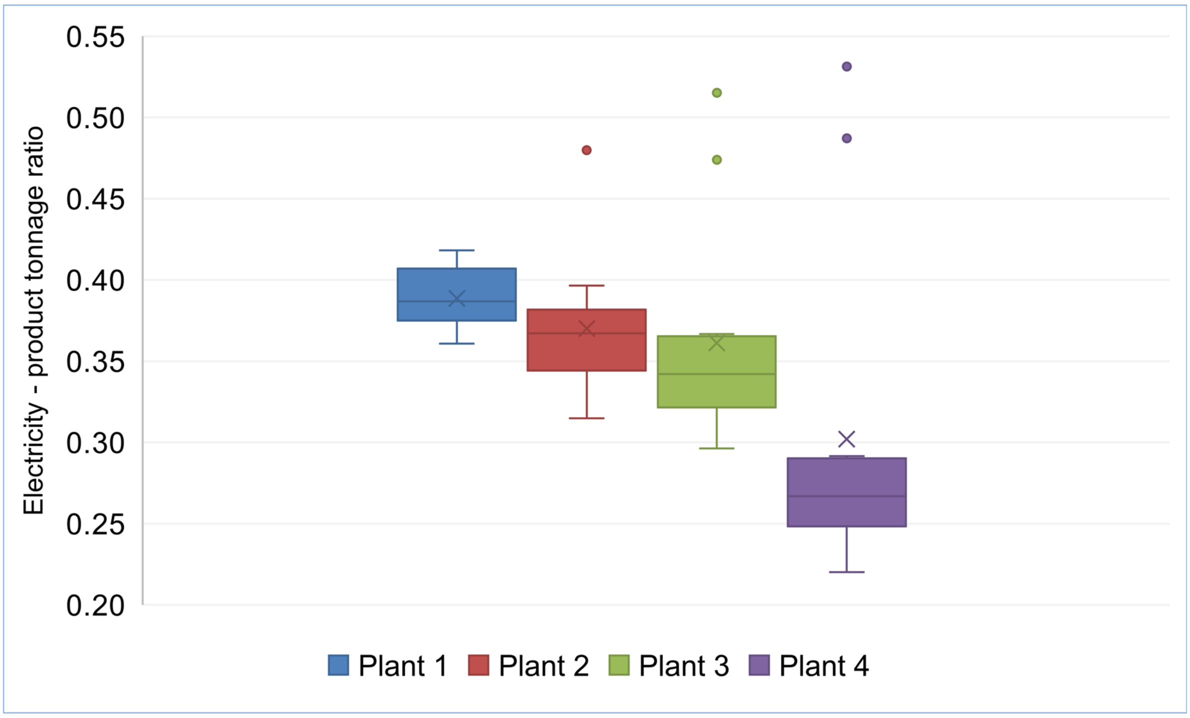

Figure 4.44: Box and whiskers plot for Electricity - Product tonnage ratio

The median for Plant 3 is closer to the top of the box, an indication that the distribution is negatively skewed. Some outliers were noted for Plant 2, Plant 3 and Plant 4. The comparison of the respective medians of box plots revealed that the median line of a box plot for Plant 1 lies outside of the box of a comparison box plot for Plant 2, an indication that there is likely to be a difference between the two groups. Significant differences were also noted between Plant 2 and Plant 3 and between Plant 3 and Plant 4. Comparison of the interquartile ranges and whiskers of box plots was also done to examine how the data is dispersed between each plant sample data. The results from Figure 4.44 shows boxes of medium length for Plant 2, Plant 3 and Plant 4, an indication that the data is moderately dispersed, while the data for Plant 1 revealed less dispersion. Some outliers were noted for Plant 2, Plant 3 and Plant 4.

A clustered column chart can display more than one data series in clustered vertical columns, allowing direct comparison of multiple data series per category and can also show change over time. Figure 4.45 shows a clustered chart for the electricity/product tonnage (kWh/tonne) ratio for the four plants before energy efficiency interventions.

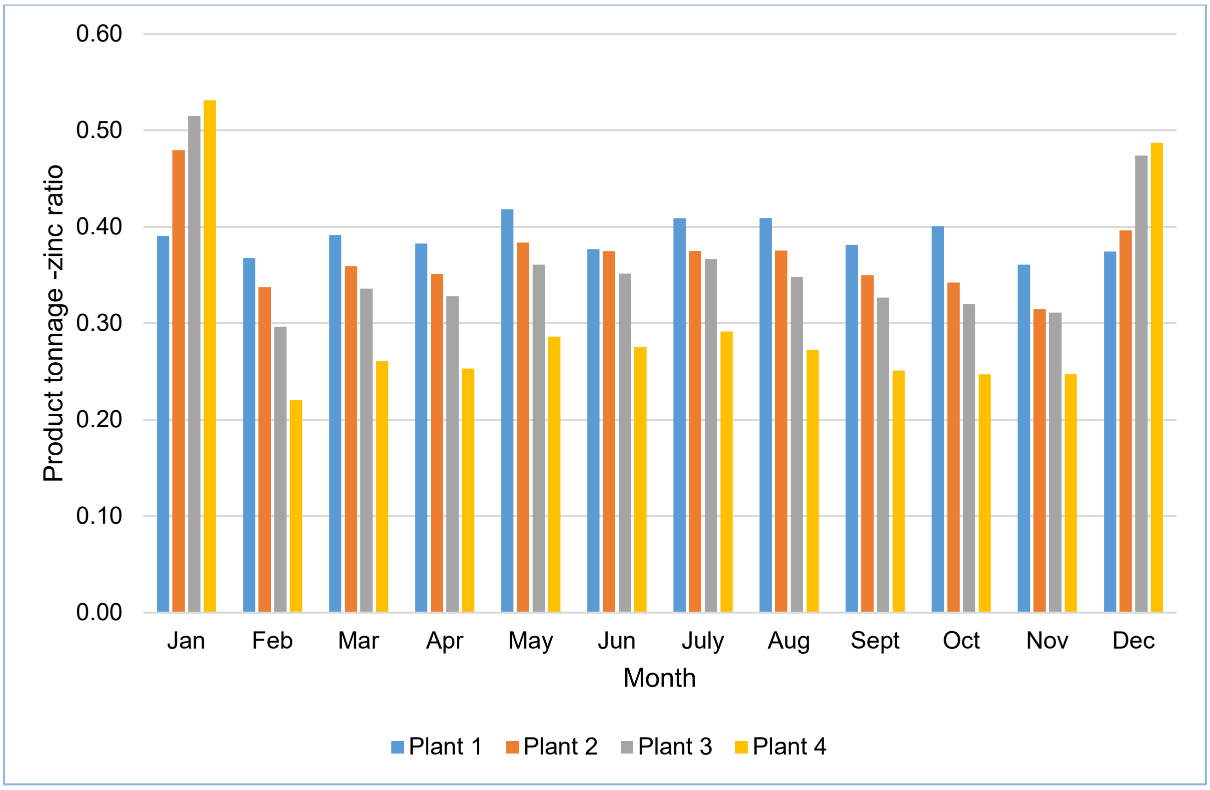

Figure 4.45: Clustered chart for electricity - product tonnage ratio

The results show an increase in the electricity/product tonnage ratio from Plant 1 to Plant 4 for January and December. A decrease in electricity/product tonnage ratio from Plant 1 to Plant 4 was noted from February to November during the baseline period. The variation was noted as a result of the product demand and organisational shut-down policies during the festive season.

4.5 Conclusion

Four plants from four organisations were assessed in terms of awareness of energy management and commitment to improving its energy efficiency. Although there was no energy policy in place, top management for Plant 1 was committed to energy cost reduction. However, management was also generally unaware that significant energy cost savings could be achieved by simple low-cost measures without huge financial investment.

The second organisation exhibited some management commitment, documentation of the roles, and the organisation's energy objectives and targets were identified and documented. However, there were no concrete energy action plans responsibility and authority for all persons who could have an influence on SEUs and the significant energy uses were not adequately been quantified and documented. Plant 3 was characterised by a very low top management commitment and a high operational management commitment while Plant 4 was characterised by a very low top management commitment and a very-operational management commitment.

The results of the measurement phase using Pareto charts for all the plants revealed that galvanising tanks followed by degreasing and pickling tanks were the significant energy users. The assessment results demonstrated that Plant 1 consumed the highest amount of electricity and hence the evaluation of energy-saving initiatives was focused on this plant. It was assumed that since these plants are almost similar in size, the identified energy-saving initiatives would be applicable in all four plants. The analysis of the plant for estimated energy and cost savings from energy minimisation options. It was revealed that covering galvanising kettle would yield huge energy savings followed by insulation of the flux tank.

The relevant electricity consumption drivers for a galvanising line that were identified include number dips per day, amount of zinc used, galvanised product tonnage, and ambient temperature conditions. Before conducting regression modelling, scatter plots of the dependent variable and predictors were analysed to verify if linear regression was appropriate. Multivariate regression analysis was conducted for Plant 1 and the best results were noted from using only one variable, production as the main driver for electricity consumption. Multivariate regression analysis was conducted for Plant 2, and the best results were noted from using the number of dips per month, amount of zinc used and ambient temperature as the relevant variables and these variables were then used to develop a regression model.

The amount of zinc used and ambient temperature conditions were considered as the relevant variables for Plant 3 to derive the regression model to predict the amount of electricity used by the plant. Concerning plant 4, the best results were noted from using the amount of zinc used and ambient temperature conditions as the relevant variables that were used to derive the regression model. Therefore, it was found that each plant is unique and different relevant variables would then drive energy consumption of a specific galvanising plant.

The energy efficiency interventions that were made at Plant 1 at the beginning of the ensuing year did not yield any decreased electricity consumption relative to the expected or baseline energy consumption that would have occurred in the absence of the interventions. Despite an increase in average production from the baseline period to the reporting period, the energy efficiency interventions made in the ensuing year by Plant 2 led to a decrease in electricity consumption relative to the expected or baseline energy consumption that would have occurred in the absence of the interventions. Concerning Plant 3, a decrease in electricity consumption was realised due to energy efficiency interventions were made in the ensuing year by covering process tanks with insulating material that prevented heat loss. Plant 4 experienced a notable increase in average production from the baseline period to reporting period. The energy efficiency interventions made in the ensuing year led to a decrease in electricity consumption relative to the expected or baseline energy consumption that would have occurred in the absence of the interventions. The energy performance of the four galvanisers in terms of EII was found to be varying from a month, and good from November to December due to high production before annual plant shutdowns.

Concerning CUSUM for Plant 1, it was found that its energy performance was poor and far from reaching targeted savings. The scenario of Plant 1 indicated a poor level of control and hence greater potential for energy savings. On the other hand, for Plant 2, it was revealed that as the level of production increased the SEC generally decreased. It was also found that both Plant 2 and 3 demonstrated improved energy performance, but these plants failed to achieve targeted savings. Plant 4 had made some changes in terms of energy management of the process tanks, and it was found that the change in performance was attributed to covering process tanks with insulating material that prevented heat loss since the plant managed to achieve substantial energy savings. Hence, given the disparity between the results of SEC for the four plants, it was recommended that SEC alone cannot be used as an EnPC since it is not influenced by production only but affected by other variables such as material handling efficiency.

Concerning energy consumption benchmarking, a box and whiskers plot for electricity/zinc ratios for the four plants before energy efficiency interventions indicated that there is likely to be a difference between Plant 1 and Plant 2. Significant differences were also noted between Plant 2 and Plant 3. However, no significant differences were noted between Plant 3 and Plant 4. A box and whiskers plot for electricity/dips ratios for the four plants before energy efficiency interventions indicated that there is likely to be a difference between Plant 1 and Plant 2. Significant differences were also noted between Plant 2 and Plant 3 and between Plant 3 and Plant 4. A box and whiskers plot for electricity/product tonnage ratios (kWh/tonne) for the four plants before energy efficiency interventions revealed a difference between Plant 1 and Plant 2. Significant differences were also noted between Plant 2 and Plant 3 and between Plant 3 and Plant 4.

CHAPTER 5 : SCHEDULING FOR ENERGY OPTIMISATION

5.1 Introduction

The results of the third objective were input to answering the fourth research question that characterised by identifying parameters that could be deployed to develop an optimal scheduling algorithm for energy optimisation of the galvanising process. A novel GECOS algorithm that considers reducing total energy consumption by the process tanks, as well as makespan, is therefore proposed in this study. The second and third objectives gave insight into the operational constraints of the galvanising process and establishing the bounds for the mathematical model and setting up the GA model. Additionally, as highlighted from the evaluation of energy-saving initiatives in the first objective, scheduling influences the energy consumption behaviour of the whole system, and by integrating energy efficiency criteria into scheduling, a reduction of energy costs may be realised. This chapter is focused on the development of an optimal scheduling algorithm for energy optimisation of the galvanising process.

5.2 Problem and Mathematical Model for Energy Consumption

The principles of heat transfer are a fundamental input for the mathematical model for energy consumption optimisation schedule, as previously mentioned in the literature survey in Chapter 2. Comprehending the various modes of energy loss during the galvanising process is crucial for the analysis of galvanising process energy consumption and the development of an optimal scheduling algorithm for energy optimisation.

The galvanising process for sample products constitutes four key energy-consuming steps that include degreasing, acid pickling, fluxing and zinc bathing. The initial preparation step is receiving the materials and subsequently jigging the ungalvanised work. The job is then sent to the first surface preparation process tank in the galvanising plant, which is the degreasing tank, usually containing a caustic soda solution used to get rid of organic contaminants such as oils and dirt from the surface of the steel. The tank is heated to a temperature of about 80ºC and can be agitated to hasten the cleaning process. The second surface preparation step is pickling where the degreased steel is immersed into a tank containing acid solution. This tank contains sulphuric acid solution, which is used to remove any mill scale or other oxides that may have developed on the surface of the steel. To increase the cleaning action, sulphuric acid must be heated to a temperature of about 60ºC. Depending on the material, pickling would take anywhere from 15 to 45 minutes.

The third surface preparation step is fluxing which involves the application of a fluxing chemical coating, zinc ammonium chloride, onto the surface of the steel part, and the duration is about 5 minutes. The fourth galvanising step is whereby cleaned steel is immersed in molten zinc usually at a temperature of between 445ºC and 450ºC, forming a thick coating comprising of a series of zinc and/or zinc-iron alloy layers.

The experimental program was based on one industrial problem and Appendix 3 shows a sample of a galvaniser’s monthly production data, revealing that an average of 45 dips or jobs per day is conducted.

The optimal scheduling algorithm for energy optimisation aims to achieve the following two objectives:

- minimise the total energy consumption during the four key energy-consuming steps which include degreasing, acid pickling, fluxing and zinc bathing;
- minimise the maximum completion time of all jobs by all the process tanks for a galvanising process to carry out a given job schedule.

The first step of the research approach comprised the development of a mathematical model for energy consumption optimisation scheduling. The total energy consumption of the hot-dip galvanising process was computed through summation of energy for ready-open-close, waiting for energy consumption and processing energy consumption. The constraint conditions that mathematical models for energy consumption optimisation scheduling, which include allocation, time constraint condition and sequence constraints, were also established. The total energy consumption *(TEC)* of the hot-dip galvanising process includes energy for ready-open-close *(PREP)*, waiting for energy consumption *(WEC)* and processing energy consumption *(PEC)*. Total Energy

Consumption is the primary energy consumed in fulfilling processing tasks and the method of calculating TEC is shown as shown in equation 4.4.

$$TEC = PREP + WEC + PEC \tag{4.4}$$

PREP refers to the amount of electrical energy that is consumed during the preparation and follow-up work after product galvanising. For instance, energy consumed in initiation, skimming when steel products emerge from the zinc bath, shutting down and movement of heavy parts via cranes. The method of calculating *PREP* is shown as shown in equation 4.5.

$$PREP = \sum_{j=1}^{P} \sum_{k=1}^{M_j} PREP_{jk} \tag{4.5}$$

where *j* represents operation, and *k* represents equipment.

Waiting Energy Consumption (WEC) is the electrical energy consumed when the process is idling. As previously stated in the literature in Chapter 2, work measurement can also play a vital role in the energy optimisation of a hot-dip galvanising process. Work measurement techniques were used to establish the start and finish times of jobs on equipment for some specified operations. It happens sometimes that there will be process idle time when two products are being processed due to some constraint conditions such as precedence constraints. WE mean the consumed energy when the process is idling and is calculated as shown in equation 4.6.

$$WEC = \sum_{j=1}^{P} \sum_{k=1}^{M_j} \sum_{i=1}^{N_{jk}} EI_{jk} \;.\left(ST_{(i+1)jk} - FT_{ijk}\right) \tag{4.6}$$

where;

N - is the number of jobs to be processed;

P - is the number of operations for products that are to be processed;

M_j - is the number of machines or tanks for parallel operations *j*;

N_{jk} - is the number of the *j* step operation on the *k* machine processed jobs;

EI_{jk} - is the waiting energy consumption of job *i* in equipment *k* in the *j* operation of processing within a unit of time;

ST_{ijk} - is the start time of job i in equipment *k* in the *j* operation of processing;

FT_{ijk} - is the finish time of job *i* in equipment *k* in the *j* operation of processing.

Processing Energy Consumption (PEC) is described as the amount of energy that is required for the galvanising process. It constitutes the biggest part of the total energy consumption with the galvanising tanks as the significant energy users. The method of calculating PEC is shown in equation 4.7.

$$PEC = \sum_{j=1}^{P} \sum_{k=1}^{M_j} \sum_{i=1}^{N_{jk}} D_{ijk} \ . E_{ijk} \qquad (4.7)$$

where;

E_{ijk}- is the energy consumption of job *i* in equipment *k* in the *j* operation;

D_{ijk} - is 0 or 1 decision variable which represents if job *i* has been processed by equipment *k* in the *j* operation. $D_{ijk} = 1$ denotes that the job was processed, and $D_{ijk} = 0$ represents that the job was not processed.

The constraint conditions that the mathematical model for energy consumption optimisation scheduling should be meet include allocation (resource), temporal or time constraint condition and sequence (procedural) constraint condition. The allocation constraint condition is concerned with satisfying the condition that any process equipment can only process one job or one job at one time, as it is shown in equation 4.8.

$$\sum_{i=1}^{M_j} D_{ijk} = \begin{cases} 0 \\ 1 \end{cases} \qquad (4.8)$$

When $D_{ijk} = 0$, it represents that equipment *k* does not execute an operation on a job *i* for operation *j*. When $D_{ijk} = 1$, it represents that equipment *k* does perform an operation on a job *i* for operation *j*. The total number of operations on equipment *k* should not more than the quantity of galvanising process equipment, *N*, that is:

$$\sum_{k=1}^{M_j} N_{jk} \leq N \tag{4.9}$$

The time constraint condition bounds the interval between the starting time and the completing time, which must be greater than or equal to the practical processing time for a particular galvanised product, as is shown in equation 4.10.

$$FT_{ijk} - ST_{ijk} \geq T_{ijk} \tag{4.10}$$

The sequence constraint condition is to ensure that the processing of job *i* must be completed before job *i+1* is processed, for any galvanising process equipment as shown in equation 4.11

$$FT_{(i+1)jk} - FT_{ijk} \geq T_{ijk} \tag{4.11}$$

where T_{ijk} represents the practical processing time for operation *j* for a job *i* on equipment *k*.

Makespan is the maximum completion time of all jobs by all the process tanks for a galvanising process to carry out a given job schedule (Xie *et al.* 2017). Hence, the second objective function was to minimise the makespan, (the amount of time for completing a set of jobs, from start to finish.

The minimisation fitness function, f(x), is described as shown in equation 4.12.

$$f(x) = \sum_{j=1}^{P} \sum_{k=1}^{M_j} C_{jk} \tag{4.12}$$

where C_{jk} is completion time for operation *j* on equipment *k*.

In summary, the following assumptions were made for the mathematical model:

- There is no interruption of operation process such as machine breakdowns and no reworks are allowed;
- A semi-active schedule is assumed, that is, each operation cannot be performed until the completion of its predecessor providing the availability of a process tank;
- Each operation can be performed only on one machine at a time;
- Finite capacity is assumed, that is, only one operation can be executed on a process tank at a time.

Table 4.30 shows the sample basic processing characteristics for two jobs, with job 1 undergoing degreasing, acid pickling, fluxing and zinc bathing, while job 2 undergoes acid pickling, fluxing and zinc bathing.

Table 4.1: Sample basic processing characteristics

Job number (i)	Operation (j)	Processing equipment (k)	Processing time (T_{ijk}), mins	Energy for ready-open-close, $PREP_{jk}$, (kWh)	Waiting for energy consumption, EI_{jk}, (kWh)	Value-added energy consumption, E_{ijk}, (kWh)
1	Degreasing	Degreaser	15	3	3	5
	Acid Pickling	Acid tank	20	2	2	4
	Fluxing	Flux tank	5	2	4	3
	Zinc bathing	Galvanising tank	5	4	2	20
2	Acid Pickling	Acid tank	25	4	2	4
	Fluxing	Flux tank	4	3	4	5
	Zinc bathing	Galvanising tank	6	2	2	18

5.3 Setting the Genetic Algorithm Problem

GA was chosen to solve the optimisation problem because conventional methods like mixed-integer linear programming (MILP) prove to be inefficient as the solution space increases in solving NP-problems i.e. (non-deterministic polynomial-time) problem. When compared to simulated annealing or Tabu search, a genetic algorithm has a wider scope and is more abstract. The application of a genetic algorithm to the galvanising shop scheduling problem considers each schedule as an entity in the population. Based on a defined fitness function value that correlates to the objective function, each entity is then evaluated for fitness.

Galvanisers should consider multiple objectives for decision making on production planning and these include minimise energy consumption, makespan, tardiness (lateness of a job if it fails to meet its due date), lateness (the discrepancy between the due date of a job and completion time), and maximising throughput. This study adopted a bi-objective GECOS approach that considers two criteria, whereby the goal is to minimise the electrical energy consumption and makespan simultaneously. The approach embraced a non-delay (greedy) schedule, which means that no machine would be kept idle while a job task is waiting to be processed.

It was assumed that jobs would have to be processed on a first-in, first-out basis (i.e. in the order of their arrival). If the arrival times and the processing times of the jobs are known, one can derive an optimal schedule to determine the makespan while concurrently considering optimising the electrical energy that is required to process all jobs (Mouzon, Yildirim and Twomey 2007; Wang *et al.* 2016).

Total Energy Consumption, TE is described as $TE = PREP + WE + PE$. The mathematical model for the bi-objective optimisation scheduling approach is as follows:

$$f_1(x) = minimise \left(\sum_{j=1}^{P}\sum_{k=1}^{M_j} PREP_{jk} + \sum_{j=1}^{P}\sum_{k=1}^{M_j}\sum_{i=1}^{N_{jk}} EI_{jk} \,.\left(ST_{(i+1)jk} - FT_{ijk}\right) + \sum_{j=1}^{P}\sum_{k=1}^{M_j}\sum_{i=1}^{N_{jk}} Y_{ijk} \,. E_{ijk}\right) \tag{4.13}$$

$$f_2(x) = minimise \sum_{j=1}^{P}\sum_{k=1}^{M_j} C_{jk} \tag{4.14}$$

where;

$f_1(x)$ is total energy consumption and $f_2(x)$ is makespan.

On setting the GA problem, Mersenne Twister was also so that every time one initializes the generator using the same seed, the same result is always obtained. In non-rigorous terms, a strong pseudo-random number generator has a statistically uniform distribution of values (regardless of previous values, bits 0 and 1 are equally likely to appear) and is characterised by a long period, that is, how many values it generates before repeating itself (Tan 2016). The program allows the user to input the parameters as desired and these include:

- Lower bound, *lb;*
- Upper bound, *ub;*
- Population size, *Npp;*
- Number of iterations, *T;*
- Distribution index for crossover, etac, η_c;
- Distribution index for mutation, etam, η_m;
- Crossover probability, P_c;
- Mutation probability, P_m .

The pseudocode for the GA is as follows:

1. Initialise random population (P)
2. Evaluate fitness (f) of P

```
for t = 1 to T
Perform tournament selection of tournament size, k
    for i = 1 to Np/2
        Randomly choose two parents
          if r < pc
            Generate two offspring using SBX-crossover
             Bound the offspring
          else
            Copy the selected parents as offspring
          end
    end
```

for i =1 to N_p

if r < p_m

Perform **polynomial mutation** of ith offspring

Bound the mutated offspring

else

No change in ith offspring

end

end

Evaluate the fitness

Combine population (μ) and offspring (λ) to perform (μ + λ)

End

where N_p is the population size, r is a random number,

The research approach of the study embraced the SBX operator since it can restrict offspring solutions to any arbitrary closeness to the parent solutions, thereby not necessitating any discrete mating restriction scheme for improved performance. Simulated Binary Crossover (SBX) simulates the single-point crossover on binary strings, requiring two parents to generate two offspring. The procedure for SBX is as follows:

1. Randomly select a pair of parents from the mating pool
2. Generate a random number (r) between 0 and 1.
3. If r ≥ p_c, then copy the parent solutions as offspring
4. If r < p_c, generate D random numbers (u) for each variable
5. Determine β of each variable
6. Generate two offspring (O_a and O_b) using equation 4.16 and 4.17 i.e.

$$O_a = 0.5[(1+\beta)P'_a + (1-\beta)P'_b] \tag{4.15}$$

$$O_b = 0.5[(1-\beta)P'_a + (1+\beta)P'_b] \tag{4.16}$$

The offspring, O_a and O_b have a spread that is proportional to that of the parents, P'_a and P'_b derived through the equation 4.18:

$$O_a - O_b = \beta(P'_a - P'_b) \tag{4.17}$$

where β is computed through

$$\beta = \begin{cases} (2\mathrm{u})^{\frac{1}{\eta_c+1}} & \text{if u} = \leq\ 0.5 \\ \left(\frac{1}{2[1-u]}\right)^{\frac{1}{\eta_c+1}} & \text{otherwise} \end{cases} \tag{4.18}$$

where u is a random number and η_c is the distribution index for crossover.

The offsprings are generated through:

$$O_a = 0.5[(1+\beta)P'_a + (1-\beta)P'_b] \tag{4.19}$$

$$O_b = 0.5[(1-\beta)P'_a + (1+\beta)P'_b] \tag{4.20}$$

For polynomial mutation, δ was computed as shown in equation 4.22:

$$\delta = \begin{cases} (2\mathrm{r})^{\frac{1}{\eta_m-1}} & \text{if r } = <\ 0.5 \\ 1-[2(1-\mathrm{r})]^{\frac{1}{\eta_m+1}} & \text{if r } = \geq\ 0.5 \end{cases} \tag{4.21}$$

where η_m is the probability distribution mean

The offspring that is generated is described as:

$$y = O + (ub - lb)\delta \tag{4.22}$$

Where O is the offspring solution, y is the offspring solution after mutation, *ub* is the upper bound and *lb* is the lower bound.

5.4 Fitness Function for GECOS

The objective of optimisation in scheduling is to minimise the total energy consumption and makespan during the four key energy-consuming steps which include degreasing, acid pickling, fluxing and zinc bathing. A static deterministic environment was assumed, where the number of jobs to be processed and their processing times were known, and no process tank breakdown would occur. The developed Matlab code for the fitness function is shown in Appendix 7. The key inputs *WEC, PREP, PEC, Schedule* and the output is optimised the total energy consumption (TEC) and makespan.

5.5 Computing Value and Non-Value Added Energy Consumption

Appendix 4 shows a Matlab Code for non-value added energy consumption for the plant. A control random number generator was adopted, using strong pseudo-random number generator Mersenne Twister so that every time one initializes the generator using the same seed, the same result is always obtained. The function *WaitEn* uses inputs *IndiWait* (electrical energy consumed when the individual machines are idling) and *Indienrg* (for calculating the energy consumption of individual preparation operations). The outputs are *WEC* (Total consumed energy when the process is idling) and *PREP* (Total electrical energy consumed for preparing all operations for all jobs on all the machines). *WEC* and *PREP* are then summed to derive *NVAEC* (Non-Value Added Energy Consumption), which is a key input to the main algorithm (Appendix 9: Matlab Code for Real Coded GA).

Appendix 5 shows the code for Value-Added Energy Consumption (VAEC) and Mersenne Twister was used to specify the seed to generate random numbers that are repeatable. The function *ProcEnCons* uses the input *IndiProcEn* (electrical energy consumed when the individual machines are processing the jobs) to derive *VAEC* (for calculating total processing energy consumption), which is also a key input to the main algorithm shown in Appendix 10 (Matlab Code for Real Coded GA).

5.6 Computing Makespan

Appendix 6 shows the code for computing makespan where a set of jobs can be processed in series or parallel. The function *Makespan* uses input *processingTime* to generate *Schedule.* Each job to be scheduled for a process tank has a known processing time, and makespan is computed as the amount of time to process all of the jobs. The duration for each process tank to process each job is given in the array *processingTime*. Random processing times can be generated, where *processingTime* (*m, i*) represents the amount of time that process tank *m* takes to process job *i*. A binary optimisation variable array is created, where process (m, i) = 1 means processor m processes job i. As a constraint, each job must be assigned to exactly one processor and a nonnegative optimisation variable named makespan is defined to represent the objective function. The time that each process tank requires to process its jobs is computed. The makespan is always equal to or greater than each compute time.

5.7 Tournament Selection

This study adopted binary tournament selection, whereby two chromosomes (randomly selected two schedules) are considered for analysis, and according to their fitness function, the better chromosome is chosen to participate in the mating pool while the weaker one is discarded. Tournament selection and rank selection are similar in terms of selection pressure, but it is computationally more efficient and more responsive to parallel execution. Tournament selection was chosen for this study because of its key advantage that since no sorting of the population is required, it can be implemented efficiently (Yadav and Sohal 2017). It is efficient to code, allows the selection pressure to be easily adjusted and works well on parallel architectures.

The input to the tournament selection operator is the fitness function value of the Npp members and the size of the population Npp. Tournament selection was coded in such a manner that it allowed each solution to participate exactly twice. A binary tournament selection is adopted, whereby in each tournament, there are two solutions and each solution in the population gets two opportunities to participate in the tournament. Mating pool is initially defined as NaN, with the size of Npp. In essence, in forming the mating pool, the focus is on determining which solution is better without seeking the decision vector but by assessing the fitness function values. Hence, only the fitness function values are sent to the mating pool. Randperm function is used for random permutation of integers by randomly shuffling the index of population members. The following loop is used to selecting one pair of population members for the tournament, select the winner (CandidateObj) based on minimum fitness value, where MatingPool represents a vector to store the index of parent solutions.

```
for i = 1:Npp-1
    Candidate = [indx(i) indx(i+1)];
```

```
        CandidateObj = f(Candidate);
        [~, ind] = min(CandidateObj);
        MatingPool(i) = Candidate (iind);
    end
```

Tournament selection between the first and last member of the index is done through the code:

```
        Candidate = [indx (Npp) indx(1)];
        CandidateObj = f(Candidate);
        [~, ind] = min(CandidateObj);
        MatingPool (Npp)= Candidate (iind);
```

The candidate index of Npp which is the last and first values of the variable index is selected and the solution with the minimum is saved in the mating pool. The full code for tournament selection is shown in Appendix 8.

5.8 Simulated Binary Crossover

Crossover is an imperative operator in GA that is generally used with a high probability to produce new individuals that exhibit traits of both parent's genetic material. Different forms of crossover approaches can be deployed and these include single-point crossover, multi-point crossover, uniform crossover, and other crossover variants such as heuristic, arithmetic, geometric, and scattered cross over functions. This study adopted the SBX operator because of its ability to restrict offspring solutions to any arbitrary closeness to the parent solutions, thereby not necessitating any discrete mating restriction scheme for improved performance. Simulated binary crossover can overcome the Hamming cliff (where more than one bit needs to be flipped to reach the nearest neighbour), fixed mapping problem and precision challenges (Katoch, Chauhan and Kumar 2020).

In order to obtain the offspring by using SBX Crossover, all the rows and corresponding columns in the mating pool are stored as parent values, which are then passed on for crossover. User-defined parameters such as crossover probability, distribution index for crossover, as well as lower and upper bound are also established as shown below:

offspring = FinalSBX(Parent, Pc, etac, lb, ub)

There is no guarantee that the offspring solutions generated by the SBX operator will be within bounds, hence the need for establishing lower and upper bounds. The research approach for using SBX Crossover commences with determining the number of population members and the size of the decision variables. The size of parent solution gives the number of rows and number of columns, whereby the numbers of rows indicate the population size and the number of columns indicate the number of decision variables i.e. [Npp, D] = size (Parent).

As previously indicated in tournament selection, the Randperm function will be used for random permutation of integers by randomly shuffling the index of population members. The shuffling of solutions through the randperm function enables the creation of a diverse population by avoiding the pairing of good solutions. The index gives the location of Npp members and the parents are arranged according to the index. The variable offspring will be used to store the generated offspring. Hence, the size of this variable is non-priory since there will be Np rows because there are Npp parents and there will be D columns since there are D decision variables. Pre-allocation of the memory through a matrix to store offspring solutions is done i.e. offspring =NaN (Npp, D).

The next step for SBX Crossover is the selection of two solutions and then using a random number to decide whether these two solutions should undergo crossover or not. A random number, r, that is between 0 and 1 were generated for each of the *D* decision variables, and checked to ascertain if it is less or equal to the crossover probability $P_{c.}$ Depending on the value of r, the beta was calculated for each variable, out of which the offspring are generated as a function of beta values and parent values. If the random number that has been generated is greater than the crossover probability, parent solutions are copied into offspring without any crossover.

The following loop is used to selecting parents in pairs for crossover, generating random numbers to decide if crossover should occur, checking for crossover probability, generating random numbers to determine beta value; and calculating beta value.

```
for i=1:2:Np
   r=rand;
   if r < Pc
      for j = 1:D
         r=rand;
         if r <= 0.5
            beta = (2*r)^(1/(etac+1));
         else
            beta = (1/(2*(1-r)))^ (1/(etac+1));
         end
         offspring(i,j)= 0.5*(((1+beta)*Parent(i,j))+(1-beta)*Parent(i+1,j));
         offspring(i+i,j)= 0.5*(((1-beta)*Parent(i,j))+(1+beta)*Parent(i+1,j));
      end
```

Each time the loop is run, two offspring are generated, and hence the loop is run Npp/2 times to get Npp solutions.

Since there is no guarantee that the offspring solutions generated by the SBX operator will be within bounds, bounding the violating variable to their lower bound, as well as bounding the violating variable to their upper bound, was also coded into SBX Crossover. If the decision is not to undertake crossover, then the parent solution is copied as offspring and there is no bounding procedure. The full code for Simulated Binary Crossover is shown in Appendix 9.

5.9 Polynomial Mutation

It was noted from the literature that there are different modes of mutation functions that can be exploited in GAs such as constraint dependent, Gaussian, uniform, and adaptive feasible mutation function. This research study adopted polynomial mutation since that enables thorough exploration of the design space for an optimisation problem allowing exploitation of any promising solutions. Walker and Craven (2020) also posited that polynomial mutation is widely used in evolutionary optimisation algorithms as a variation operator and the experimental results demonstrated that the proposed adaptive polynomial algorithm performs well in terms of convergence speed, generational distance and hyper-volume performance metrics.

Polynomial mutation commences with the definition of user-defined parameters such as mutation probability, distribution index for mutation, as well as lower and upper bound as input parameters for function offspring. i.e.

function offspring = FinalMutPoly(offspring, Pm, etam, lb, ub)

Similarly, as with SBX Crossover, the next step is determining the number of population members and the size of the decision variables. The size of the parent solution gives the number of rows and number of columns, whereby the numbers of rows indicate the population size and the number of columns indicate the number of decision variables i.e. [Nppp, D] = size (Parent). [Npp, D] = size(offspring);

The following loop is used for checking for mutation probability, generating random numbers and calculating the delta value.

```
for i = 1:Np
    r = rand;
    if r<Pm
        for j =1:D
            r = rand;
            if r<0.5
                delta = (2*r)^(1/(etam+1))-1;
            else
                delta = 1-(2*(1-r))^(1/(etam+1));
            end
```

The loop shows that a random number, r, that is between 0 and 1 is generated for each of the D decision variables, and checked to ascertain if it is less or equal to the mutation probability, Pm, otherwise, no mutation will be conducted. Depending on the value of r, delta, δ, is calculated for each variable, out of which the offspring are generated as a function of δ values and parent values. If the random number that has been generated is greater than the mutation probability, parent solutions are copied into offspring without any mutation.

Since there is no guarantee that the offspring solutions generated by the polynomial mutation operator will be within bounds, bounding the violating variable to their lower bound, as well as bounding the violating variable to their upper bound, was also coded into polynomial mutation Crossover. If the decision is not to undertake mutation, then the parent solution is copied as offspring and there is no bounding procedure. The fully developed code for polynomial mutation is shown in Appendix 10.

5.10 Functional Specification of the Real Coded Bi-objective GECOS

This section presents a unique approach to designing a real coded bi-objective GECOS which enables overcoming the premature convergence problem in local extremums. Besides, it embraces the combined use of SBX Crossover and Polynomial mutation operators to significantly improve the time efficiency of real coded GAs, as well as proximity to optimum (the quality of the decisions obtained), thereby providing a more diverse population of potential decisions (individuals). The representation of chromosomes closely simulates the scheduling for a hot-dip galvanising process. The main advantages of real coded GA are robustness, efficiency, and better accuracy.

The first step of the algorithm is assigning a vector to store the fitness function value of the population (initially assigned as *NaN* to change to the appropriate value as the program is executed), a vector to store the fitness function value of the offspring, and determining the number of decision variables in the problem. The code is built for k =2 and when tournament selection is conducted, a comparison is done for 2 schedules or solutions.

The second step is population initialisation, whereby the initial population of 10 schedules is randomly generated. The following loop is for determining the fitness function value for each member of the initial population. Each time the loop is run, the entire

p^{th} row is sent to the function handle *prob,* and *f(p)* evaluates the fitness of each member.

```
for p =1:Npp
    f(p)= prob(P(p,:));
end
```

Therefore, the loop is used to evaluate the fitness of the randomly generated population and once the fitness is evaluated, the genetic algorithm is then executed.

The iteration loop for the genetic algorithm is executed *T* times for tournament selection, crossover and mutation. Under tournament selection, the index of population members which constitute the mating pool is obtained from tournament selection. These population members are accessed from the mating pool which is not a set of solutions, but merely indicates the index of the solution. It is from the index that one would access the population members and be able to assign them to the variable parent. The parent is then fed into the Crossover SBX to derive the offspring, which in turn undergo polynomial mutation to derive the final offspring. The objective function is then evaluated for the final offspring. The number of offspring will be equal to population size. The initial population *P* is then combined with the offspring.

Similarly, the objective functions are combined and sorted to get the vector to store the fitness function value of the population, *f* and also track which variable has been stored in which position or index. The size of the population will be *2Npp* and the size of *ind* will also be *2Npp*, and only the first *Np* will be extracted and stored in *f* for the subsequent iteration. The first *Npp* solutions are extracted and stored in the variable *P*.

```
MatingPool = FinalTornSel (f, Npp);
```

MatingPool is a vector containing integers, not reflecting the entire solution vector, but the location or indices of the vector solution that will be available in the mating pool. Knowledge of the indices would then necessitate the exaction of the entire actual solution using the population. As shown in the statement below, in the reproduction or selection operator, the parent is equal to P of MatingPool, thus the rows and their corresponding columns are selected and stored in the relevant parent, and these are good solutions that should undergo crossover.

Parent= P (MatingPool,:);

It was then vital to determine the crossover probability, P_c, which is to determine whether crossover needs to happen for a particular pair. However, there is no guarantee that the solutions or offspring that are generated by the SBX crossover operator are bounded, hence the need for the lower bound, *lb*, and upper bound, *ub*.

Concerning mutation, each of the offspring from mutation is sent to the objective function using the function handle *prob*. One can determine its fitness function which is stored in the *jth* location of the variable offspring *obj*.

```
 offspring = FinalMutPoly(offspring, Pm, etam, lb, ub);
for j=1:Np
   OffspringObj(j) = prob (offspring (j,:));
end
```

There are now *Npp* parents and Npp offspring which are combined to give a combined population of *2Npp* rows of decision variables. For instance, if the population size is 6, then the combined population will be 12 rows multiplied by the number of decision variables. Combined population stores the solution while the fitness function is stored in *f*. *OffspringObj* is stacked and sorted such that the sorted fitness function and the index variable that helps to identify which solution was placed into which position. Therefore, by using the *ind* variable, one can extract the best *Npp* population, after sorting, the best solution or schedule with the lowest makespan *(minimum f*) will be at the top. The fully developed code for real coded GA is shown in Appendix 11.

5.11 Simulation Results for Bi-objective Optimisation

The bi-objective optimisation function GECOS was simulated using the code shown in Appendix 12. This is a stochastic technique that is based on GA, which when run multiple times, every time would generate a Pareto front, of which the Pareto points can be sorted to obtain the best values. The generated set is called the non-dominated set for a given set of Pareto-optimal solutions. The output of the function includes the decision variable, fitness function value (*fval*), the reason for termination (*exitflag*), output (additional information for the solution procedure), final population and its score. The objective is to determine a set of non-dominated points. We define the lower and upper bounds, define the number of decision variables, nvars, define fitnessfcn, which is a function handle GECOS. The problem is a minimisation problem, both objectives must be minimised, hence we plot minimise f1 against minimise f2.

Figure 4.46 shows the optimal Pareto front for total energy consumption against makespan. The graph shows 12 non-dominated Pareto points, which means none of the points is inferior to the other.

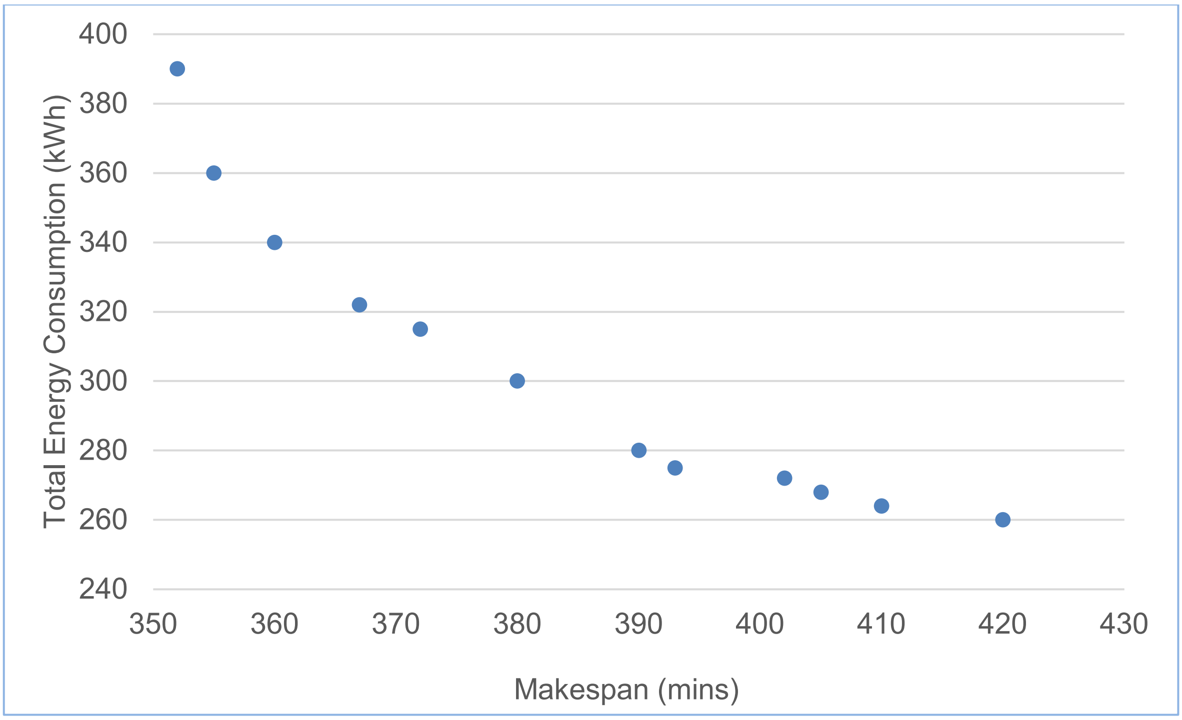

Figure 4.1: Pareto front for total energy consumption against makespan

A Pareto front can be continuous or discontinuous depending on the nature of the problem and the performance of the GA (Jaber, Lafon and Younes 2020). The least total energy consumption occurs when the makespan is the longest. Similarly, the highest total energy consumption corresponds to the shortest makespan. Therefore, improving the performance of one objective requires some sacrifice for the other competing objective for solutions within the Pareto set.

The results demonstrate that the extreme Pareto solutions (352, 390) makespan to total energy consumption when compared to (420, 260), makespan to total energy consumption, there is a 19.3% increase in energy consumption and a 33% decrease in the makespan. Hence, it is imperative that the top management at a galvanising plant tradeoff between the decision to save energy and choosing a schedule that would minimise the makespan, so that they can deliver the product to the customer on time. The decision could be to choose any of the non-dominated solutions based on secondary objectives. For instance, the decision-maker would analyse the trade-off between total energy consumption and total completion time when making the final production planning decisions.

5.12 Comparison of GECOS with other Scheduling Algorithms

The data for Plant 4 was selected for simulation of results since it demonstrated better performance when compared to other plants. Data was used for daily production quantities, customer due dates, and time studies were conducted to ascertain the duration of the pretreatment and galvanising process.

The results were derived by using a user-friendly TORSCHE Scheduling Toolbox for MATLAB. The TORSCHE toolbox is designed for researches in operations research or industrial engineering and it focuses on scheduling, with particular attention to graphs and graph algorithms due to their large interconnection with scheduling theory. The object problem in the TORSCHE environment is a structure describing the classification of deterministic scheduling problems using a notation that consists of three parts $\langle \alpha | ß | \gamma \rangle$ where α describes the processor environment, ß denotes the task characteristics of the scheduling problem as precedence constraints, or release times and γ describes the optimality criterion.

A scheduling problem for parallel machines is characterised by the allocation of jobs to machines and then generating a sequence of the jobs on a machine. A minimal makespan represents a balanced load on the processing machines.

The selected case-in-point galvanising plant that was simulated is characterised by the following problem variables:

- Number of processing lines = 4
- Average number of jobs per day = 50
- Average productive working hours per day = 6
- Total processing time from setup + pre-treatment + galvanising + transfer time

The adopted simulation approach considered *n* jobs J_i (i = 1*,2, 3, ..., 50*) with job times in taskset *T* (*i* = 1*, 2, 3,..., 50*) to be processed on *m* identical parallel galvanising lines *M*1*,..., M4*. i.e.

T = taskset([30 42 40 28 43 33 31 34 38 39 36 45 41 46 28 38 42 31 27 34 37 33 47 35 38 29 30 33 34 37 29 35 44 31 36 42 37 39 33 41 32 36 44 38 34 37 41 31 38 44])

T.Name = {'J1' 'J2' 'J3' 'J4' 'J5' 'J6' 'J7' 'J8' 'J9' 'J10' 'J11' 'J12' 'J13' 'J14' 'J15' 'J16' 'J17' 'J18' 'J19' 'J20' 'J21' 'J22' 'J23' 'J24' 'J25' 'J26' 'J27' 'J28' 'J29' 'J30' 'J31' 'J32' 'J33' 'J34' 'J35' 'J36' 'J37' 'J38' 'J39' 'J40' 'J41' 'J42' 'J43' 'J44' 'J45' 'J46' 'J47' 'J48' 'J49' 'J50'}

McNaughton's algorithm, GECOS algorithm, Shortest Processing Time Algorithm, and Integer Linear Programming algorithms were executed for a set of 50 independent jobs for assignment to 4 parallel process lines to minimise makespan.

5.12.1 McNaughton's Algorithm

McNaughton's algorithm solves the scheduling problem P|pmtn|Cmax, where a set of independent tasks is scheduled on identical processors to minimise schedule length. Appendix 13 shows the Torsche Scheduling Code for parallel processors for McNaughton's algorithm. The algorithm considers preemption of the task and the resulting schedule is optimal. McNaughton's algorithm is shown in the code below and the resulting Gantt chart is shown in Figure 4.47.

TS = mcnaughtonrule (T, problem, processors)

>> T = taskset (task [1, 2, 3 ………………….48, 49, 50]);

>> T.Name = {'t1' 't2' 't3' 't4' …………….. 't47' 't48' 't49' 't50'};

>> p = problem ('P|pmtn|Cmax');

>> TS = mcnaughtonrule (T, p, 4);

>> plot (TS);

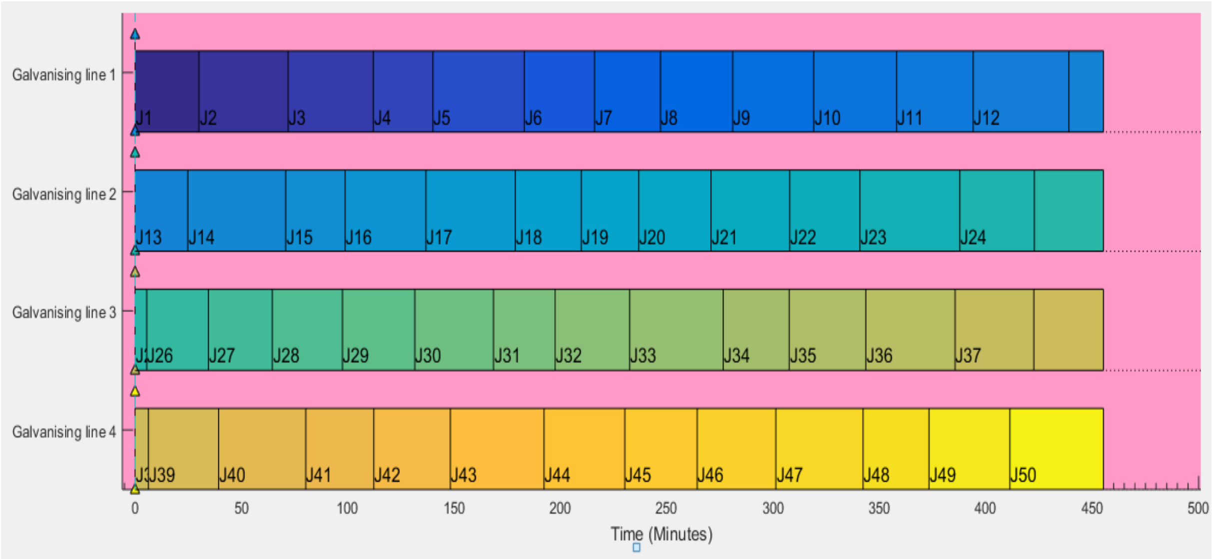

Figure 4.2: Gantt chart for schedule from McNaughton's algorithm

Galvanising line 1 would process 12 jobs, galvanising line 2 processes 12 jobs, while galvanising line 3 and 4 would each process 13 jobs. The makespan for the 50 jobs processed on the four galvanising lines was 451 minutes.

5.12.2 GECOS Algorithm

As previously mentioned, the GECOS approach embraced a non-delay (greedy) schedule which means that no machine would be kept idle while a job task is waiting to be processed to minimise the makespan. Figure 4.48 shows the Gantt chart for schedule and sequencing of the 50 jobs from using the GECOS algorithm.

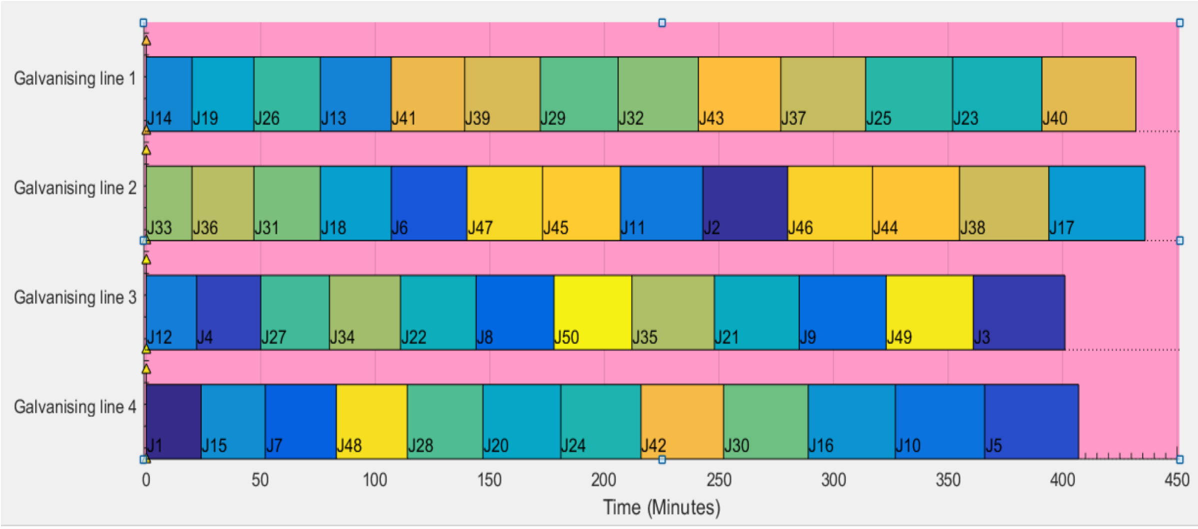

Figure 4.3: Gantt chart for schedule from using GECOS algorithm

Galvanising lines 1 and 2 would process 13 jobs each while galvanising lines 3 and 4 would each process 12 jobs. The makespan for the 50 jobs processed on the four galvanising lines was 440 minutes.

5.12.3 Shortest Processing Time Algorithm

Shortest Processing Time (SPT) is a strategy for a list scheduling algorithm in which the tasks are arranged in non-decreasing processing time p_j order, before the application of the list scheduling algorithm, intended to solve P||Cmax problems. The time complexity of SPT is that the running time essentially grows in proportion to the logarithm of the input size i.e. O(n·log(n)). Concerning the list scheduling algorithm, if a machine becomes idle, the first available job on the list is scheduled and subsequently eliminated from the list. Availability of a job means that the job has been released and if there were any precedence constraints, then all predecessors would have been processed. The algorithm is terminated when all the 50 jobs from the list are scheduled. The algorithm follows the following iteration steps:

Step 1: Select processor with minimal time;
Step 2: Select the first available task from list;
Step 3: Remove task from list to processor.

The syntax for the code is:

p = problem('P|prec|Cmax');

TS = listsch(T,p,4,'SPT');

plot(TS);

Where *listsch* is a function is a list-scheduling algorithm for parallel processors, *P* denotes identical processors, and *prec* denotes precedence constraints.

Figure 4.49 shows the Gantt chart for schedule and sequencing of the 50 jobs from using the Shortest Processing Time Algorithm. Galvanising lines 1 and 2 would process 13 jobs each while galvanising lines 3 and 4 would each process 12 jobs. List scheduling terminated after 7.8125 sec and the makespan for the 50 jobs processed on the four galvanising lines was 472 minutes.

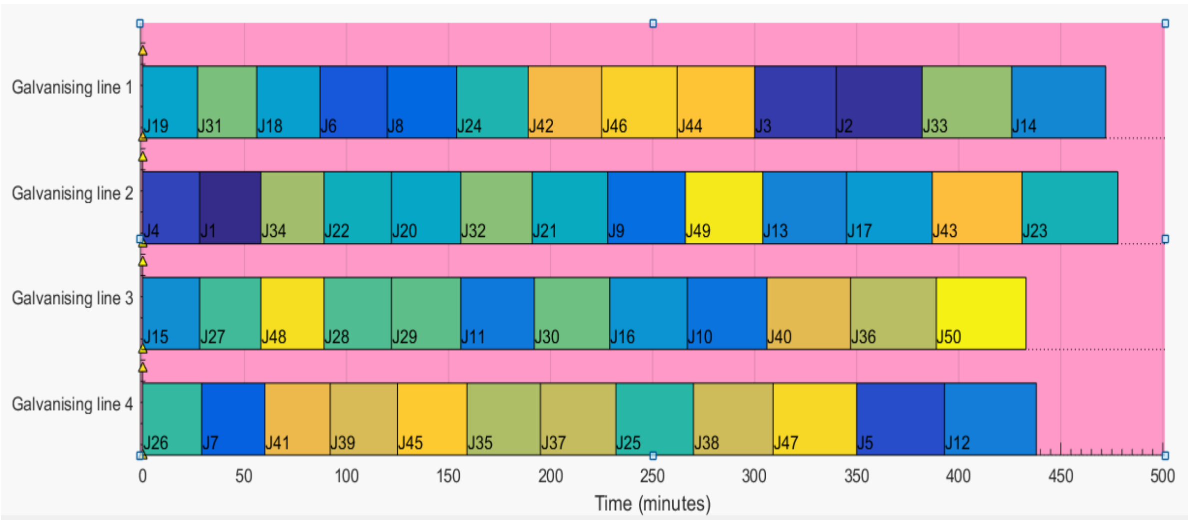

Figure 4.4: Gantt chart for schedule from SPT Algorithm

5.12.4 Integer Linear Programming Algorithm

The algorithm derives an optimal schedule using ILP and solves problem P||Cmax, where a set of independent tasks has to be assigned to parallel identical process tanks to minimise the schedule length. In this case, preemption is not allowed. Figure 4.50 shows the Gantt chart for schedule and sequencing of the 50 jobs from using the ILP Algorithm. Galvanising lines 1 would process 15 jobs, while galvanising lines 2 and 3 would each process 12 jobs. Galvanising lines 4 would process 14 jobs and the makespan for the 50 jobs processed on the four galvanising lines was 452 minutes.

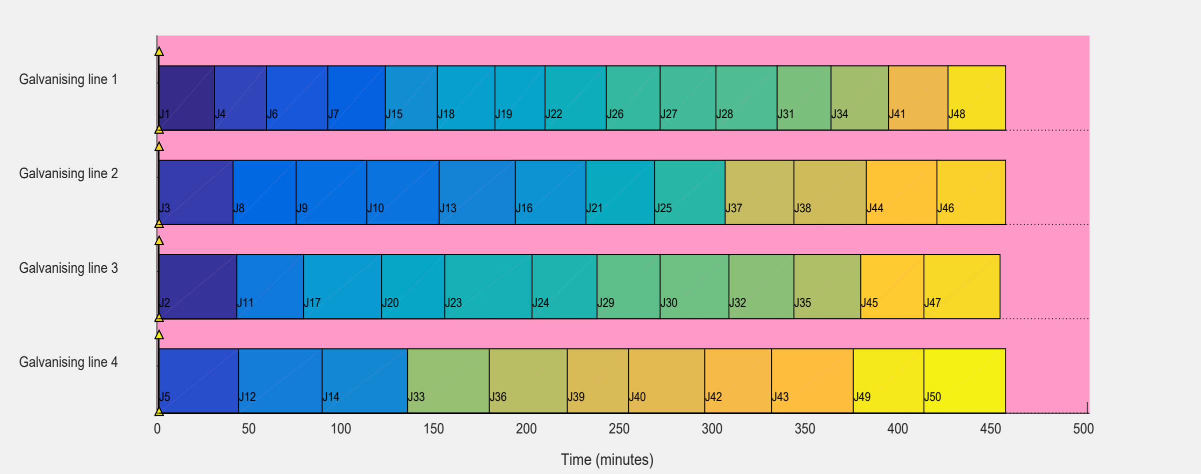

Figure 4.5: Gantt chart for schedule from ILP Algorithm

5.12.5 Summary for Makespan

Table 4.2: Summary of algorithms' makespan

No	Algorithm	Makespan (minutes)
1	McNaughton's algorithm	451
2	GECOS	440
3	Shortest Processing Time	472
4	Integer Linear Programming	452

The results shown in Table 4.31 demonstrated that GECOS outperformed other algorithms on minimising the makespan on parallel processing machines while the Shortest Processing Time algorithm performed the worst.

5.12 Conclusion

It was established that the galvanising process for sample products constitutes four key energy-consuming steps that include degreasing, acid pickling, fluxing and zinc bathing. A novel bi-objective GECOS algorithm that considers reducing total energy consumption by the process tanks, as well as makespan, was therefore proposed in this study. The algorithm was developed on a Matlab platform and the key inputs were the non-value adding energy consumption, value-adding energy consumption and makespan.

The results for bi-objective optimisation were simulated using GA multi-objective function GECOS which when run multiple times, every time generated a Pareto front, of which the Pareto points were sorted to obtain the best values. It was imperative that the top management at a galvanising plant trade-off between the decision to save energy and choosing a schedule that would minimise the makespan, so that they can deliver the product to the customer on time. McNaughton’s algorithm, GECOS algorithm, Shortest Processing Time Algorithm, and Integer Linear Programming algorithms were executed for a set of 50 independent jobs for assignment to four parallel process lines to minimise makespan. It was concluded that that GECOS outperformed other algorithms on minimising makespan on parallel processing machines while the Shortest Processing Time algorithm performed the worst. The next chapter focuses on the recommendations and conclusions of the study.

CHAPTER 6 : RECOMMENDATIONS AND CONCLUSIONS

6.1 Introduction

The products that are fabricated by galvanising organisations have unique characteristics when compared to products that are manufactured by other manufacturing companies. The ubiquity of climate change challenges, unsecured energy supply, and rising energy prices are issues of increasing importance for the hot-dip galvanising sector. It is thus imperative for galvanising sector to deploy energy performance indicators to quantify the energy performance of the whole business or its various parts, and thus would be a measure of energy intensity used to gauge the effectiveness of energy management efforts. The subject of energy optimisation is vital for the hot-dip galvanising sector and production scheduling with multi-objectives is crucial for these organisations. This chapter focuses on the recommendations and conclusions of the study. The objectives of the study were:

- To conduct an energy assessment and evaluation of a batch hot-dip galvanising process to identify potential opportunities for the reduction and more efficient use of electrical energy;
- To identify the relevant electricity consumption drivers for a galvanising line;
- To develop energy performance indicators for a galvanising plant;
- To develop an optimal scheduling algorithm for energy optimisation of the galvanising process.

6.2 Research Concluding Remarks

6.2.1 Conclusions on Evaluation of Electrical Energy Consumption

The first research objective was concerned with identifying potential opportunities that would characterise a batch hot-dip galvanising plant concerning the reduction of the use of electrical energy. The results for assessment of organisation 1 in terms of its awareness of energy management and commitment to improving its energy efficiency.

Although there was no energy policy in place, top management was committed to energy cost reduction. However, management was also generally unaware that significant energy cost savings could be achieved by simple low-cost measures without huge financial investment.

As opposed to organisation 1, the plant for the second organisation exhibited that there was some management commitment, documentation of the roles, and the organisation's energy objectives and targets were identified and documented. However, there were no concrete energy action plans responsibility and authority for all persons who could have an influence on SEUs and the significant energy uses were not adequately been quantified and documented. Plant 3 was characterised by a very low top management commitment and a high operational management commitment. This was due to the involvement of low-level management in training sessions offered by external stakeholders, which did not involve top management. Plant 4 was characterised by a very low top management commitment and a very operational management commitment. This was due to the non-involvement of both low-level management and top management in training sessions that could be offered by external stakeholders.

The results of the measurement phase using Pareto charts for all the plants revealed that galvanising tanks followed by degreasing and pickling tanks were the significant energy users. Thus, it was concluded that the first significant energy users (SEUs) are the galvanising kettles, followed by degreasing and pickling tanks. It was assumed that since these plants are almost similar in size, the identified energy-saving initiatives would be applicable in all four plants. The analysis of the plant for estimated energy and cost savings from energy minimisation options and 125 760 kWh of electricity at an estimated cost of R242 913 would be saved by implementing the stated four energy minimisation opportunities. About 124.5 tonnes of carbon emissions would have been avoided.

6.2.2 Conclusions on Relevant Electricity Consumption Drivers

The second research objective was to identify the relevant electricity consumption drivers for a galvanising line. The relevant variables are typically quantifiable factors such as production, weather conditions, and hours of operation, which would influence the galvaniser's energy consumption. The four relevant variables or energy drivers that were considered include number dips per day, amount of zinc used, galvanised product tonnage, and ambient temperature conditions. It is advisable to develop a scatter plot matrix of the dependent variable and predictors before a regression model is selected, to check if linear regression is appropriate and, if suitable, what model should be adopted.

Multivariate Regression Analysis was conducted for Plant 1 and a high R-squared value was noted, an indication that the regression equation model was accurate in modelling the linear, positive relationship between electricity consumption and the number of dips per month for the galvanising plant. The scatter plot shows a strong correlation between the amount of zinc used and the electricity consumption by the galvanising plant. The regression equation model was moderately accurate in modelling the linear, positive relationship between electricity consumption and product tonnage. The regression equation model was found to be less accurate in modelling the linear, negative relationship between electricity consumption and ambient temperature. Further analysis was then executed using different combinations using 3 relevant variables, then subsequently combinations for 2 relevant variables and the results for R2 were improving but the p- values were yet above 0.05. The best results were noted from using only one variable, and these results show that zinc used (production) is the main driver for electricity consumption for Plant 1.

It was vital to develop a model that estimates the relationship between dependent and independent variables to predict an outcome variable, which is the amount of electricity used by Plant 2. Four relevant variables include the number of dips per day, amount of zinc used, galvanised product tonnage, and the ambient temperature conditions. The initial regression analysis using all the four variables yielded a good R2 value of 0.788 but the p-values were less than 0.05 for dips per month, zinc used and ambient temperature at a 95% confidence level. Further analysis was also executed using different combinations using 3 relevant variables, then subsequently combinations for 2 relevant variables and the results for R2 were improving but the p- values were yet above 0.05.

The best results were noted from using the number of dips per month, amount of zinc used and ambient temperature as the relevant variables and these variables were then used to develop a regression model for plant 2. It was also vital to develop a model that estimates the relationship between dependent and independent variables to predict the amount of electricity used by Plant 3. The best results were noted from using these two variables, with an R^2 value of 0,6627, Significance F of 0,0075, and p- values were less than 0.05. The amount of zinc used and ambient temperature conditions were considered as the relevant variables for Plant 3 to derive the regression model to predict the amount of electricity used by Plant 3.

Concerning plant 4, the best results were noted from using the amount of zinc used and ambient temperature conditions as the relevant variables that were used to derive the regression model to predict the amount of electricity used by Plant 4. Therefore, it was concluded that each plant is unique and different relevant variables would then drive energy consumption of a specific galvanising plant.

6.2.3 Conclusions on Energy Performance Indicators for Galvanising Plant

The third research objective embraced establishing the energy performance indicators for a galvanising plant concerning the comparison of actual consumption and expected consumption, Energy Intensity Index, Cumulative Sum, and Specific energy consumption. Energy consumption benchmarking was also done as analyses energy performance data of comparable activities to evaluate and compare performance between the four galvanising plants. Concerning Plant 1, the energy efficiency interventions that were made at the beginning of the ensuing year did not yield any decreased electricity consumption relative to the expected or baseline energy consumption that would have occurred in the absence of the interventions.

Concerning Plant 2, despite an increase in average production from the baseline period to the reporting period, the energy efficiency interventions made in the ensuing year led to a decrease in electricity consumption relative to the expected or baseline energy consumption that would have occurred in the absence of the interventions. An increase in average production was noted from the baseline period to reporting period for Plant 3. A decrease in electricity consumption was realised due to energy efficiency interventions were made in the ensuing year by covering process tanks with insulating material that prevented heat loss. Plant 4 experienced a notable increase in average production from the baseline period to reporting period.

The energy efficiency interventions made in the ensuing year, except in March, led to a decrease in electricity consumption relative to the expected or baseline energy consumption that would have occurred in the absence of the interventions. EII is essential for monitoring the process to establish the existing pattern of energy consumption, and hence, targeting to identify energy consumption level which is appropriate as a management goal to strive for energy efficiency. The energy performance of the four galvanisers was found to be varying from month to month, and good from November to December due to high production before annual plant shutdowns.

Concerning CUSUM for Plant 1, during the reporting period, energy performance was found to be deteriorating at a uniform rate from January to April, decrease at a slightly higher rate from April to May, improves slightly from May to June and deteriorates again from June to November, and finally improves in December. Since it was known that during the baseline period, the case-in-point galvaniser had no changes in the energy system, the change in performance can be attributed to poor housekeeping, poor control, or maintenance. It was concluded that Plant 1 energy performance was poor and far from reaching targeted savings.

Concerning CUSUM for Plant 2, since it was known that the galvaniser made some changes in terms of energy management of the process tanks, the change in performance can be attributed to covering process tanks with a thick insulating material that prevented heat loss. Concerning CUSUM for Plant 3, it has been established that an increase in average production was noted from the baseline period to reporting period and a decrease in electricity consumption was realised when energy efficiency interventions were made in the ensuing year. It was concluded that both Plant 2 and 3 demonstrated improved energy performance, but these plants failed to achieve targeted savings. Plant 4 had made some changes in terms of energy management of the process tanks, and it was thus, concluded that the change in performance was attributed to covering process tanks with insulating material that prevented heat loss since the plant managed to achieve substantial energy savings.

It was established that the level of production affects the specific energy consumption. The scenario of Plant 1 indicates a poor level of control and hence greater potential for energy savings. On the other hand, for Plant 2, it was revealed that as the level of production increased the SEC generally decreased. The level of production during the reporting period was found to be higher than the production level during the baseline period, while on the other hand SEC decreased during the reporting period for Plant 3. On the other hand, for Plant 4, the level of production during the reporting period was found to be lower than the production level during the baseline period, and the SEC also decreased during the reporting period. Hence, given the disparity between the results of SEC for the four plants, it can be concluded that SEC alone cannot be used as an EnPC since it is not influenced by production only but affected by other variables such as material handling efficiency.

Energy consumption benchmarking was also done as analyses energy performance data of comparable activities to evaluate and compare performance between the four galvanising plants. The essence of energy consumption benchmarking was to increase general awareness of energy efficiency among the galvanisers which in turn may influence a behaviour change provides objective, reliable information on energy use and the benefits of improvements. A box and whiskers plot for electricity/zinc ratios for the four plants before energy efficiency interventions indicated that there is likely to be a difference between Plant 1 and Plant 2. Significant differences were also noted between Plant 2 and Plant 3. However, no significant differences were noted between Plant 3 and Plant 4.

A box and whiskers plot for electricity/dips ratios for the four plants before energy efficiency interventions indicated that there is likely to be a difference between Plant 1 and Plant 2. Significant differences were also noted between Plant 2 and Plant 3 and between Plant 3 and Plant 4. A box and whiskers plot for electricity/product tonnage ratios (kWh/tonne) for the four plants before energy efficiency interventions revealed a difference between Plant 1 and Plant 2. Significant differences were also noted between Plant 2 and Plant 3 and between Plant 3 and Plant 4.

6.2.4 Conclusions on Scheduling Algorithm for Energy Optimisation

The fourth research objective embraced establishing the parameters which must be deployed to develop an optimal scheduling algorithm for energy optimisation of the galvanising process. A novel bi-objective GECOS algorithm that considers reducing total energy consumption by the process tanks, as well as makespan, was therefore proposed in this study. It was established that the galvanising process for sample products constitutes four key energy-consuming steps that include degreasing, acid pickling, fluxing and zinc bathing.

A Matlab Code for non-value adding energy consumption for the plant. A control random number generator was adopted, using strong pseudo-random number generator Mersenne Twister so that every time one initializes the generator using the same seed, the same result is always obtained. The function *WaitEn* uses inputs *IndiWait* (electrical energy consumed when the individual machines are idling) and *Indienrg* (for calculating the energy consumption of individual preparation operations) to generate WEC (Total consumed energy when the process is idling and PREP (Total electrical energy consumed for preparing all operations for all jobs on all the machines). WEC and PREP are then summed to derive NVAEC (Non-Value Adding Energy Consumption),

The bi-objective optimisation function GECOS was simulated and generated a Pareto front, of which the Pareto points were sorted to obtain the best values. The generated sorted set is called the non-dominated set for a given set of Pareto-optimal solutions. The results demonstrated that the extreme Pareto solutions (352, 390) makespan to total energy consumption when compared to (420, 260), makespan to total energy consumption, there is a 19.3% increase in energy consumption and a 33% decrease in the makespan.

Hence, it was concluded that it is imperative that the top management at a galvanising plant should trade-off between the decision to save energy and choosing a schedule that would minimise the makespan, so that they can deliver the product to the customer on time. McNaughton's algorithm, GECOS algorithm, Shortest Processing Time Algorithm, and Integer Linear Programming algorithms were executed for a set of 50 independent jobs for assignment to four parallel process lines in order to minimise makespan. It was concluded that GECOS outperformed other algorithms on minimising makespan on parallel processing machines while the Shortest Processing Time algorithm performed the worst. The results of this study will significantly add to the knowledge base on striving to reduce the energy consumed by galvanising processes, improve sustainability in manufacturing and foster reduction of global carbon footprint. The research output can be positively exploited by the galvanising communities to realise substantial energy savings and better sustainability by implementing companies.

6.3 Contributions to the Body of Knowledge

The key contributions to the body of knowledge from the study include a unique evaluation of electrical energy consumption by a hot-dip galvanising plant and optimisation of electricity consumption for a galvanising plant through comparative analysis of regression analysis and genetic algorithm. Previous research focused on continuous galvanising plants with gas-fired furnaces and less attention has been given to batch-mode galvanising plants that utilise electric furnaces. Hence the development of an energy consumption baseline and performance indices for a hot-dip galvanising plant significantly contributes to the body of knowledge in this niche research area. The other key contributor to the body of knowledge from the study is the developed novel bi-objective GECOS algorithm that considers reducing total energy consumption by the process tanks as well as makespan. Parallel processor scheduling algorithms were also compared to minimise makespan in a galvanising plant.

6.4 Future Research Work

In the future, considering recent trends in big data modelling, more plant data should be collected. Applying energy consumption modelling extensively to more galvanising plants would help the galvanisers to gain more insight into energy efficiency and process optimisation. There is also room for improvement on methods used to calculate the heat losses. For instance, it was assumed that heat loss from the surface was calculated from only one emissivity applied to the materials on the surface and it was assumed that temperature distribution is uniform. However, from a practical perspective, a pot surface has a combination of metals, metal oxides, and metallic compounds that float on the surface, and their quantities and compositions are difficult to measure. Therefore, an improved way is required to assess the magnitude of heat losses when studies are conducted in the future.

Deterministic scheduling tools were developed and used in this research; hence future research work on optimisation of galvanising processes may focus on stochastic scheduling tools such as dynamic scheduling could be considered. Real-time events encountered in dynamic scheduling such as process tank downtimes, temperature variation, change of customer due date and arrival of urgent job could be considered. There is also a growing trend of combining different nature-inspired metaheuristic algorithms to improve their performance. Hence future research work may focus on the hybrid genetic algorithm - artificial immune system scheduling tools that would derive synergy from the advantages of both algorithms to improve the performance.

The impetus of rising electrical energy costs and power outages in South Africa augment for galvanisers to improve the performance of galvanising plants through incorporating off-grid or grid-tied PV systems. Future work would therefore focus on conducting feasibility of implementing such systems through modelling and simulation of these high energy-intensive processes. The system must be sustainable, environmentally friendly and economically viable, hence multi-objective optimisation modelling should embrace CO_2 emissions, energy and other resources to ensure robust sustainability.

6.5 Conclusion

The study was focused on energy assessment and scheduling for energy optimisation of a hot-dip galvanising process. The first research objective was concerned with identifying potential opportunities that would characterise a batch hot-dip galvanising plant. The objective was achieved, four energy minimisation opportunities were identified and quantifiable energy and cost savings, as well as avoided carbon dioxide emissions, were derived from the analysis of one of the plants.

The second research objective was to identify the relevant electricity consumption drivers for a galvanising line. The four relevant variables or energy drivers that were considered include number dips per day, amount of zinc used, galvanised product tonnage, and ambient temperature conditions. The second research objective was achieved, production or zinc used was identified as the main driver for electricity consumption for Plant 1, while the number of dips per month, amount of zinc used and ambient temperature were identified as the relevant variables for developing a regression model for Plant 2. The amount of zinc used and ambient temperature conditions were considered as the relevant variables for Plant 3 while the amount of zinc used and ambient temperature conditions were identified as the relevant variables used to derive the regression model for Plant 4.

The third research objective embraced establishing the energy performance indicators for a galvanising plant. The objective was achieved through a comparison of actual consumption and expected consumption, Energy Intensity Index, Cumulative Sum, and Specific energy consumption. The fourth research objective was to develop an optimal scheduling algorithm for energy optimisation of the galvanising process. This objective was achieved through the development of a novel bi-objective GECOS algorithm that considered reducing total energy consumption by the process tanks as well as makespan. GECOS outperformed the other three algorithms on minimising makespan on parallel processing machines while the Shortest Processing Time algorithm performed the worst.

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Appendix 1: Turnitin report for plagiarism

Final thesis

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Appendix 2: Questionairre for assessment of company's energy management

Question	Titles	Score
1. Does the top management know that significant energy cost savings can be achieved by simple low cost measures without necessitating financial assessment?	Accept potential	2
2. Is the top management committed to energy cost reduction and is there an approved energy policy in place?	Management commitment	3
3. Have roles, responsibilities and authority been identified for all persons having an influence on significant energy use and is this documented?	Roles and responsibilities	3
4. Have the significant energy uses been quantified and documented?	SEUs	4
5. Has a baseline of energy performance been established against which progress can be measured?	Baseline	3
6. Have indicator(s) or metrics been identified to use in measuring progress against your baseline?	EnPIs	2
7. Have the organisation's energy objectives and targets been identified and documented?	Objectives and targets	5
8. Have energy action plans been established?	Action Plan	4
9. Is the energy management system evaluated at least once a year and are improvements made based on the results of the evaluation.	Internal audit	3

Appendix 3: Sample monthly production data for Plant 1

Date	Tons Per Day	Open Dip	Close Dip	Dips Per Day	Zinc Used	Ratio	Accumulated Tonnage	Accumulated Zinc Used	Average Ratio	Average Kg Per Dip	Accumulated Dips	Average Dips Per Day	Ave Tons Per Day
1-Oct	35215	369	377	47	1040	3.0	35215	1040	3.0	749.3	47	47	35215
2-Oct	29748	377	313	39	1152	3.9	64963	2192	3.4	762.8	86	43	32482
3-Oct	29522	313	259	46	1447	4.9	94485	3639	3.9	641.8	132	44	31495
4-Oct	26486	259	198	42	581	2.2	120971	4220	3.5	630.6	174	44	30243
7-Oct	25579	198	217	55	2470	9.7	146550	6690	4.6	465.1	229	46	29310
8-Oct	27473	217	232	52	1950	7.1	174023	8640	5.0	528.3	281	47	29004
9-Oct	30191	232	262	39	3900	12.9	204214	12540	6.1	774.1	320	46	29173
10-Oct	31277	262	284	47	2860	9.1	235491	15400	6.5	665.5	367	46	29436
11-Oct	30415	284	302	40	2340	7.7	265906	17740	6.7	760.4	407	45	29545
14-Oct	29428	302	244	36	776	2.6	295334	18516	6.3	817.4	443	44	29533
15-Oct	29450	244	272	34	3640	12.4	324784	22156	6.8	866.2	477	43	29526
16-Oct	30697	272	302	47	3900	12.7	355481	26056	7.3	653.1	524	44	29623
17-Oct	27901	302	240	42	620	2.2	383382	26676	7.0	664.3	566	44	29491
18-Oct	56590	240	260	79	2600	4.6	439972	29276	6.7	716.3	645	46	31427
21-Oct	28451	260	281	36	2730	9.6	468423	32006	6.8	790.3	681	45	31228
22-Oct	31765	281	290	46	1170	3.7	500188	33176	6.6	690.5	727	45	31262
23-Oct	29547	290	243	42	824	2.8	529735	34000	6.4	703.5	769	45	31161
24-Oct	34731	243	266	51	2990	8.6	564466	36990	6.6	681.0	820	46	31359
25-Oct	39416	266	295	62	3770	9.6	603882	40760	6.7	635.7	882	46	31783
28-Oct	47981	295	344	51	6370	13.3	651863	47130	7.2	940.8	933	47	32593
29-Oct	44647	344	380	61	4680	10.5	696510	51810	7.4	731.9	994	47	33167
30-Oct	40175	380	381	64	130	0.3	736685	51940	7.1	627.7	1058	48	33486
31-Oct	33927	381	419	56	4940	14.6	770612	56880	7.4	605.8	1114	48	33505

Appendix 4: Code for Non-Value Adding Energy Consumption

```
function [WEC, PREP]  = WaitEn(IndiWait,Indienrg)
rng(1,'twister');% Specifying the Seed to generate Random Num-
bers That Are Repeatable
IndiWait = zeros (4,5)
STjk = randi([5 10],4,5)
FTjk = randi([1 4],4,5)
EIjk = randi([1 6],4,5)
[mach op] = size(IndiWait)
IndiWait = EIjk.*( STjk- FTjk)
WEC = 0
for j = 1:op           % The loop  for number of operations
for k = 1:mach          % The loop  for number of machines
WEC = WEC + IndiWait (k,j)
end
end
% The outer loop is for calculating energy consumption of prep-
aration operations
Indienrg = randi([1 10],4,5)
[op mach] = size(Indienrg)
PREP = 0
for j = 1:op
for k = 1:mach
PREP = PREP + Indienrg (j,k)
end
end
 NVAEC = WEC+ PREP
end
```

Appendix 5: Code for Value- Adding Energy Consumption

```
function PEC = ProcEnCons(IndiProcEn)
rng(1,'twister');% Specifying the Seed to generate Random Num-
bers That Are Repeatable
IndiProcEn = zeros (4,4)
Yijk = randi([1 1],4,4)
Eijk = randi([10 20],4,4)
[mach op job] = size(IndiProcEn)
PEC = 0
for j = 1:op           % The loop  for number of operations
for k = 1:mach          % The loop  for number of machines
IndiProcEn = Yijk.*Eijk
PEC = PEC + IndiProcEn (k,j)
end
end
```

Appendix 6: Code for Computing Makespan

```
function Schedule = Makespan (processingTime)
rng default % for ensuring reproducibility
numberOfProcessors = 4;
numberOfTasks = 50;
processingTime = [11;8;4;5] .* rand(numberOfProcessors,num-
berOfTasks);
process = optimvar('process',size(processingTime),'Type','in-
teger','LowerBound',0,'UpperBound',1);
assigneachtask = sum(process,1) == 1;
makespan = optimvar('makespan','LowerBound',0)
computetime = sum(process.*processingTime,2);
makespanbound = makespan >= computetime;
scheduleproblem = optimproblem('Objective',makespan);
scheduleproblem.Constraints.assigneachtask = assigneachtask;
scheduleproblem.Constraints.makespanbound = makespanbound;
options = optimoptions(scheduleproblem,'Display',"off");
[sol,fval,exitflag] = solve(scheduleproblem,'Options',options)
processval = round(sol.process);
maxlen = max(sum(processval,2)); % Required width of the ma-
trix
% Then compute the schedule matrix
Schedule = zeros(numberOfProcessors,maxlen);
ptime = Schedule;
for m = 1:numberOfProcessors
    schedi = find(processval(m,:));
    Schedule(m,1:length(schedi)m) = schedi;
    ptime(m,1:length(schedi)) = processingTime(i,schedi);
end
```

Appendix 7: Function file for objective function

```
function f = GECOS(WEC, PREP, PEC, Schedule)

   f(1) = PREP + WEC + PEC;

   f(2) = C_1+ C_2+ ⋯… C_n;

end
```

Appendix 8: Matlab Code for Tournament Selection

```
function MatingPool = TournamentSelection(f, Npp) ; %Tournament selection allows each solution to participate exactly twice

MatingPool=NaN(Npp,1);     % Vector to store the index of parent solutions

indx = randperm (Npp)   % Randomly shuffling the index of population members

for i = 1:Npp-1        %Pool size is Np

Candidate = [indx(i) indx(i+1)]; % Selecting one pair of population members for tournament

CandidateObj = f(Candidate);

[~, ind] = min(CandidateObj);         % Selecting winner based on minimum fitness value

MatingPool(i) = Candidate (iind) ;         % Storing the index of the winner

end

% Tournament selection between the first and last member

Candidate = [indx (Npp) indx(1)];

CandidateObj = f(Candidate);

[~, ind] = min(CandidateObj);

MatingPool (Npp) = Candidate (iind);
```

Appendix 9: Matlab Code for CrossoverSBX

```
function offspring = CrossoverSBX(Parent, Pc, etac, lb, ub)
[Np, D] = size (Parent); % Determining the population and decision
variable
indx =randperm;    % Permutating numbers from 1 to Np
Parent = Parent (indx,:);  % Randomly shuffling parent solutions
offspring =NaN (Npp, D);  % Matrix to store offspring solutions
 for i=1:2:Npp  % Selecting parents in pairs for crossover
    r=rand;  % generating random numbers to decide if crossover
   if r < Pc     % Checking for crossover probability
    for j = 1:D
     r=rand; % generating random numbers to determine beta value
   if r <= 0.5
    beta = (2*r)^(1/(etac+1));  % Calculating beta value
   else
   beta = (1/(2*(1-r)p))^ (1/(etac+1)); % Calculating beta value
    end
offspring(i,j)=0.5*(((1+beta)*Parent(i,j))+(1-beta)*Parent(i+1,j));
offspring(i+i,j)=0.5*(((1beta)*Parent(i,j))+(1+beta)*Parent(i+1,j))
  end
offspring(i,:)= max(offspring(i,:), lb)% Bounding the violating var-
iable to their lower bound
offspring(i+1,:)= max(offspring(i+1,:), lb)    % Bounding the vio-
lating variable to their lower bound
offspring(i,:)= min(offspring(i,:), ub) % Bounding the violating
variable to their upper  bound
offspring(i+1,:)= min(offspring(i+1,:), ub) % Bounding the violating
variable to their upper  bound
    else
offspring(i,:)= Parent (i,:); %Copying the first parent solution as
first offspring
offspring(i+1,:)= Parent (i+1,:); % Copying the second parent solution
as first offspring
    end
end
```

Appendix 10: Matlab Code for Polynomial Mutation

```
function offspring = MutationPoly(offspring, Pm, etam, lb, ub)

[Npp, D] = size(offspring);

for i = 1:Npp

    r = rand;

    if r<Pm                 % Checking for mutation probability

        for j =1:D          % Generating random numbers

            r = rand;

            if r<0.5

                delta = (2*r)^(1/(etam+1))-1;  % Calculating the
delta value

            else

                delta = 1-(2*(1-r))^(1/(etam+1));  % Calculating
the delta value

   end

offspring(i,j)= offspring(i,j)+(ub(j)-lb(j))*delta; % Mutating
each variable of offspring

        end

offspring(i,:)= max(offspring(i,:), lb); % Bounding the violat-
ing variables to their lower bound

offspring(i,:)= min(offspring(i,:), ub); % Bounding the violat-
ing variables to their upper bound

        end

    end

end
```

Appendix 11: Matlab Code for Real Coded GA

```
clc                                          % To clear command window
clear                                        % To clear the workspace
rng(2,'twister')
% problem settings
lb = [0 0]                                % Lower bound
ub = [25 25]                                % Upper bound
prob = @GECOS                         % Fitness function

% Algorithm parameters
Npp = 10                                   % Population size
T = 10                                     % Number of iterations
etac = 20                                        % Distribution index for
crossover
etam = 20                                        % Distribution index for
mutation
Pc = 0.8                                  % Crossover probability
Pm = 0.2                                   % Mutation probability

% Genetic Algorithm
f = NaN (Npp, 1)                              % Vector to store fitness
function value of the population
OffspringObj = NaN (Npp, 1)           % Vector to store fitness
function value of the offspring
D = length(llb)                          % Determining the number of
decision variables in the problem

rng(1,'twister');% Specifying the Seed to generate Random Num-
bers That Are Repeatable

P = [f(1) f(2)] % Generation of initial population
for p =1:Np
```

```
    f(p)= prob(P(p,:))          % Evaluating the fitness function
of the initial population
end
% Iteration loop
for t=1:T
    % Tournament selection
    MatingPool = FinalTornSel(f,Np)     % Peforming tournament
to select tournament size k
    Parent= P (MatingPool,:)       % selecting parent solution
    % crossover
    offspring = FinalSBX(Parent, Pc, etac, lb, ub)
    % Mutation
     offspring = FinalMutPoly(offspring, Pm, etam, lb, ub)
    for j=1:Np
        OffspringObj(j) = prob(offspring(j,:)) % Evaluating the
fitness of the offspring
    end
    CombinedPopulation = [P; offspring]
        [f,ind] = sort([f;OffspringObj])  % mu + labda selection
    f = f(1:Np)
    P = CombinedPopulation (ind(1:Np),:)
end

[bestfitness, ind]= min(f)
bestsol = P (ind,:)
```

Appendix 12: GA Multi-objective script in Matlab

```
clc; clear; close all

 ub = [600 600 600];

lb = [100 100 100];

nvars = length (llb);

fitnessfcn = @GECOS;

[x, fval, exitflag, output, population, scores]  = gamultiobj
(fitnessfcn, nvars, [ ], [ ], [ ], [ ],lb, ub, [ ]);

hold on

plot (fval(:,1), fval(:,2), 'b*')

xlabel ('Minimise f_1')

ylabel ('Minimise f_2')
```

Appendix 13: McNaughton’s algorithm Torsche Scheduling Code

```
function [TS] = mcnaughtonrule (T, prob, No_Proc)
m = No_Proc;             %amount of processors
n = size(T);             %amount of tasks
t_proc = zeros(1,m);                    %processor's disponibil-
ity time
 for i=1:n
    ProcTime{i}(1)= T.ProcTime(i);
    processorSchedule{i}(1) = 0;        %vector of task as-
signment to a processor
    s{i}(1) = inf;                      %task performing start
end
 C_max = max(max(T.ProcTime),sum(T.ProcTime/m));
%task Ti and processor Pj
t = 0;
full = zeros(1,m);
finished = zeros(1,n);

for j=1:m
    for i=1:n
      if (full(j) == 0 )
        if (finished(i) == 0)
            if ((t_proc(j) + ProcTime{i}(1) <= C_max))
                processorSchedule{i}(1) = j;
                s{i}(1) = t_proc(j);
                t_proc(j) = t_proc(j) + ProcTime{i}(1);
                finished(i) = 1;
            else
         ProcTime{i}(1) = t_proc(j) + ProcTime{i}(1) - C_max;
         ProcTime{i}(2) = C_max - t_proc(j);
         processorSchedule{i}(2) = j;
         processorSchedule{i}(1) = j + 1;
```

```
                s{i}(2) = t_proc(j);
                s{i}(1) = t_proc(j+1);
                t_proc(j) = C_max;
                t_proc(j+1) = ProcTime{i}(1);
                finished(i) = 1;
             end
        end
        if t_proc(j) == C_max
               full(j) = 1;
        end
      end
    end
end
 description = ('Preemptive Scheduling according to McNaughton
rule');
add_schedule(T, description, s, ProcTime, processorSchedule);
%assignment of schedule to the taskset
 TS = T;
 % end of file
```