



**EVALUATION AND OPTIMISATION OF BIOGAS
PRODUCTION IN MUNICIPAL WASTEWATER
TREATMENT PLANT USING COMPUTATIONAL
INTELLIGENCE APPROACH:
POTENTIAL TO GENERATE ELECTRICITY**

Submitted in fulfillment of the requirements for the degree of Master of
Engineering in the Department of Civil Engineering and Geomatics,
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Technology

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ABSTRACT

Development and optimisation of valued added derivatives from wastewater represent the future sustainability paradigm. Among the various challenges in the management of wastewater treatment is the energy consumption for the treatment process that could render this process inefficient in terms of cost and energy consumption. This study focusses on the evaluation of egg-shaped digesters treating municipal wastes, and the optimisation of biogas production using computational intelligence approach (CIA) for sustainable energy production and policy implementation. The study further estimates the amount of electricity that could be generated from the optimised biogas produced from the anaerobic digesters.

Historical 5-year (2010-2015) data of the anaerobic digesters were obtained from the Darvill Wastewater Treatment Plant in the KwaZulu-Natal Province of South Africa. The raw data were pre-processed for data cleaning, integration, reduction and data transformations using a rigorous scientific method to test their accuracy, reliability, consistency, and localisation gaps with different multivariate statistical tools. Computation intelligence methods using partial least square (PLS), principal component analysis (PCA) and Fuzzy Logic algorithms were used in this study for simulating the best operational condition and predicting the biogas production. The study further created a contextual framework against the assessment of biogas to energy potential and uses an excel-based tool to determine the bio-economy of energy recovery from an anaerobic egg-shaped digester per cubic meter of treated sludge. In average, the actual methane production was 59.60% while, predicted by Fuzzy-Logic was 65.4%. This shows that the model employed in the improvement of methane production from biogas plants by varying the operational parameters at; Inflow = 590m³/day, Temp = 32.3°C, pH = 7.12, TS = 3.47%, VS = 43.4% and COD = 510 mg O₂/L. The obtained total biogas production was 802.80 m³/day based on status quo conditions and process configurations. The biogas production translates to electrical energy of 4580.5 KWh/day with an estimated saving (at R1.90 per kWh electricity) of approximately R3.1 million per annum.

DECLARATION

I hereby declare that the work reported in this thesis '**Evaluation and Optimisation of Biogas Production in Municipal Wastewater Treatment Plant using Computational Intelligence Approach: Potential to Generate Electricity**' is my original research work. A comprehensive list of references was cited and acknowledged. I hereby certify that the work contained in this thesis has not previously been submitted either in its entirety or in part for a degree at this or any other university.

Zesha Ramrathan

20802488

DEDICATION

Unconditional care, unfaltering love, absolute support and utmost pride boasted by my dearest Grandad who promoted my interest in pursuing post graduate studies. This dissertation is dedicated in memory of my dearest Grandad (Nana):

MR BALA HARICHARAN

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LIST OF ABBREVIATIONS

AD	Anaerobic Digestion
AIS	Artificial Immune System
ANFIS	Adaptive neuro-fuzzy Inference System
ANN	Artificial Neural Networks
AI	Artificial Intelligence
ARIMA	Autoregressive Integrated Moving Averages
BD	Biodegradability
CA	Computational Algorithms
CHP	Combined Heat and Power
CI	Computational Intelligence
COD	Chemical Oxygen Demand
CIA	Computational Intelligence Approach
DOE	Department of Energy
DFPS	Digester Feed Pump Station
ESD	Egg-shaped Digester
EC	Evolutional Computation
ES	Expert System
EMOA	Evolutionary Multi-objective Optimisation Algorithms
FIS	Fuzzy Inference System
FL	Fuzzy Logic
FA	Factor Analysis
GA	Genetic Algorithms
MWWTP	Municipal Waste Water Treatment Plant
PCA	Principal component analysis
PLS	Partial Least Square
PLSR	Partial Least Square Regression
PSO	Particles Swarm Optimisation
PID	Proportional-Integral-Derivative
R^2	Coefficient of determination
R	Correlation coefficient
RPE	Relative percentage error

RMSE	Root mean square error
SRT	Sludge Retention Time
TOC	Total organic carbon
TS	Total Solids
VS	Volatile Solids
VFA	Volatile Fatty Acids
VIP	Variable Importance Projection
VLM	Vertical Linear Mixer
WWT	Waste Water Treatment
WWTP	Waste Water Treatment Plant

LIST OF PUBLICATIONS

Two research articles were identified and are being prepared. All articles are to be submitted to a journal and conference proceeding paper.

(1) Journal articles to be published:

1. Ramrathan Z., Khin Aung Han., Enitan A. 2021. Energy efficient wastewater treatment plant: exploiting opportunities for generating electricity.
2. Ramrathan Z., Khin Aung Han., Enitan A. 2021. Poor quality of data recording and management: Inefficiencies compromising optimisation in wastewater treatment processes

CHAPTER 1

INTRODUCTION AND BACKGROUND

1.1 BACKGROUND

Globally, wastewater treatment and management have evolved substantially to produce fertilising nutrients and as a renewable energy source due to scarce natural resources. The world is currently heading towards a crisis related to natural resources that includes water, food, and energy sources which are considered as diminishing significantly (Cai et al., 2018). Several attempts have been made to slow down the depletion of our natural resources and one such attempt is in renewable energy that is accessed through recycling of wastewater. Conventional energy sources include oil, coal and natural gases which have been proven to be highly effective drivers of global economic progress (Zou et al., 2016), however they have also demonstrated to be extremely detrimental to the environment and human health (Munawar, 2018). These conventional energy sources are major contributors to the greenhouse effect.

However, renewable energy is becoming a new regime to reduce and mitigate environmental pollution and in meeting the required economic and global energy demands (Gielen et al., 2019). Renewable energy utilises energy sources that are replenished naturally and that are not detrimental to the environment. Wind, solar, geothermal, hydropower, tidal, biomass and biogas are amongst the most well-known renewable energies, which are also considered as viable solutions to meet future energy needs (Petrescu et al., 2017). It also serves as an alternative measure to ameliorate the growing global concern of high energy cost and related environmental challenges due to wastewater treatment (Gheraout et al., 2018). These alternatives to clean energy generation has also been a major implementation task framed by environmental legislation on renewable sources (Kraft, 2017).

According to The Department of Energy (DOE) (DOE overview report, 2018) about 96.7% of South African electricity generation is from a state-owned company called Eskom and out of this percentage of electricity generated, 85% is from coal. In the same report the Department of Energy has forecasted that South Africa's energy consumption needs will

grow to more than 50,000 MW by 2025 . Eskom currently installed capacity of around 47,000 MW but with the plant's financial troubles along with production and maintenance challenges faced, are only able to supply around 26,000 MW . Much of the energy produced in South Africa is through the utilisation of fossil coal. However, it has been noted that the production of electricity through coal comes with environmental challenges (Sarkodie and Adams, 2018). These challenges include the discharge of greenhouse gases into the atmosphere as a result of the burning of fossil fuels which ultimately contributes to global warming (McGlade and Ekins, 2015).

With the country's growth and urbanisation there is an increasing demand for energy, more so for cleaner energy that would have minimal or zero CO₂ emission. South Africa has been faced with an ongoing energy crisis from 2007 to date (Sarkodie and Adams, 2018). As a means of crisis management there is an implementation of load shedding which has been in place as temporary measures to manage the infrastructure failure and insufficient generation capacity. While the dominant discourse on renewable energy is on solar, hydro and wind, there is a growing interest as part of the bio-economy and value chain processes on energy derivative from wastewater treatment. There are ongoing research and efforts made to deal with the challenges of increased energy demand, one of which is through renewable energy generation from wastewater treatment plants (WWTP) (Kollmann et al., 2017).

Although, wastewater or sewage sludge is considered hazardous, aesthetically offensive and could pose danger to the lives and health of the community if not properly managed and discharged, it has become an important alternate source of raw material for usable energy and nutrients production. This alternative source of energy and nutrients is now a defined paradigm shift in the treatment of wastewater and sewage sludge for recoverable sources of energy, nutrients, materials, and water (Fersi et al., 2015). This paradigm shift in renewable recoverable source of energy through sludge management practice is from a liability perspective on treatment to a recovery perspective of the fundamental energy assets in wastewater treatment. Scientific techniques are now being employed for implementation of semi-centralised urban infrastructure system to allow substantial water- and energy saving. These techniques provides new opportunities for energy recovery from bio-waste to biogas production notwithstanding the use of nutrients in sewage sludge to

produce bio-solids for agriculture and other uses emerging from anaerobic digestion systems (Edwards et al., 2015).

Anaerobic digestion (AD) is basically the breakdown of organic materials or the decomposition of substrate by different bacteria in the absence of oxygen to form biogas especially, carbon dioxide and methane mixture (Enitan et al., 2018). AD process is divided into four stages based on the metabolites produced by the organisms. These stages include hydrolysis, acidogenesis, acetogenesis and methanogenesis (see chapter 2 for a detailed engagement on anaerobic digestion). Realised benefits of most anaerobic digestion system has made them one of the fast growing technologies in treating sludge and wastes products (Ma et al., 2018). Some of these growing technologies in AD include structural innovations such as egg-shaped AD and process changes such as the temperature-phased AD either manually controlled or auto-controlled processes to enhance volatile solids destruction with a view to reaching high sludge standards (Sawatdeenarunat et al., 2016); (Kariyama et al., 2018). High solids centrifuges and heat dryers are also gaining new solutions and popularity for their dewatering abilities and protection of a dryer sludge cake (Jafari Giv, 2018). Precipitation of struvite directly after AD results in salvage of phosphorous and nitrogen for other uses, thereby creating new solutions and preventing environmental pollution (Wei et al., 2018). Benefits and ability of AD systems in producing beneficiary by-products have created a fertile environment to explore optimisation through computational intelligence on the production process based on real-time production.

Biogas potential to produce electricity has been a focus of many renewable energy research studies and this has become one of the most significant resource recovery interest in the developed countries (Grando et al., 2017; Khan et al., 2017; Kretschmer et al., 2016). Many developed and developing countries, including United States of America, Germany, Austria, Switzerland and Scandinavia have assessed the possibilities and potentials of renewable energy generation during wastewater treatment. Arising out of these assessments, it was established that the process does not only provides electricity to the treatment plant, but also contributes to the energy mix that the grid supplies to the consumers (Burkhardt et al., 2016; Zhou et al., 2019). Optimisations of operational efficiency in WWTPs has also been identified as possible solution in addressing global

concerns, to increase the production of renewable energy such as biogas for electricity generation (Gu et al., 2017; Lu et al., 2019).

In pursuit of increasing efficiency in energy recovery from bio-waste, researchers have exploited computational intelligence (CI) to determine optimisation benefits. The CI is a computer based platform that uses big data to solve problems (Velvizhi et al., 2020, Xinhua et al., 2015). Computational intelligence is used interchangeably with computational algorithms (CA) because CA is the basis for CI (Diamant, 2016; Beni, 2020). In process analysis, both methods designed to identify and predict real life problems. According to Chen & Li (2018) computational intelligence is defined as “the computational models and tools of intelligence capable of inputting raw numerical sensory data directly, processing them by exploiting the representational parallelism and pipelining of the problem, producing reliable and timely responses and resisting high fault tolerance” (Chen and Li, 2018). CI presents a shift in emphasis from the human-based focused solutions to computer-based solutions (Yanase and Triantaphyllou, 2019; Mueller and Massaron, 2018). The methods resemble the human's way of reasoning in producing control actions that can be adapted to real problems (Gershman et al., 2015). The application of the in-built optimisation algorithms models to process involves the selection of best solution from all possible management alternatives which make the method more practical and accurate (Lund et al., 2017; Phung et al., 2017).

There are several CI methods, which include; Genetic Algorithms (GA), Particles Swarm Optimisation (PSO), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Artificial Immune System (AIS), Fuzzy Support Vector Machine (FSVM) and Artificial Neural Network (ANN) (Faizollahzadeh Ardabili et al., 2018a; Srivastava et al., 2020). These techniques can be used individually or combine to optimise real problems in the environment (Faizollahzadeh Ardabili et al., 2018a; Kalantari et al., 2018).

The optimisation process using computational intelligence has become part of the modern day wastewater treatment process and is considered essential for feasibility and forward planning studies for renewable energy extraction and capital investment strategy (Abdelshafy et al., 2018). The central concern that is informing the research agenda of renewable energy extraction is largely in response to two global issues on the increasing

energy costs and global climate change as a result of greenhouse gas emissions. To this end, this study, aims to evaluate the production of biogas in a municipal WWTP, which has egg-shaped digesters. Darvill Wastewater Treatment Plant located in KwaZulu-Natal, one of nine Provinces of South Africa, was selected as a case study. The units of operations have undergone significant changes in structure, form and processes. The methodology employed in this study consists of a mixed design approach, where the theoretical aspects of the subject matter was used in conjunction with secondary data collected from the stakeholders operating the selected egg-shaped digesters. Thereafter, the project explores the optimisation of energy production recovery from bio-waste through biogas production using computational intelligence approach (CIA) for electricity generation.

The employed methodology for this research was broken into sub-sectors based on the study-specific objectives. The first subsector is to predict the best operational condition of an anaerobic egg-shaped digester in the treatment of wastes from municipal WWTPs. This subsector includes the procedural step employed which includes discussion and information derived from the pre-model analysis. The pre and post data analysis was used as input in configuring the partial least square regression (PLSR) and Fuzzy Logic computational simulation models in predicting and optimising the biogas production (methane produced) in comparison. The second subsector includes, an excel-based multi-modal algorithm which was used to determine the bio-economy of energy recovery from the selected WWTP of the optimised biogas generated using the respective computational simulations. This excel-based multi-modal algorithm to determine energy recovery will therefore contribute to the green energy economy that is needed within the South African context which, otherwise, would have been lost if further exploration of optimisation was not considered as potential sources of energy supply.

1.2 STATEMENT OF THE PROBLEM

Production of wastewater is increasing due to global factors such as urbanisation, population growth and industrialisation. This increase means that more and efficient wastewater treatment systems will need to be built, resulting in large amounts of sludge being produced daily (Buonocore et al., 2018; Laugesen et al., 2010; Sharma et al., 2019a). This increase in the amount of sludge being produced from wastewater means more energy

would be required for treatment of sludge, resulting in major cost implication for municipalities if the traditional way of managing solid wastes from treatment plant is maintained. With innovations in wastewater treatment and the efficient use of its by-products, these two concerns can be addressed with positive outcomes. Managing the growing wastewater treatment processes and its trajectory of increasing costs cannot be sustained without alternate energy sources. One source of alternate energy was found in the treatment of wastewater sludge in the form of biogas that could be used in the production of energy (Kougias and Angelidaki, 2018). While much development in the production of biogas from sludge has happened over the decades, there is the problem of inefficient processes to exploit the production processes in order to derive its full potential, especially in terms of energy outputs to meet the energy requirements by the treatment process. In this study I attempt to show how such processes of producing biogas from waste water treatment can be made more efficient. In this respect, the innovations in exploiting the full potential of extraction for biogas production includes the integration of computational processes to optimise anaerobic digester. As new insights emerge within the computational intelligence domain, opportunities to optimise outputs are possible and this study contributes to this quest for optimal operational benefits in wastewater treatment.

Noting further that there is a scarcity of natural energy sources to meet the growing demands of society, alternate energy sources are being sought. Wastewater treatment was established as that potential source to supply much needed energy to societies. While energy is being produced from through wastewater treatment processes, poor control systems and recording of accurate data to inform the processing systems continues to be a problem. This study, therefore identifies the areas of concern within the control systems and explores its influence in the optimal production of energy that could be used to sustain a wastewater treatment plant. In this respect, exploiting the potential to maximise the output of energy from wastewater treatment would go a long way in contributing to the energy mix needed for the growing needs of society. Hence, optimisation in wastewater treatment is therefore needed. This study contributes to this optimisation process of deriving optimal energy to generate electricity to support, both, the energy needs of wastewater treatment plants as well as directing excess energy production for general public consumption, including the needs of the economy. This study, therefore, addresses

the optimisation of biogas production during the treatment of sludge using a digester and to evaluate potential bio-economic of converting bioenergy to electricity.

1.3 STUDY AIM AND OBJECTIVES

The aim of this study is to evaluate the efficiency of an egg-shaped anaerobic digester treating sludge producing from municipal wastewater treatment plant as well as the optimisation of biogas production using computational intelligence with the potential for sustainable energy policy implementation.

1.3.1 Objectives of the Study

- To predict biogas production (methane produced) in an anaerobic egg-shaped digester treating sludge produced from the selected municipal wastewater treatment plant.
- To develop and calibrate a simulation model to optimise biogas generation from the egg-shaped anaerobic digester using computational intelligence techniques.
- To estimate the amount of electricity that could be generated from the optimised biogas produced from an egg-shaped anaerobic digester.

1.4 RATIONALE AND JUSTIFICATION FOR THE STUDY

Major natural resources, such as water, food and energy are diminishing substantially (Kibler et al., 2018; Cai et al., 2018) therefore, the potential crisis of the diminishing natural resources could be averted by exploring and exploiting alternate systems of reusable by-products, such as wastewater and sludge for energy production. There are several works that have been documented on the extraction of re-usable resources in the forms of water and energy as well as the generation of products that can support the growing agricultural sector (Bringezu et al., 2016; Jamil et al., 2016). In addition, domestic wastewater has been identified as being very resourceful in the production of biogas that could be used in the production of electricity. More specific to the aims of this study is the re-use of sludge from WWTP which has been developed substantially over the years to a point where real benefits are being realised (Akyol et al., 2020; Ahmad et al., 2016). In working towards

this realisation and with the innovations in CI, sludge production and its concomitant biogas production can be revisited to enhance the efficiency of biogas generation, hence increase the rate of electricity generation.

In this study, the focal point on innovations towards the knowledge gap identified, has been on refining and adapting existing processes of wastewater management and treatment to optimise its potential. The optimising potential is for the betterment of human existence and for the production of biogas to meet the process of self-reliance for the expansion of renewable energy demand by the society. This study, therefore, identified the treatment of high-strength wastewater and spent sludge produced from municipal wastewater treatment plant (MWWTP) using egg-shaped digester as a rich source for renewable energy and electricity generation. Waste (sludge) extracted from the WWTP is being channeled by the operators into the digesters, where the process of conversion to biogas takes place.

The high amount of sludge produced from MWWTPs which were previously incinerated at high cost on daily basis, makes a compelling case for exploring innovations in sludge utilisation and management (Sawatdeenarunat et al., 2016; Bora et al., 2020). Therefore, wastewater re-use is considered a beneficial paradigm shift in communities for the way in which wastewater is viewed and managed (Vairavamoorthy et al., 2015). It is a holistic approach to manage wastewater and freshwater uses as well as nutrients recovery in an integrated system that fits the growing urban development (Ma et al., 2015). This holistic approach makes it imperative to change from the current unsustainable status to sustainability, zero greenhouse gases emission targets, recycle and recover resources, including nutrients and bioenergy during anaerobic wastewater treatment (Ma et al., 2015; Zodrow et al., 2017). In addition, an evolution of anaerobic digestion systems provides new opportunities to explore optimisation of re-usable outputs, including the generation of renewable energy such as biogas. Studies have shown that egg-shaped digesters are cost effective and more efficient in the treatment of waste materials that are high in organic matter for generation of renewable energy and electricity generation (Singh et al., 2019; Srivastava, 2020).

While substantive research has been done on management of wastewater, treatment of sludge from wastewater within a recycling process has been found to be an alternate source

of energy supply (Angelakis et al., 2015). This study focused more on how such processes can be optimised to produce methane gas. The optimised methane gas output from sludge treatment would then contribute to the alternate energy needs of both, the treatment of wastewater as well as utilisation of excess electricity for societal needs. Research in this field has shown possibilities for managing this wastewater treatment process more efficiently through the production of biogas that could be used to supply energy to the treatment plant as well as for general use. It is within this domain, that this study examined the optimisation of biogas generation from anaerobic digester located in municipal wastewater treatment plant.

1.5 SCOPE OF STUDY

The scope of the study was limited to the following areas:

- 1.5.1 To evaluate the biogas production process and operational characterisation that would influence bio-economy production rate.
- 1.5.2 The application of different multivariate statistical techniques to test the reliability, distribution, correlation, and determination of multiple factors as influenced by the choice of dataset to use towards minimisation of localisation error among the selected data variables.
- 1.5.3 The use of Partial Least Square (PLS) model to forecast biogas generation and evaluate against operational biogas generated.
- 1.5.4 The application of Fuzzy-Logic (FL) as an advanced computational method for optimisation of biogas generation for energy yield quantification.
- 1.5.5 To determine the bio-economy potential of energy recovery from the selected anaerobic digester located in Darvill Municipal Wastewater Treatment Plant.

1.6 LIMITATION OF THE STUDY

One of the critical limitations of computational modelling is the quality and availability of the egg-shaped digester input data. Having reviewed the obtained five-year data, there were gaps in the recording processes as well as with the recorded data. For example, there were instances where data was not recorded for some period due to shutdowns, systems overload

and/or plant malfunctions. In addition, within each field of recorded data, there were many missing data. In an attempt to deal with the recorded data limitations, several meetings were held with the staff recording the data at this site to better understand the nature and form of data that were recorded. Having this understanding, a selected five years' period of recorded data wherein there were minimal omissions was used in this study for the computational process.

This study is limited to evaluation and optimisation of biogas production in municipal wastewater treatment plant using computational intelligence approach. The quoted values in figures and tables were limited by the accuracy of secondary and primary data collection. By delineating the municipal processes, the selected operation condition was contextualised within the South African environment only for the optimisation study. The derivation of the best acceptable model was limited to current market price and constraints of optimisation software used.

1.7 THE STUDY AREA

The Darvill Wastewater Treatment Works Plant located in Pietermaritzburg, the capital city of the Province of KwaZulu-Natal in South Africa was used as the case study site. The site is on the outskirts of an urban area, serving a population of approximately 530,442 and a growing industry sector. A large agricultural sector is in close proximity of the Darvill site. The site originally had two egg-shaped digesters and more recently additional egg-shaped digesters were built. This WWTW was constructed in the mid 1950's with a design capacity of 27 ML/d. In 2008, it was upgraded to a full biological nutrient removal plant with a capacity of 65 ML/d. Due to further urbanisation, the increase in organic loading on the plant and the Department of Water Affairs new limit of NH_3 concentration in discharge effluent, the plant needed to be upgraded, and this upgrading is currently underway. The new upgrade is designed to increase the capacity to treat 200ML/d. There are also many upgrades to some of the processes within this treatment plant facility, one of which this study focuses more on, is the anaerobic digesters from which biogas is produced. The anaerobic digestion process has over the years undergone significant changes in structure, form and processes. Although cylindrical shaped digester has widely been used for anaerobic digestion of wastes (Fagbohunge et al., 2015), the developments on the

structure and form of digesters included a structural type known as egg digester, largely because it was shaped like an egg. It was found that egg-shaped digesters were more efficient and cost-effective in the conversion process to produce methane gas due to some shortcomings of other digester configurations (Wu, 2010; Singh et al., 2020).

This case study site is the only treatment works within South Africa that has an egg-shaped digester for treatment of sludge produced from the wastewater treatment and generation of biogas that could be used for electricity production. Some of the structural benefits of having an egg-shaped digester (ESD) is that its steep bottom eliminates grit accumulation and therefore no or little cleaning is needed. The top of the structure is smaller and allows scum to be kept liquid for easy disposal. Currently, the upgrade of the plant required the construction of two new ESD's and the installation of an electricity co-generation process (Combined Heat and Power - CHP). The two ESD's has a holding capacity of 25,000kg/day each thus, allowing the biogas obtained to be used to generate electricity supply. Figure 1.1 shows the layout of the egg-shaped anaerobic digesters used in treating municipality sludge at the selected wastewater works.



Figure 1.1 Egg-shaped anaerobic digesters used in the treatment of sludge obtained from Darvill Wastewater Treatment Plant

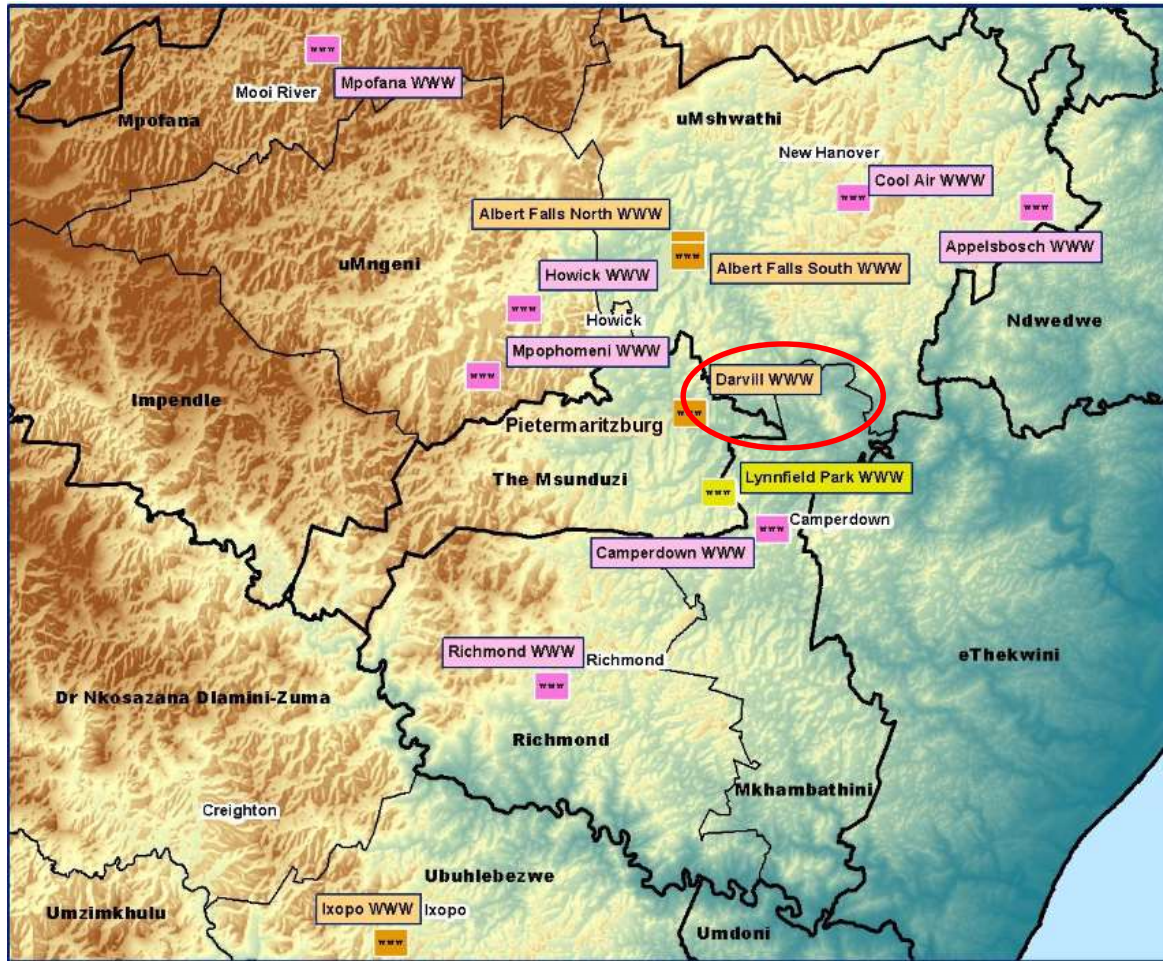


Figure 1.1 Map indicating the location the Darvill Wastewater Treatment Plant within South Africa

1.8 OUTLINE OF THE DISSERTATION

1.8.1 Chapter One - presents the background knowledge on the optimisation of renewable energy production in Municipal Wastewater Treatment plant using anaerobic digestion systems and introduction to the selected egg shaped digester used as case study.

1.8.2 Chapter Two - provides the literature review on the topic and its economic importance in electricity production as well as optimisation of anaerobic digester to enhance bioenergy generation using Computational Intelligence (CI) approach. It further elucidates the emerging methodologies used in bioenergy generation.

1.8.3 Chapter Three - discusses the pre-processing method used to normalise the obtained digester data and employed partial least squares (PLS) regression models for predicting biogas production.

1.8.4 Chapter Four - presents the results and discussion on the optimisation of biogas production using Fuzzy Logic as the forecast tool.

1.8.5 Chapter Five - presents the predicated potential generation of electricity from the optimised biogas from the Fuzzy Logic approach.

1.8.6 Chapter Six - the general conclusions and recommendations are presented.

1.9 CONCLUSION

This chapter presented a background and context of wastewater treatment in general as it relates to recycling, reuse and potential benefits of treating sludge from treatment plant. The chapter also presents some concerns relating to wastewater management, treatment and cost implications that necessitates a need to optimise treatment processes to extract the maximum benefits, including that of generating energy to sustain and contribute to the energy mix needed by society. Having presented a background to the study, this chapter presented the aims, objectives and scope of the study and concluded with a description of the site where the research was conducted.

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

The previous chapter contextualised the aim of the study within the broader process of wastewater treatment and within the context of the crisis noted in the depletion of natural resources. In this chapter, a review of literature that frames the study follows. The review focuses on two aspects. Firstly, the illumination from reviewing historical works done on wastewater treatment, its benefits to societies and the challenges experienced across its evolutionary trajectory that necessitated further exploration and innovations in the treatment process. Through this review an argument is made for a continuation of research and development along its evolutionary path. Secondly, the potential outputs from wastewater treatment and how these outputs can be optimised to meet the expanding demands of societies across the globe is presented. The intent is to explore the potential to optimise such outputs on an on-going basis as new information and new methodologies emerge in optimising current and potential outputs that could be beneficial to the process of wastewater treatment as well as future use of the outputs of treatment process. The literature review in this section further explores the governance and legislation that has been put in place to manage wastewater treatments and re-use of products emerging from these treatments. The purpose of presenting this legislative framework is to demonstrate the demands made on wastewater treatment within the context of environmentally sensitive issues and on regulating the conditions for ensuring optimal safety and health issues emerging from the process of treating wastewater.

The literature review concludes with a description of wastewater treatment using engineering and biochemical processes to address challenges, perceptions of concerns from the public on the re-use of the products emerging from the treatment processes. The exploration aims to find appropriate modelling processes to optimise the production of biogas and assess the potential electricity that can be produced from this optimised biogas. Hence, a review of literature that frames the biological treatment processes used in the production of biogas is presented, with a view to illuminating the potentially usable outputs from such treatment processes. The specific focus is on biogas production for alternate energy generation through which electricity would be a distinct output of this study. This

distinct focus on electricity generation allows the evaluation and modelling of biogas produced from the digester treating sludge coming from municipal wastewater treatment. Hence, municipal wastewater treatment and reuse will also be subject of engagement in this chapter.

2.2 EVOLUTION TRAJECTORY TO MODERN DAY WASTEWATER TREATMENT

The use and treatment of wastewater can be traced back to centuries of human existence with the purpose of diverting it from human settlements (Angelakis and Snyder, 2015). Historically, wastewater treatment evolved substantially from the simple process of discarding waste to more complex processes that involved the recovery of re-usable elements. Its evolutionary development, critiques, challenges and opportunities at each stage of treatment formed the basis of research, innovation and development to wastewater treatment plants (Angelakis and Snyder, 2015). The evolutionary process of wastewater treatment supports the historical perspective that depicts it to be a journey that has no end point in the foreseeable future and that its evaluations and exploration potentials are an ongoing activity. Angelakis and Snyder (2015) captured a synopsis of the advancement of wastewater treatment emerging from human settlement within a historical perspective. The author showed how wastewater treatment and its reuse, has evolved over time and some of the concerns that were raised which led to relevant innovations and advancements. Although there are significant advancements in wastewater treatment and usage, the evolutionary process still depends on several factors, including the population size of the human settlement, financial costs, operational parameters of treatment plant and environmental concerns.

The diversion from human settlements opened up the potential re-use of wastewater and sludge produced during treatment for land applications, more particularly for irrigation of and fertilisation of farmland. This land application using wastewater from domestic households suggests that the value of re-use of wastewater was realised in ancient societies. Noting this potential, communities developed sewage farms that grew in size over time and spread across contexts for disposal and to support agriculture to improve crop productions. The increased number of sewage farms drew concerns for health and other

environmental issues. Angelakis and Snyder (2015: 4888) sum up these concerns by expressing that:

The use of the land treatment systems continued into the twentieth century in central Europe, USA, and other locations all over the world, but not without causing serious public health concerns and negative environmental impacts. However, by the end of the first half of the current century, these systems were not easily accepted, due to drawbacks such as large area requirements, field operation problems, and the inability to achieve the higher hygiene criteria requirements required.

These health, environmental and space concerns, intensified not only by heavy industrialisation, climate change and urbanisation, but management of wastewater in the rural area due to its high usage for agricultural purposes (Cosgrove and Loucks, 2015; Yuan et al., 2018). In dealing with these emerging and expanding concerns emanating from wastewater treatment as a result of the expansion of sewage farms and the channelling of wastewater and spent sludge to the farms and re-usable products back to the human settlements, more advanced systems of wastewater treatment began to emerge. The channelling process then led to an additional evolutionary process.

Among the challenges recorded in wastewater treatment, includes the expansion in urbanisation and human settlements; and channelling the wastewater to treatment plants with increase costs and energy demand. Other challenges include production of large amounts of sludge from the treatment plant as well as rising infrastructure cost for storage of re-use products and public perceptions on reclaimed products which seems to be the greatest challenge on consumption.

Reuse of water extracted from wastewater extraction is challenged by perceptions about the quality of such water sources and the periodic outbreak of diseases carried through wastewater and water streams. Such perceptions are the major obstacle in the reuse process and the potential benefits, most notably to the strained resource of natural water. A possible way to reduce the negative perceptions on the re-use of water derived from wastewater treatment is an engineered process, which is rapidly unfolding globally. Bringing engineering into the wastewater treatment process seems to insert a trust and confidence element due to its disciplinary confidence. One of the benefits is channelling of effluent water and sludge for re-use in deriving valuable products like biogas.

2.2.1 Integrated Wastewater Resourcefulness and Management Towards Renewable Energy

Wastewater has been identified as resourceful in the production of biogas that could be used for the production of electricity. Sludge extracted from the WWTP is channelled into the digesters, where the process of conversion to biogas takes place. Traditionally, cylindrically shaped digester has widely been used for anaerobic digestion of wastes (Kariyama et al., 2018).

More recently, it was found that egg-shaped digesters were more efficient and cost-effective, from an integrated waste water management perspective, in the conversion of sludge to produce methane gas due to some shortcomings of other digester configurations. Such shortcomings were identified as inefficient mixing, dead spaces, grit accumulation as a result of poor mixing, high operation costs and the large surface area results in scum and foam formation (Fagbohunge et al., 2015; Wu, 2010). The operation of the AD is shown in Figure 2.1.

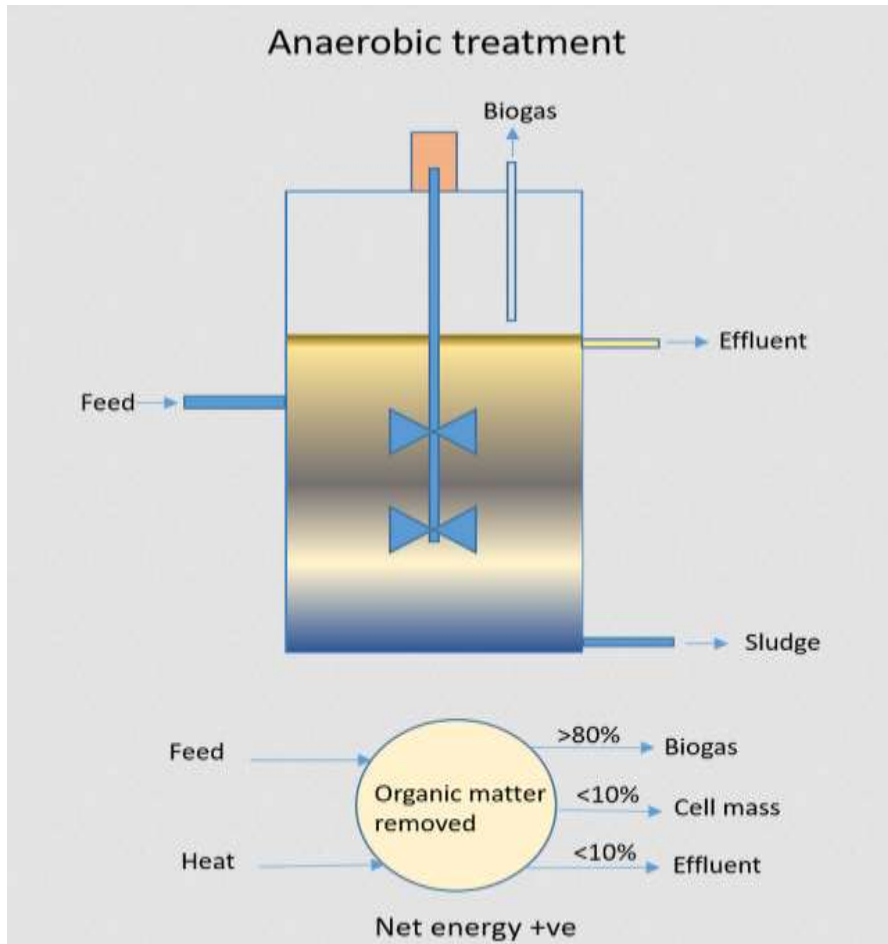


Figure 2.1 Operation of the anaerobic digester (Source: Google Chrome, Website celignis.com)

i. Energy resources challenges

South Africa's energy supply is around 42,000 MW and there are ongoing efforts to meet up with the challenge of increased energy demand. This is important for the sustainability of transportation and the energy needs for domestic energy use as well as for manufacturing and tourism if economic growth is to be sustained (Figure 2.2).

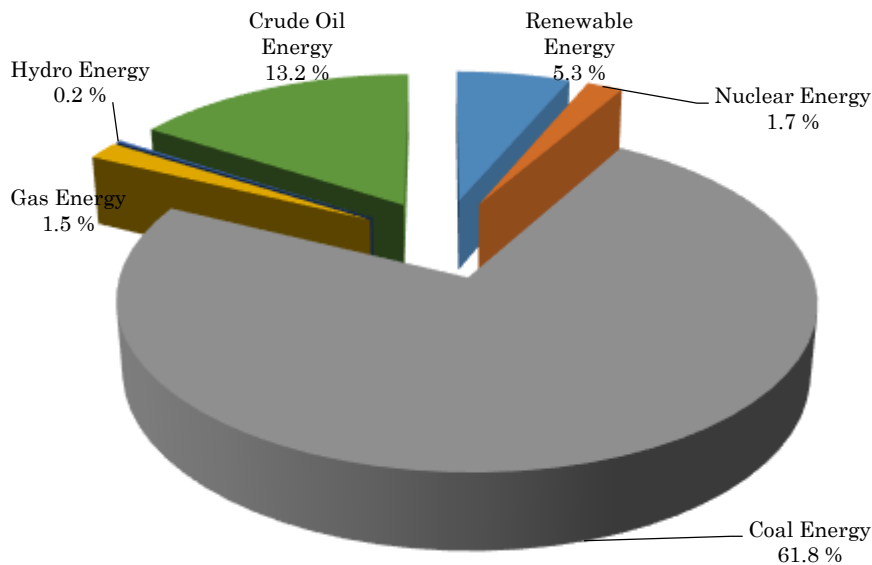


Figure 2.2 Supply of Primary Energy sources in South Africa in 2009 (Source: Africa, 2012)

The energy mix for the primary supply is from a range of sources. These include renewable resources which constitutes the third highest source of energy within the South African context. Fossil fuels in the form of coal are the dominant energy resource in South Africa and as such this country is ranked the 14th largest emitter of greenhouse gases (GHG). Noting this concern, a comprehensive review of the present energy mix is needed to shift the country towards a more sustainable and a low carbon emission environment. The annual report of the Department of Energy in South Africa, proposed an increase in energy contribution of 23% from nuclear energy sources by 2030 (see Figure 2.3) (Africa, 2012; Department of Energy South Africa, 2011). The nuclear energy proposal exceeds the global contribution trend of 5.8% (Moriarty and Honnery, 2012; Anwar et al., 2019). The possibility of meeting this proposed increase in energy from nuclear power may be limited considering the global trends of around 5.8%. Hence, to move towards reducing greenhouse gas emissions, renewable energy sources and the management thereof, are an option for cleaner and greener energy resources.

Hydro, wind, solar, tidal, geothermal, and biomass are also viable options for energy security and sustainability. However, the bio-organic energy resource option from wastewater holds a favourable opportunity for not only renewable energy sources but also for the production of a variety of products for numerous applications (Gielen et al., 2019).

However, in South Africa contributions of renewable energy resources are still minimal compared to its potential in South Africa (Figure 2.3).

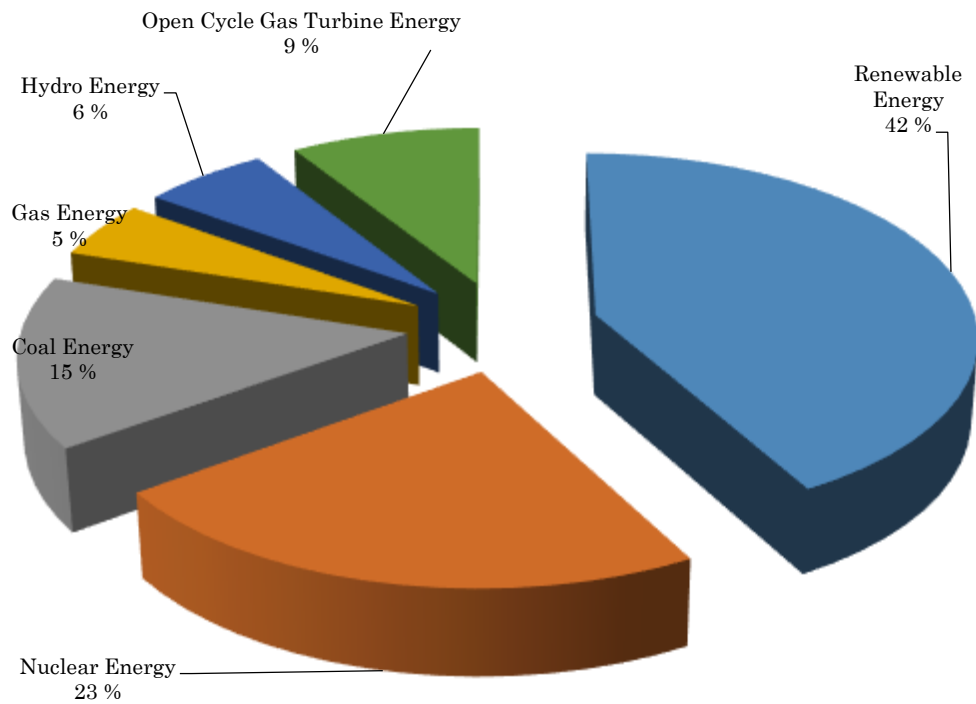


Figure 2.3 Proposed Energy Mix Capacity Plan for Next Twenty Years – 2030 (Department of Energy South Africa, 2011)

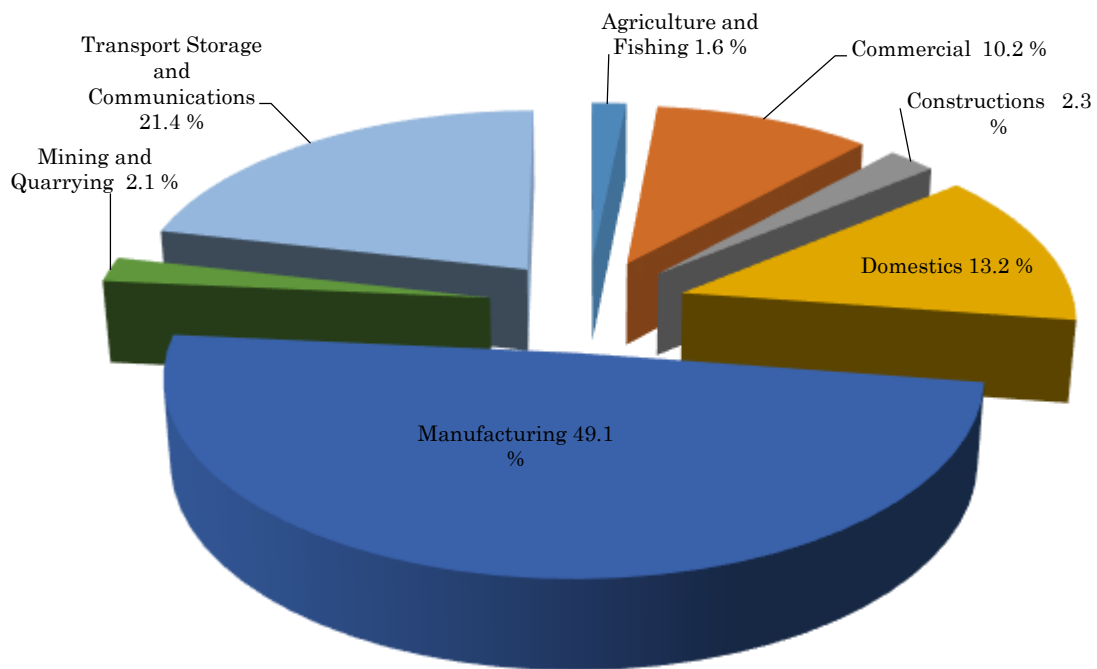


Figure 2.4 Main Consumers of Energy in South Africa 2009 (Africa, 2012)

Demirbas (2009) reported a positive projection that indicated a high demand for biofuel from renewable energy resources which shows the future demand for clean and green resources. Hence, derivatives from pre-treated and post-treatment of wastewater and sludge will produce a consistent feedstock (organic wastes) for possible energy conversions (Morgan-Sagastume et al., 2015, Battista et al., 2020).

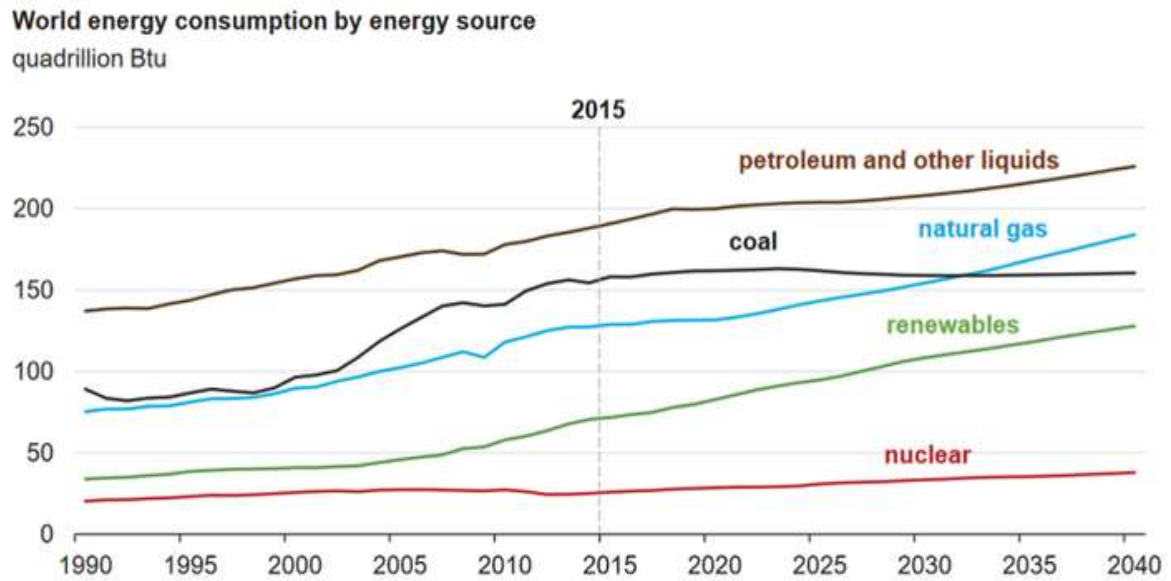


Figure 2.5 World energy alternative fuel source consumption projection. Source: (Oil & Gas Journal, 2017)

Returning to wastewater treatment, it was noted that most developed and developing countries had feasible wastewater management processes, some of which are fairly well established and advanced in its technological processes. Most countries have blueprint policies that enumerate their achievable national development programmes in wastewater management. The challenges that most of these developing countries face is that of translating these development programme intentions into implementation due to competing demands for limited resources. South Africa, being a water-stressed country and having been reported as the 30th driest in the world also finds itself in similar situations as its counterparts in developing countries (Jonker, 2007; Dai, 2013; Hove et al., 2013; Lee et al., 2017b). While there are substantive policies and frameworks guiding the treatment of wastewater, the translation into sustainable, implementable processes is on-going and subject to on-going research endeavours to exploit opportunities and optimise output assets.

2.3 GOVERNANCE AND LEGISLATION RELATED TO WASTEWATER MANAGEMENT

Noting that South Africa is a water-stressed country, the legislative authority for the management and treatment of water has been given to the Department of Water and Sanitation (DWS). This Department is in control for the development, implementation and regulation of policies, legislation and acts to manage its water services in general. Their primary goal is located within the constitution of the country and in accordance with the Bill of Rights, for example, the role of the department is to ensure that humans have access to sufficient and safe water within a healthy environment, as a basic right. As such, the legislative frameworks cover all aspects related to abstract, usages and treatment processes that will provide safe and sufficient water to the people of South Africa. Wastewater management is one of their mandates, with responsibilities devolved to municipalities.

According to Ntombela, et al. (2016), water service authorities have been given the responsibility within municipalities to provide portable water and sanitation to all persons within its jurisdiction, wastewater treatment and sewage disposal also forms part of their mandate. One of the main water pollution problems identified by the authors include poor and insufficient wastewater treatment in South Africa, especially in terms of being non-compliance with national norms and standards, legislation and policies for water resources.

There are several challenges to compliance with the regulatory framework. These challenges include the improper treatment of wastewater before being discharged. The improper treatment is as a result of several factors and includes, amongst others, incomplete or non-functional Wastewater Treatment Works (WWTW), overloaded and mismanaged plants, lack of trained operators, limited budget treatment works resulting in insufficient funds for infrastructure maintenance and upgrades, and poor planning for increasing urbanisation (Ntombela et al., 2016). Hence, while there are cumulative legislative frameworks that regulate wastewater treatment, the implementation of these frameworks is compromised by the challenges identified above.

According to DWS (2015), South Africa is ranked globally in wastewater treatment, as being the 56th out of 178 countries that are included in the Environmental Performance

Index. This poorly ranked position suggests that the challenges experienced in South Africa in relation to wastewater treatment are in dire need of redress. To improve the situation, several other programmes have been put in place. These include the grading systems such as the Green Drop Programme that is based on an incentive-based approach to wastewater treatment and management (DWA, 2011). The programme tracks and monitors compliance by WWTPs with the focus on improving the treatment efficiency. Treated wastewater within South Africa can be used for, amongst others, industry for its water needs and agriculture for its nutrients (e.g. fertiliser), soil conditioner and energy.

This usage is not inconsistent with the global usage of treated wastewater. Providing quality water to the consumers is the major challenge faced by municipalities in South Africa, especially relating to the management of WWTPs. In 2008, an incentive based Green Drop certification programme was launched to support progressive improvement and implementation in wastewater management through incentives. The process involved in this programme examines the performance of wastewater treatment (WWT) with respect to specified standards, much of which relate to increasing consciousness in the public service departments such as local governments, as well as amongst the media and the public.

This incentive system tracks and identified shortcomings in the wastewater treatment process, hence, ensure corrective measures with respect to poorly performing MWWTPs. The system also encourages competition amongst the poorly performing municipalities. Department of Water Affairs (2011) describes this programme to be informative and educational by design and, as such, has built-in capacity building characteristics to overcome challenges experienced. As this is a scoring system, the categories of scoring are in relation to several performance areas in wastewater management. The total scoring categories then constitute an overall wastewater system score. This overall score then determines the state of wastewater treatment and could assume one of five grades that ranges from 'critical' to 'excellent'. The municipalities that achieve an 'excellence' grade are awarded 'Green Drop' status. In the accounting year of 2015/16, all 824 municipal wastewater systems recorded a total wastewater flow of 5128 Ml/day. In that accounting year the average score across all of the municipalities was 45%, an increase of 8% from the previous accounting year (Ntombela et al., 2016). While this increase was noted as

positive, 56% of the municipalities were scored as unacceptable, signalling the potential for self-improvement.

An engagement on the legislative framework for managing wastewater treatment was presented to show that contributory reasons for the poor performance include lack of insight into the increasing benefits of wastewater treatment. In addition, if biogas production became the central focus of wastewater treatment as a source of renewable energy, there would be potential to self-sustain positive outflow of energy for other uses within the context of limited natural energy sources and the cost thereof. Hence, the search for optimisation in the production of biogas would contribute to adherence of the legislative framework in regulating wastewater treatment with added benefits to the country and to the globe as natural resources continue to decline.

2.4 MUNICIPAL WASTEWATER TREATMENT PROCESS

Wastewater management and disposal treatments and methods have evolved through the centuries. This evolution comes from understanding the nature of wastewater, its source and location of the treatment, the characteristics of the wastewater and its environmental impact. The treatment methods and processes are based on the origination of the wastewater and its quality such as surface and storm water, groundwater, residential, commercial and industrial. According to the United Nation's (2017) report on wastewater treatment, the quality of the wastewater can be identified through its physical, chemical and biological composition. In managing this complex nature of wastewater, this report indicated that the municipal WWTP processes are combined into a variety of systems and are referred to as primary treatment, secondary treatment and tertiary treatment. The wastewater treatment unit and processes can also be described as (drawing from Adekunle et al., 2015; Pramanik et al., 2019; Jørgensen, 2009):

- a. Primary Unit Operations includes the screening, comminution, flow equalisation, sedimentation, flotation and granular-medium filtration.
- b. Chemical Unit Operations includes the chemical precipitation, adsorption, disinfection, de-chlorination and other Chemical applications.

- c. Biological Unit Operations that include activated sludge process, aerated lagoon, trickling filters, rotating biological contractors, pond stabilisation, anaerobic digestion and biological nutrient removal.

The report also recognises that not all municipal wastewater treatment plants operate with the above unit operations, as it is dependent upon the location of the plant and the product it is receiving to treat. The reports suggest that WWTPs worldwide with the above-listed systems and processes have improved the quality of water treated, but also recognises that there is, however, a high cost and high amounts of energy input in the treatment processes. These MWWTP's are ranked amongst the top energy consumers run by municipalities. The amount of energy demand in wastewater treatment is based on the location, size of the plant and treatment processes. WWTP are now being viewed as a potential energy source for biogas production.

Wastewater treatment within the municipalities has expanded substantially due to the recognition that waste products are rich in sources of reusable products. Traditionally wastewater treatment and management were designed and operated for health and environmental protection processes but more recently, stringent measures have been adopted for optimal resource handling to maximise inherent resources such as renewable carbon, energy and minerals (Carlsson et al., 2016). Energy resource management has escalated within WWTP with a view to operating with a neutral or positive energy output realised from the chemically bound energy in wastewater. This escalation has created a fertile ground for exploring the potential to optimise energy from municipal wastewater treatment for positive energy outputs. In this respect, an increased focus on energy production from chemically bound energy in wastewater has emerged using wastewater treatment systems involving anaerobic digestion of biological sludge emanating from the primary operation of the municipal treatment process. The main output from this AD process is biogas and this process is now a well-established process globally.

The sludge produced from the primary processes of wastewater forms the basis for further treatment in the production of biogas. Sludge from raw sewage contains organic and inorganic liquid or semi-solid. These solids make up between 0.25 to 12 percent by weight and the variations are dependent upon the treatment operations and processes used (Lin et

al., 2020). Sludge can be treated using a variety of processes including anaerobic degradation. Anaerobic digestion has the capacity to produce useful elements that can be used for a range of products, including the production of methane gas for electricity generation. The raw sewage is biologically active and therefore needs a stabilisation process for further processing. One such stabilising process in anaerobic digestion is the use of a digester. The digester has four stages (Hydrolysis, acidogenesis, acetogenesis and methanogenesis) for the decomposition of organic matters and breaking down of carbohydrates, fats and proteins to methane gas, carbon dioxide and other trace gases (Adekunle et al., 2015; Kiyasudeen et al., 2016).

However, the composition of produced biogas depends largely on the raw materials within the digestion and fermentation process. Biogas production from waste digestion is an efficient way to manage wastes and produce renewable energy for electricity (Cremiato et al., 2018; Moya et al., 2017). The methane production from AD of waste materials varies for various inputs of wastes (Kiyasudeen et al., 2016). The efficient input materials and the quantity with which these materials can be added to the digester of a biogas producing plant influences the productivity of methane (Shah et al., 2015; Bharathiraja et al., 2018). This study will help to understand the need for modeling to then guide the operating parameters within a biogas production plant to optimise operational benefits from such a plant (Behera et al., 2015; Xie et al., 2016a).

2.5 ANAEROBIC DIGESTION PROCESS FOR THE BIOGAS PRODUCTION

Biogas accounts for a sizable share of renewable energy consumption in the world (Khan et al., 2017, Cheng et al., 2014). Biogas produced through the AD process is an environmentally friendly fuel. This fossil fuel occurs naturally and is a combustible mixture of gases. These gases are formed from a biological process called anaerobic digestion (AD), a bacterial decomposition of organic material. The potential sources of biogas generation are from biomasses such as kitchen waste, industrial and municipal wastes, animal faeces and crop wastes. In anaerobic digester, complex organic compounds are broken down by anaerobic bacteria in defined stages.

Anaerobic digestion (AD) involves 2 phases, that of, liquefaction and gasification which can be further broken down to 4 main processes: hydrolysis (a), acidolysis (b), acetolysis (c) and methanogenesis (d) (see Figure 2.6). In practice, all four stages take place in a single reaction vessel. The respiration realised through the decomposer microorganisms is what forms the biogas, the composition of which can vary depending on what is being decomposed (Figure 2.6). The typical composition of biogas is methane CH_4 (50 -70%), Carbon Dioxide CO_2 (20 -40%), Nitrogen N_2 (0-2%), Hydrogen Sulphide H_2S (0 -3%), Hydrogen H_2 (0 -2%) and Oxygen O_2 (0 -2%). If the substances that is being decomposed have a high content of carbohydrates such as glucose and high-molecular compounds, the methane production or percentage composition of the biogas would be low. If the substances, on the other hand, have high fat contents then the methane production or percentage of the biogas would be high (Pramanik et al., 2019; Jørgensen, 2009).

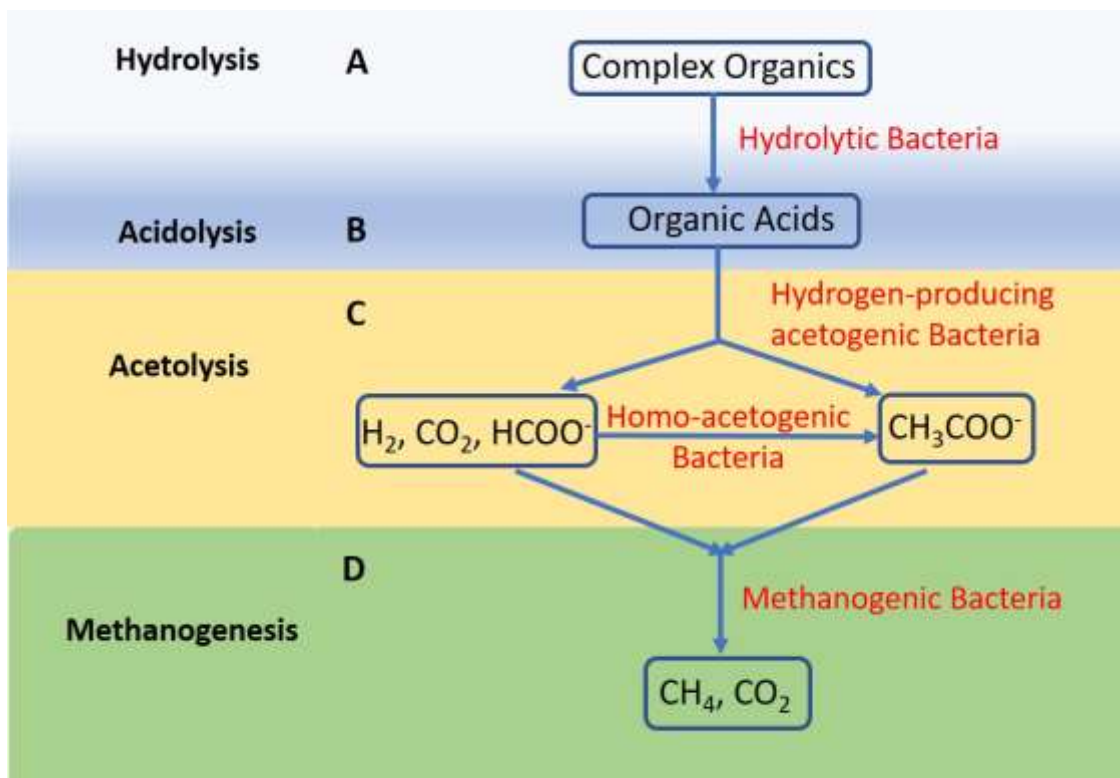


Figure 2.6 Generic process of biogas production during anaerobic fermentation

i. Hydrolysis

Hydrolysis is a chemical reaction, which is regarded theoretically as the first step/phase in AD, involving the decomposition of complex organic matter, known as polymers, into less complex elements, known as mono- and oligomers. It is during this phase that the polymers (carbohydrates, proteins, nucleic acids and lipids) are broken down into less complex molecules (e.g. fatty acids, amino acids, and simple sugars) through a process involving exo-enzymes (e.g. amylase, lipase, cellulose and protease) which are excreted by fermentative microorganisms (see Figure 2.6). The hydrolysis step is relatively slow with great implications on the overall anaerobic digestion rate (Van Haandel and Van Der Lubbe, 2007; Li et al., 2019). The rate of hydrolysis is also dependent upon a range of variables such as particle size in the substrate, the acidity or alkalinity levels of the substrate (pH values), enzyme production, diffusion and adsorption within the digestion process (Li et al., 2019; Panigrahi and Dubey, 2019).

ii. Acidogenesis

Immediately after hydrolysis, an acid forming step/phase known as acidogenesis is initiated (Lu, 2017; Panigrahi and Dubey, 2019). Acidogenesis can be divided into two processes which are known as hydrogenation and dehydrogenation. The basic pathway of this step involves the breakdown of biomass products after hydrolysis by means of acidogenic micro-organisms. The fermentative bacteria create an acidic environment by producing hydrogen (H_2), carbondioxide (CO_2), Hydrogen sulphite (H_2S), shorter volatile fatty acids, carbonic acids, alcohols, as well as small amounts of other by-products. The bacteria involved in this process are mostly strict or facultative anaerobes, for example, *Bacterioides*, *Clostridia* and *Streptococci* (Mao et al., 2015, Wang et al., 2018b).

iii. Acetogenesis

Acetogenesis is the third phase in an AD process and involves the formation of acetate ($HCOO^-$ and CH_3COO^-) from carbon and energy sources by acetogens like *Acetobacterium woodii* and *Clostridium acetium* (Li et al., 2019; Adekunle and Okolie, 2015). The by-products from acidogenesis cannot be directly converted to methane by the methanogenic bacteria. Rather acetogens help in the production of necessary secondary metabolites. Volatile fatty acids (VFA) and alcohols are oxidised into methanogenic substrates like acetate, hydrogen and carbon dioxide. Hydrogen and Acetate are released in this phase

because of oxidisation of VFA with carbon chains longer than one unit is. Hydrogen and acetate are key intermediate products for the process of methane digestion. The acetogenesis phase depicts the efficiency of biogas production (Nualsri et al., 2016; Ziemiński and Frąc, 2012).

iv. Methanogenesis

Methanogenesis is the fourth, final and critical phase in the entire AD process for methane production. The reaction between methanogenic archaea (mostly Archaea family like *Methanococcus jannaschii* and *Methanococcus thermoautotrophicum*) produces CH₄ and O₂ under strict anaerobic conditions (Wang et al., 2018a). The operational parameters like composition of organic matter, feeding rate, temperature, pH, VFA, etc. affect the performance of methanogens in biogas production. Therefore, this phase is closely monitored by determining the loading rate, temperature changes and oxygen demand entering the digester because these factors could negatively affect the production of methane (CH₄) to the point of termination. From acetate, ±70% of methane can be formed whilst the balance is derived from the conversion of hydrogen and carbon dioxide (Montingelli, 2015; Ayalew, 2017).

v. Biogas Production Through AD Process

The above processes are considered generic processes in the management and treatment of sludge to produce methane gas. The extent to which these processes are manipulated would influence the output of methane gas. Some argue that the quality of the sludge before it is subjected to the above processes may also influence the production of methane gas (Van Haandel and Van Der Lubbe, 2007; Li et al., 2016). Hence, the production of energy through the wastewater treatment processes is a complex process that involves several steps, each having the potential to influence the overall outputs of re-usable products. For example, Carlsson et al. (2016) through their manipulations in the process of producing energy have found that the energy balance performance of a WWT system is dependent upon the biodegradability (BD) of biological sludge excess.

Carlsson et al. (2016) further argue that by increasing excess biological sludge, the biodegradability through sludge thermal pre-treatment or by manipulating the rate of the process and its sludge retention time (SRT) can enhance the energy production realised

through increased methane yields in WWT. Their main argument is that accurate analysis of BD of the sludge plays a key role in energy assessment in WWT plants. They have shown through several examples of how the extent to which energy is produced by manipulating and recording several variables associated with the WWT processes. In other manipulative processes of exploring biochemical methane potential, the potential increase in energy output by manipulating the chemical oxygen demand (COD) within an anaerobic digester treating mixed sludge substrate explored differences in the correlation between the COD/TOC (Total organic carbon) ratio and methane production potential. In a study by Ersahin (2018) a positive correlation between the COD/TOC ratio, as a measure of oxidation state of the organic C, and BD was established. A low COD/TOC ratio of the sludge indicates a higher C oxidation state, and potentially a more stabilised sludge with lower stoichiometric methane production potential. Based on these studies no clear relationship was established, suggesting that previous knowledge on the production of methane through WWT plants needs to be revisited as more information becomes available. This brought about the on-going exploration, of established processes in order to obtain improved yielded outcomes. Therefore, Carlsson et al. (2016) main argument is useful in that it keeps open the possibility to explore in depth and on an ongoing basis the potential to increase energy efficiency in WWT plants. This study, therefore, takes its cue from this potentiality of endless exploration, manipulation of variables in the energy production processes within WWT plants and recording of outputs from such treatment works.

The AD technology for wastewater treatment finds wide utilisation to produce renewable energy, which can support a variety of application (e.g. fuel). The initial re-use of wastewater was for irrigation and through its (re-use) evolutionary trajectory to modern day treatment, more complex and involved process that is governed by laws and policies and with immense potential to benefit society for a sustainable future emerged and continue to emerge. In its evolutionary process, computational intelligence was explored to represent the shift from the reasoning and decision making by human to that made by CI such as Fuzzy Logic. This compels the computational system to learn from experiential data, and operate like the biological evolutionary computation. This is consistent with the hallmarks of the fourth industrial revolution that combine human, digital and environment influence in resolutions of opportunities, problems and challenges faced. Evolutional

computation (EC) is a process involving a combination of natural selection, learning theory and probabilistic methods in dealing with uncertainty and imprecision. Among the most popular approaches used in EC is the biologically inspired algorithms (Fotovatikhah et al., 2018; Yap et al., 2018). There are many algorithms such as the swarm intelligence, genetic algorithms, differential intelligence, artificial immune systems and the fuzzy algorithms. The evolutionary computation process is often confused with computational intelligence. The difference in these two processing systems is that, while they have similar goals, the distinction is in the data mining process and the imaging process (Fotovatikhah et al., 2018; Yap et al., 2018).

Artificial intelligence (AI) can be defined as a simulation of human intelligence whereby machines are programmed to ruminant like humans and has the ability to rationalise, take actions that have the most likely chance of achieving the required goal (Gupta and Tu, 2020). AI will help to predict the potential energy generation from treating industrial and domestic wastewater using anaerobic digester (Çetinkaya and Yetilmezsoy, 2019; Antwi et al., 2017). Therefore, some of the benefits of AI include:

- i) Model application for full-scale plant design, operation and optimisation;
- ii) It forms a basis for model development and validation studies for comparative analysis;
- iii) Optimisation and control for, direct implementation in full-scale plants;
- iv) It helps in assisting technology transfer from research to industry.

2.6 STRUCTURES OF ANAEROBIC DIGESTERS USED IN THE PRODUCTION OF BIOGAS

Having presented the process involved in the production of biogas and the possibilities within the established processes for optimisation at the various interfaces within these processes, the structure elements add a further opportunity to explore ways in which the biodegrading of sludge can be optimised. Within this scope of optimisation, I explore how the digesters have been constructed as a mechanical aid to hasten sludge digestion.

Anaerobic digesters have a long history of existence and with time, have evolved to become more efficient in its processing of sludge. The early history of digesters suggests that these structures were built for slow rate digestion process and were mainly cylindrical in shape with a sloping bottom and either a flat or a domed roof (Guo et al., 2015). No mixing was provided and therefore the slow rate of digestion. The gases would rise to the top and would then be extracted. The digested bio-solids would collect in the sloping bottom to allow for disposal. The slow rate digestion would take between 30 and 60 days to process (Kariyama et al., 2018, Mao et al., 2015).

Improvements to the slow rate digesters included heating, mixing through stirring and uniform flowing resulting in high rate digestion of the sludge. The structural shape remained the same but reduced in size due to the higher throughput levels recorded (Kariyama et al., 2018). The heating elements were included prior to entry of the sludge into the tanks, active mixing allowed for stability and efficiency of the degrading process. Depending upon the usage of the anaerobic digesters, mesophilic (sludge processing at normal temperatures – between 30 and 38 degrees C) or thermophilic (sludge processing at escalated temperatures – between 50 and 57 degrees C) processes were possible, each with its distinct advantages and disadvantages (Syed-Hassan et al., 2017). A further evolution of the high rate digester was the inclusion of a second tank in the processing of sludge. The second tank acts as a storage of biodegradable solids and gas with no further intervention in the degrading process. The first tank is for the hydrolysis and acidogenesis processes of the anaerobic digestion and the second tank is for methane phase digester. The two-phase design digester was known for its higher content level of methane in its final gas production emanating from the digestion process (Rahman et al., 2018).

2.7 FACTORS THAT INFLUENCE BIOGAS PRODUCTION

In this section of the literature review, the researcher explores factors that influence biogas production from wastewater treatment and the potential to optimise this production. Hence, research on such factors is presented with a view to establishing what has been done to optimise biogas production (Westerholm et al., 2018, Hagos et al., 2017). Further insights can then be gleaned on how to take forward the optimisation process as the search for systems and process continue to unfold through innovations and mathematical modelling.

While there are several influential factors in the production of biogas, there are among other factors such as operating temperature, pH, total solid content and volatile solid content that have an effect on the performance of the microbial activity and the production of the methane gas (Nsair et al., 2020) that has significant influence on biogas production (Noraini et al., 2017). These key factors are the subject of manipulation in the optimisation process of biogas production.

In order to ensure the maximum biogas yield, special attention needs to be given to these key factors as they are known to directly affect the gas production rate and the digestion process efficacy. In addition, organic material added as inoculums and the size of such inoculums in the fermentative organic substrate affects the rate of gas generation (Noraini et al., 2017; Li et al., 2016). According to Li et al. (2016) inoculums is required in the substrate to initiate the reactions caused by the appropriate amounts of microorganisms in a normal batch digester.

2.7.1 pH Value Range

The pH value within the AD process is a pivotal factor for the production of biogas. Experiments within controlled environments have proven that the yield of biogas production and the degradation efficiency is higher when AD process are operating at an optimum range of pH6.5 -7.5 (Bharathiraja et al., 2018). Within the methanogenic stage, the pH influences the micro-organism to the extent that they become highly sensitive to acidic conditions as the acidic environment inhibits the growth, thereby affecting the methane production. The bacteria activity fermentation process within the AD process is sensitive to the change of pH values, hence the control of pH is important for biogas production (Sarker et al., 2019).

2.7.2 Operating Temperature

Temperature control is critical to the AD process, as it has a strong influence on the quantity and quality of the biogas production. Studies have shown a relationship of the behaviour of the methanogenic bacteria and the change of temperature within controlled environments (Mao et al., 2015). There are two optimum ranges of temperature for bacteria that have been identified within AD reactors, the first being mesophilic temperature. The second is known as thermophilic temperature (Panigrahi and Dubey, 2019). At thermophilic temperature range the digester permits higher loading rates and therefore increases the production of methane gas. However, this operating temperature range requires greater energy input and minor changes in the AD environment disrupts the operation and takes some time to adjust. The mesophilic temperature range is employed for most AD processes as this process has a higher tolerance for environment changes, provides more stability, ease of maintenance and consumes less energy. However, this range requires a greater retention period to maximise the biogas yield (Anukam et al., 2019).

2.8 DEVELOPMENT OF COMPUTATIONAL INTELLIGENCE APPROACH

A branch of computer sciences, which emphasises the development and creation of intelligent machines that work and react like humans is referred to as Artificial Intelligence (AI). The term “Artificial Intelligence” was coined in 1956 at the Dartmouth conference (Venkatasubramanian, 2019; Copeland, 2015). The attraction by scholars to this concept has led to the development of sound theories and principles that informs gaming, automation and medical with a recent extension towards process control that estimate difficulty in measuring parameters. These process control tools are known as estimators. These estimators are developed using software like MATLAB, XLSTAT and LabView. Once developed, these estimators are implemented on specific process units to predict unmeasured states, such as temperature, concentration, impurities, heat flux and molecular weight. For example, the AI-based estimators compose a set of computational algorithms that predicts the unmeasured parameters that are considered significant in developing a computational system (Ali et al., 2015). Examples of such algorithms include artificial neural network (ANN), Fuzzy Logic, Genetic algorithm (GA), Principal Component Analysis (PCA), Partial Least Square (PSL) and expert system (ES) (Sen et al., 2018). Computational Intelligence, a sub-field of AI, has two types of machine intelligence - hard computing and soft computing (Bezdek, 2016; Dounias, 2018).

Hard computing involves a binary logic based on two values: The Booleans is either true (0) or false (1). These binary logics are the basis upon which modern computers are conceptualised. The challenge in using these binary logic is that our natural language cannot always be translated into categorical values like true/false or 0/1 (Yaseen et al., 2015). In response to this challenge, soft computing has been established. Soft computing is based on Fuzzy Logic which, more closely resembles the way the human brain works. Fuzzy Logic aggregates data to partial truths and is considered as an exclusive aspect of CI (Sharma et al., 2019b). Another logic, known as crisp logic works similarly to that of Fuzzy Logic, one of the differences between them relates to whether an element is included or not in a CI system. Crisp logic makes clear decisions on whether to include or exclude elements in the computational process while Fuzzy Logic will allow elements to be partial in a set of aggregated data, thereby giving a degree of membership rather than an either/or situation (Barocas and Selbst, 2016). The main applications of CI include data analysis,

engineering, computer science and medicine. CI tools for learning purpose includes, amongst others, constraint satisfaction problem solving techniques, neural network learning graph searching, stochastic local search, and robot control.

In the last two decades, these methods have found application in optimisation models development. It has been used extensively in the management and control of water quality (Loucks and Van Beek, 2017; Corcoran, 2010). With the application of the optimisation models, the process of selecting the best solution from all possible management alternatives has become more practical and accurate. This study herein used linear optimisation algorithms in excel environment to develop an efficient biogas management system. This was validated with simulated-scale biogas production data collected, using appropriate CI technologies.

2.9 QUANTITATIVE FORECASTING MODELS

According to experts Benkachcha et al. (2013) and Misaghi and Sheijani (2017) quantitative forecasting models using CI, can be grouped into two categories: the time series models and the causal methods. Time series models base their analysis for extrapolation into the future on historical events recorded in the data. The forecast through this extrapolation is based on the belief that a historical event will repeat itself over time. This category of models includes, amongst others, the naïve method model, moving average model, trend curve analysis model, exponential smoothing model and the Autoregressive Integrated Moving Averages (ARIMA) model (Sahn, 1989; Raza and Khosravi, 2015). The techniques within each of these models rely on general patterns or tendencies at the exclusion of factors affecting the variable to forecast (Sahn, 1989; Raza and Khosravi, 2015).

Forecast models have been successful to predict seasonal time series, while linear form is not always suitable for complex real-world problems (Zhang, 2003; Cheng et al., 2015). The limitation related to its linear process of modelling has created more opportunities for further modelling as well as different usages of modelling. For example, different mathematical and statistical methodologies have been developed for modelling and optimising a variety of wastewater treatment operations. Artificial neural network (ANN)

and Fuzzy Logic algorithms are some of the AI that have been used in the optimisation of wastewater treatment parameters (Corominas et al., 2018; Vijayaraghavan and Jayalakshmi, 2015). In the sub-sections that follow, aspects related to CI are discussed.

2.9.1 Evolutionary computation in CI

The evolutionary computation was based on the strength of natural evolution as conceptualised by Charles Robert Darwin. It involves the optimisation process called “selection” which involves identification of influencing variable and the controlling of input variables in developing new artificial evolutionary algorithms (Coello et al., 2016). Commonly referred to as problem solvers, this principle has been applied to a wide range of problems in which traditional mathematical techniques have not been effective (Brunelli and von Lüken, 2009; Vikhar, 2016). The application of evolutionary multi-objective optimisation algorithms (EMOA) has been found useful for DNA Analysis and scheduling problems in crop planning models. Several studies implementing the application of EMOAs in the solution of multi-objective planning models have also been reported in the literature (Ikudayisi et al., 2018; Adeyemo and Olofintoye, 2014; Brunelli and von Lüken, 2009).

2.9.2 Learning theory within CI approaches

Learning theory is one of the main approaches of CI. It represents a way of "reasoning" close to the humans' one. Learning is the process of bringing together cognitive, emotional and environmental stimuli to acquire, enhance or change knowledge, skills, behaviours, values and world views (Olsson et al., 2020; Mersinas et al., 2019). Learning theories help understand how the stimuli are processed and its resultant effects on individuals. Learning theories are useful in making predictions to be based on previous experience (Lu et al., 2015; Xing et al., 2015).

2.9.3 Probability forecasting methods in CI processing

In a data driven complex world and with multiple sources of data, the quality of data for computational processes become compromised (Zhou et al., 2016). Han, Jian and Michelin (2006) argues that available data sets are compromised by missing and inconsistent data because of their typically large size and of their multiple and heterogeneous origins resulting in low-quality data being available for computational purposes (Han et al., 2006;

Farsi et al., 2018). They further argue that low quality data leads to low-quality mining results. Hence, probabilistic forecasting methods are the commonly used techniques to bring out the possible solutions to a reasoning problem. Probabilistic forecasting methods are based on randomness and aims at evaluating the outcomes of a CI system. The random aspect is one of the main elements of Fuzzy Logic. Therefore, before the development of prediction models, data pre-processing and randomisation are pre-requisite in ensuring a substantial improvement in the overall quality of the system process (Ramaswami et al., 2019). Therefore, prediction can only be accurate in preponderance to the quality of data use.

2.9.4 Data Pre-Processing for computation

Data pre-processing is an essential step in computational analysis. In this respect, data pre-processing includes data cleaning, data reduction, data transformation and data reduction (Chen et al., 2019). Data cleaning, for example, involves a process of removing, what is commonly referred to as noise and inconsistencies or adding in values in the data set. Examples of data cleaning include a process of determining and filling in missing values and removing outliers. Determining and filling in missing value processes may include using the mean or the most frequent value in a data set. Modelling can also predict a missing value of a variable (Che et al., 2018). However, this is dependent on the nature of the values available. Data cleaning for outliers is usually done using boxplots. The observation of the outliers in boxplots can be identified as the points found outside the boxes (Chen et al., 2019).

Extreme values in a set of data are referred to as outliers. Such values are either much higher or much lower than the other numbers in a data set. In statistics, an outlier is considered to be an observation point that is distant from other observations (Aggarwal, 2015; Aggarwal, 2017). An outlier may occur as a result of extreme variability in the measurement in a specific variable or it could be due to an experimental error. Such extreme values in a data set are often excluded in the computational process. Outliers tend to affect the mean value of a measurement. The median or mode of that variable is less affected by outliers (Aggarwal, 2015; Kwak and Kim, 2017).

Data reduction is another aspect of data pre-processing. In the data reduction process, high dimensional data is transformed into a data representation consisting of a reduced number of dimensions, while preserving most of the information from the original source (Adão et al., 2017). Strategies to accomplish this are the dimensionality reduction, such as normalisation. The importance of data pre-processing is that, when applied before mining, the overall quality of the patterns mined is substantially improved as well as the time taken for the actual mining is substantially reduced (Dzyuba et al., 2017; Han et al., 2006). After eliminating the outliers, the next step in data processing is to test the dataset by means of a reliability analysis test.

2.9.5 Reliability analysis test

Research is based on measurement and should be concerned with accuracy or dependability which is commonly referred to as reliability of measurement (Benton, 2015). A coefficient of reliability would demonstrate the validity of the dataset measurements. This process is known as a reliability analysis test of the dataset. The higher the correlation coefficient in reliability analysis, the greater the reliability of using the data (Koo and Li, 2016). The normal distribution, correlation and standardised Cronbach's alpha (α) and Guttman's reliability (λ_{max}) test were different methods used to test data reliability. These data are used to draw a cumulative frequency polygon against the upper-class boundaries to graphically summarise and display the distribution of the process data set in a histogram.

The Cronbach's alpha is a convenient test used to estimate the reliability, or internal consistency, of a composite score (Taber, 2018). It depicts how closely related a set of items are as a group based on the covariance matrix of the standardised data. Cronbach's alpha (α) tends to underestimate the true reliability, whereas Guttman's reliability (λ_{max}) may over-estimate reliability when the sample size is small or there are a large number of items. It turns out that Guttman's reliability is a good measure of reliability and produces a higher value than the Cronbach's alpha. A "high" value for alpha does not imply that the measure is unidimensional, it only states the internal consistency calling for additional analyses (Trizano-Hermosilla and Alvarado, 2016). In this study, both the Cronbach and Guttman's reliability test was used on the dataset, this allowed for a comparison and better understanding of the dataset for further analysis. The formula for the standardised

Cronbach's alpha (α) and Guttman's reliability (λ_{max}) is defined as equation 2.1 and 2.2 respectively.

The formula for Cronbach's alpha is:

$$\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N-1) \cdot \bar{c}} \quad (2.1)$$

Where;

N = the number of items.

\bar{c} = [average covariance](#) between item-pairs.

\bar{v} = average [variance](#).

Guttman's reliability is defined as;

$$\lambda_{max} = \max (\lambda: \text{all possible split halves}) \quad (2.2)$$

2.9.6 Principal Component Analysis

In the age of large data sets across many disciplinary areas, managing and interpreting these data sets are becoming increasingly difficult to interpret. This is where principal component analysis (PCA) becomes useful. Jolliffe and Cadima (2016) indicated that PCA is increasingly being used to drastically reduce and interpret such large data sources while at the same time preserving the data. While there are many techniques available, PCA is considered one of the oldest techniques in data reduction. PCA is a statistical technique that is used to analyse several tables of variables simultaneously. These statistics provides values and charts to study relationship amongst observations, variables, and tables (Audigier et al., 2016). This method is useful in visual analysis as it provides tables and charts in two or three-dimensional space for easy recognition of patterns, variances and conformity through data reduction techniques. The principle behind PCA is the ability of the statistical computation to search for new variables that have linear functions with the original data set and through its reduction solves an eigenvalue/eigenvector problem (Jolliffe and Cadima, 2016). Principal component analysis can be based on either a covariance matrix or correlation matrix. The main uses of PCA are descriptive, rather than inferential and is exploratory in nature.

2.10 DEVELOPMENT OF PREDICTION MODELS IN CI

Having explored various aspects to CI, this section presents literature on prediction models that can be used to estimate future values as it relates to wastewater treatment. In the context of wastewater management, future wastewater usage and reclaim can be predicted using models based on calculated variables like capita water use, growing population and development (Qasim, 2017; Roozbahani et al., 2013). The South Africa Bureau of Statistics (2010) provides population statistics in the province (in millions). Based on predictions of population growth, planning for wastewater treatment using prediction models has become a necessity. For example, a reservoir or storage system is required in a WWTP (Howe and Koundouri, 2003). The size, number of such reservoirs and storage systems and alternate systems for managing future flow sequences need to be predicted to accommodate the future increase in population. In this respect, King and Brown (2010) concluded that it is crucial to generate synthetic future inflow sequences with a view to analysing alternative designs, operation policies and rules for wastewater resources systems.

Another group of predictive modelling is the Stochastic forecasting models. These models are flexible tools that allow for circumventing shortcomings in the historically used predictive modelling processes (Wang et al., 2009). The Stochastic models work on probability distribution techniques using Normal, Log-Normal (LN), Pearson III, Log-Pearson type III (LP3), Gumbel extreme value type1 (EVI) and Log-Gumbel (LG) functions. They offer a long-term time series of projected available wastewater.

2.10.1 Partial Least Square (Regression)

According to Nitzl et al. (2016) Partial least square (PLS) is considered to be a soft modelling process that involves the use of many and highly co-linear factors. It is used for predictive purposes, where responses are key focus of the prediction and understanding the relationships between the factors is not of great importance in this modelling process. While this model was developed as an econometric technique, its uses in other fields like chemical engineering have gained significant attention (Xu, 2019). Its uses have also

expanded from predictive uses into monitoring and controlling industrial processes that involves large numbers of variables and outputs.

The strength of this modelling lies in its ability to identify a few, amongst the many variables or factors that may account for the variations. These few variables that are identified by the model are referred to as latent factors and these are used for the prediction purposes. For the PLS technique the extended factors (X factors) and the predicted scores (Y scores) are chosen so that the relationship between successive pairs of scores are strong and when this happens a more robust form of redundancy analysis takes place leading to more accurate response predictions.

The use of PLS regression is for an attempt to exploit the merits of PLS regression in modelling reaction condition of an anaerobic digester through its dimensional reduction function. The calibration using PLS is expected to simplify and reduce the number of latent variables for prediction responses within a digester (Xu, 2019). It is also capable of mapping a latent relationship between multivariate matrices, thereby allowing parameters calibration in a guided manner for optimisation.

2.10.2 Fuzzy Logic

Fuzzy Logic was a tool introduced in the year 1965 by Lotfi Zadeh. It is a mathematical tool, which was developed to deal with uncertainty. As described earlier, AI has sub-fields within the types of machine intelligence - hard computing and soft computing, Fuzzy Logic falls within the soft computing fields (Ray, 2018). The Fuzzy Logic approach provides a technique to deal with situations or scenario's that are imprecise and information granularity and has a mechanism representing linguistic constructs such as "low", "often", "many". Fuzzy Logic offers an inference system that enables human reasoning capabilities to a task (problem). This approach involves the mapping of nonlinear inputs to an output/s.

i. Fuzzy inference system

The fuzzy inference system (FIS) distinguished itself from probability processing system in that it works with uncertainty in the definitions of concepts rather than the frequency of occurrence of a phenomenon (Yetilmezsoy et al., 2012). The concept of Fuzzy Logic is

derived from its ability to accurately describe imprecise values of variables such as temperature, speed and height. The Fuzzy Logic is dependent upon the number of rules, inference systems and types of membership function applied to its modelling system (Delrot, Guerra, Dambrine & Delmotte, 2012; Lam, 2018)

Fuzzy Logic consists of several elements such as the fuzzy rules, linguistic variable and values, fuzzy inference, membership function and defuzzification (Delrot et al., 2012). It is a type of logic that is referred to as multi-valued logic and goes beyond discrete values (true/false or 0/1). Rather, it represents degrees of truthfulness and falseness in the range of $[0, 1]$ where 0 is the absolute FALSE and 1 is the absolutely TRUE (Lam, 2018).

This technique employs a wide range of domains and includes control, image processing and decision-making (Zohuri and Moghaddam, 2017). Fuzzy Logic is a well-established concept and is even found in homes (e.g. washing machines and microwave ovens). In video technology, Fuzzy Logic is used for stabilising the recorded images whilst the camera is hand held. Other areas of application, according include medical diagnostics in medicine, foreign exchange trading in finances, and business strategy selection in leadership and management of business. Fuzzy Logic does not have learning abilities and therefore focuses on approximate reasoning (Annabestani et al., 2019). A topology step of Fuzzy Logic is as depicted in Figure 2.7.

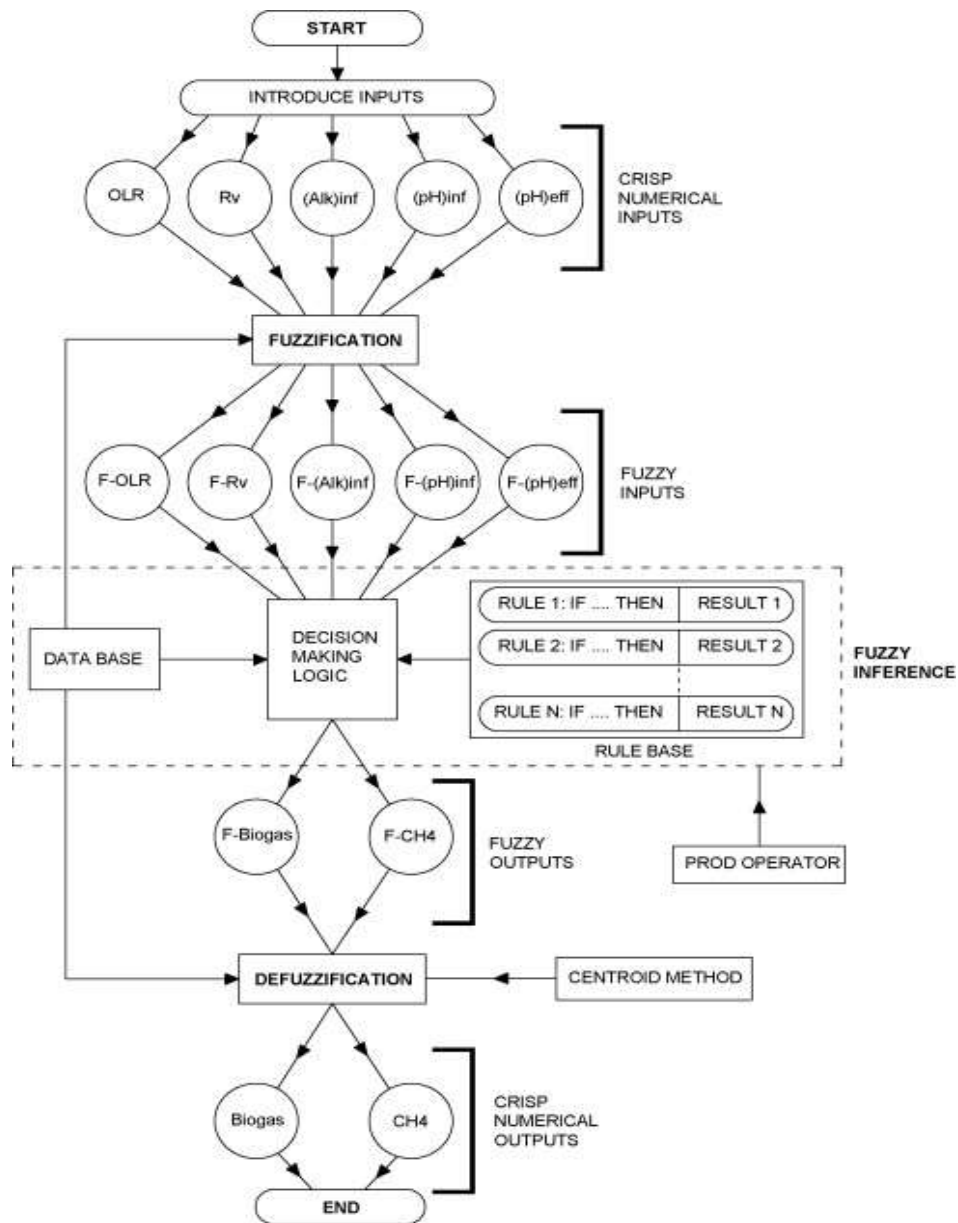


Figure 2.7 Topology step of Fuzzy Logic computation method application (Turkdogan-Aydinol and Yetilmezsoy, 2010)

Rizvi et al. (2020) describe a fuzzy inference system (FIS) as being composed of three blocks, which can be represented as follows:

- (a) Fuzzification - this involves the transformation of the input data set from a numerical value/crisp value into a fuzzified value using linguistic terms and membership functions. The fuzzified value using the linguistic terms is set between 0 and 1.

- (b) Rule Based Reasoning - Inference engine that obtains fuzzified output values for the given fuzzified input values using control rules present in the rule-base. The Fuzzy input dataset membership values are mapped to classify the output through a frame of if-then rules. The fuzzy rules identified are expressed as a logical implication $p \rightarrow q$ where p represents the antecedent of the rule and q represents the consequence of the rule.
- (c) Defuzzification - this involves a process that converts the fuzzified output value into a numerical value from the rule aggregation result. There are several defuzzification methods, viz., weighted average, max-membership, center of gravity, and center of sums. Each of these methods listed have advantages and disadvantages, however the centroid method is the most common approaches used (Rizvi et al., 2020).

The FIS and models have been successfully applied to nonlinear control problems as they are able to provide a framework to incorporate the linguistic fuzzy dataset. Most FIS are classified by two types, the first being Mamdani which was identified in 1975 (Erturk and Sezer, 2016). This type of FIS was developed by Ehsan Mamdani to be used to control the steam engine through synthesis of a set of fuzzy rules (Mohanraj and Prakash, 2018). The Mamdani type of FIS uses the collection of IF-THEN rules whose antecedents and consequents use fuzzy valued dataset. The second type of FIS is the Takagi-Sugeno Fuzzy model and was developed in 1985 by Takagi, Sugeno and Kang. This type is used to describe nonlinear systems and uses a rule structure of fuzzy antecedent and functional consequent values (Boulkaibet et al., 2017). The Sugeno FIS approach approximates a nonlinear structure with a combination of several linear structures, by disintegrating the input dataset into several partial fuzzy spaces and the output dataset of each rule is a linear arrangement (Walia et al., 2015).

2.11 CONCEPTUALISATION OF ENERGY PRODUCTION FROM WASTEWATER TREATMENT

Studies have shown that anaerobic treatment of domestic wastewater has the potential to achieve net energy production and the energy produced through this process could be harnessed and converted to electrical energy (Wei et al., 2014; Shoener et al., 2014; Batstone and Viridis, 2014; Mei et al., 2016). A concern, however, in this conceptualisation of energy production is the balance between input energy needed for the treatment and conversion process, and the output energy derived from the treatment of waste process. In addressing this concern, research has expanded to include efficiency in energy-producing processes (Mei et al., 2016; Kollmann et al., 2017). Gude (2015) presents the energy issues that needs to be understood and conceptualised in the treatment of wastes for energy production, one of which is related to self-sufficiency . This implies that input energy needs to be lower than output energy, making the process of producing productive energy self-sufficient.

Gude (2015) presents a scenario where wastewater treatment requires between 0.3 and 0.6 kW h/m³ while the energy content of the same contains approximately 10 times the energy used in the treatment process, suggesting that there is potential to optimise the efficiency of the output energy. There are several routes of resources from waste. Tyagi and Lo (2013) lists a number of these routes which include anaerobic digestion, which they say is the most popular sludge stabilisation technology in the current market. The process transforms sludge organic solids into biogas in an anaerobic environment for production of electricity. The authors further argued that conversion of waste sludge for electricity generation is an increasingly emerging field and requires on-going research to upscale the production process of biogas. The most widely employed method for sludge treatment is AD incorporating a breakdown of organic matter into carbon dioxide and methane in the absence of oxygen (Van Haandel and Van Der Lubbe, 2007; Moraes et al., 2015). Oloko-Oba et al. (2018) suggested that traditional shapes of anaerobic digesters were largely cylindrical. Egg-shaped digesters are now also used in the AD process. This type of digester allows higher mixing efficiency and greater gas production as compared with others. Such structural developments also help to improve the efficiency of biogas production.

The optimisation through computational intelligence approach will contribute significantly to the efficiency of wastewater management and utilisation in the field of energy generation. Michael-Kordatou et al. (2015) argues that sustainable application of biologically based units for the treatment of wastewater at MWWTPs depends on the comprehensive studies in order to determine the impact of different operational conditions on the efficiency of organic matter removal and generation of renewable energy. Due to limited knowledge with highly complex and non-linear digestion processes, optimisation and control strategies with respect to external influences and different process disturbances, creates opportunities for on-going research with respect to efficient operation of AD treatment plants for bioenergy generation (Connor, 2015; Enitan et al., 2018).

Like many other natural real-world problems, AD processes are conflicting in nature. Hence, computational intelligence technique is required for solving optimisation and other problems AD processes. The outcome of CI technique is a generation of an optimum set of solutions, which are regarded as better solutions based on conflicting objectives of the problems under consideration. This may not be an easy task due to the complexity and variations in the organic content of the wastewaters, but few studies on modeling and optimisation of anaerobic digestion using computational intelligence approaches to enhance biogas production for energy generation have been reported (Yetilmezsoy, 2012; Enitan et al., 2018). Hence, this study intends to evaluate the efficiency of developing simulation models that will predict the optimum operating conditions for biogas generation from the selected municipal anaerobic digester. The study further determined the bio-economy value of the renewable energy.

2.11.1 Renewable Energy development in South Africa

According to the 2nd South Africa Environment Outlook Executive summary on the state of the environment (2016), energy is viewed as having an important role in the revolution of today's world and highlights how the human livelihood is largely dependent on the use of energy. Energy as defined by Encyclopedia Britannica (Britannica, 2020) "in physics, the capacity for doing work. It may exist in potential, kinetic, thermal, electrical, chemical, nuclear, or in other forms." There are two sources of energy:

- Renewable energy in the form of solar energy, geothermal energy, wind energy, biomass and hydropower;
- Nonrenewable energy in the form of petroleum products, hydrocarbon gas liquids, natural gas, coal and nuclear energy.

Energy is finite thereby creating concern with growing global urbanisation and its increasing demands for more energy. There are many facets whereby energy has a critical implication such as; environmental sustainability, sustainable developments, economic development, and social development. South Africa is rich with reserves of fossil fuel in the form of coal and natural deposits of minerals and is therefore a major contributor to its economic development. South Africa's economic development has been dominated by the extraction and processing of minerals and fossil fuel (coal), which is also, an energy-intensive activity (RSA, 2016). According to the 2nd South Africa Environment Outlook, Executive summary, coal has been established as the main source of primary energy supply and contributes towards +- 90% of electricity generation (Department of Water Affairs, 2016). This highlights South Africa's economic dependency on fossil fuel. This statistic has also highlighted major concerns and awareness within the environmental sector. Coal along with other fossil fuels used for electricity generation has proven to be detrimental to the environment. This is due to high gaseous emission levels.

South Africa is listed to be one of the top-ranked countries responsible for high carbon dioxide emitters (South Africa Environment Outlook 2016; Adams and Nsiah, 2019). Fossil Fuels such as coal, oil, petroleum, and gas are largely composed of carbon and hydrogen. From the process of generating electricity, combustion is required thereby releasing carbon dioxide, which in turn causes air pollution and contributes to the greenhouse effect. This has a major impact on the natural ecosystem and climate changes and is considered hazardous to human health which overall hinders sustainable development and effects the environmental footprint (Omer, 2008; Modi et al., 2005; Bouzarovski and Petrova, 2015).

Due to this hazard, South Africa had stepped forward to voluntary pledge at the COP 15 Climate conference in Copenhagen in 2009 for emissions reductions. In order to keep

with this pledge and attempt to reduce the gaseous emission, the Department of Energy needed to turn their focus to renewable energy sources for electricity generation. In doing so, a new programme was initiated termed The Renewable Energy Independent Power Producer Procurement Programme in August 2011. This programme opened the platform for the integration of renewable energy within South Africa's electricity mix (WWF Report 2017; Jain & Jain, 2017). The National Climate Change Response White Paper, highlighted the potential of renewable energy sources to mitigate climate change and pointed out that investment in renewable energy programmes was one of the most favourable options in the electricity sector (Ratshomo and Nembahe, 2018).

2.11.2 Biogas production and energy recovery

Typical biogas contains 55-70 % methane, 30-40% CO₂ and small amounts of N₂, H₂, H₂S, water vapour and other gases. Biogas that is produced in the digesters could be used to generate electricity. The energy content of digester gas is typically in the range of 24 MJ/m³ (Chen et al., 2015; Neshat et al., 2017). Gas production can also be estimated crudely on per capita basis, where the norm yield is 15-22 m³/1000 persons /day for primary treatment plants and up to 28 m³ /1000 persons/ day in the secondary treatment plants (Deeptha et al., 2015; Techobanoglous et al., 2014; Metcalf, 2014). Building on work done by GIZ and SALGA in the field of biogas Metcalf and Eddy (2014) used an excel-based tool to calculate the potential for energy recovery from the WWTPs. Their tool was sensitive towards digestion temperature and retention time. The results for biogas to energy potential at a national WWTW is summarised in Table 2.1.

Table 2.1: National overview of biogas to energy potential at WWTW

	Min	Max	Ave	SD	Total
Biogas produced, m ³ /d	98	22 299	1 970	1 977	282 671
Thermal power at 23 MJ/m ³ , kWt	26	6 003	535	513	77 099
Electrical power at 36% eff, kWe	10	2 161	193	185	27 757
Electrical energy per day, kWh/d	229	51 865	4 584	223 334	657 765
Electrical energy cost per year at R0.60/kWh, R/a	2 130	3 539 321	1 002 864	1 097 649	143 942 502
Primary sludge produced kg/d	140	48 620	3594	3790	548 302
Secondary produced, kl/d	29	35370	2289	2713	368917

According to these authors further investigations on biogas production for energy recovery identified various factors influencing the efficiency in the anaerobic processes that produced biogas. Among these various factors, Zheng, et al. (2015) found that the pH of the digesters affects CO₂ release to the gas phase, which impacts on CH₄ production. It was also found that heating of digesters affects methane production (Arikan et al., 2015) and thickening of the digester feeds sludge was found to increase the sludge retention time (SRT) (Bharambe et al., 2015).

Research (e.g. Pullen, 2015) has also shown that energy recovery and monetary saving potential can be adjusted upward when considering the following improvement and adjustments:

- Full use of each plant's design capacity;
- Upgrading or refurbishing digesters with heating and mixing equipment; structural refurbishment of anaerobic digesters;
- Improved operations of various sludge handling processes responsible for the volume and quality of sludge input into the digesters, especially the settling tanks and waste sludge handling from activated sludge plants.

2.12 THE NEED FOR SUSTAINABLE NATURAL RESOURCES MANAGEMENT

The depletion of natural resources to a crisis point suggests the need to manage these resources in a sustainable way. George et al. (2018) regards natural resource as materials that occur in nature and are essential or useful to humans, such as water, air, land, forests, fish and wildlife, topsoil, minerals and energy. The management of the natural resources may include ideas, innovations and processes that will reduce society's dependency on such resources with a view to preserving or substantially diminishing our dependency on such resources. Noting this broad conception of natural resources and the essentiality of these to humans, it is no wonder that the management of such natural resources is critical for the longevity of human lives on earth. Concerns about the depletion of natural resources raised by researchers, amongst others, like Pillot, et al. (2019), are as a result of global trends such as urbanisation, growth in population, progression in consumption, environmental degradation and global warming. These global trends are placing pressure on the availability and usability of natural resources. In responding to the imminent crisis related to natural resources, alternatives have been suggested as a way of decreasing dependency on such resources. For example, wastewater through human consumption has been a source of exploration for decades with very promising rewards that not only caters for recycled water to be put to further use, but to extract other benefits, like fertilisers and energy for productive reuse.

Innovations in wastewater treatment are striving to meet acceptable standards of treatment. It is therefore, within the context of the fourth industrial revolution, opportunities for revisiting innovations through data prudence to understand what natural resources are, and to focus our attention on innovative ways to slow down the dependency rate and to find alternate resources to meet society's needs. Data-driven mechanisms have opened a spectrum of possibilities to either refine existing processes, adapt and reform existing processes or find new and novel processes. Therefore, domestic wastewater has been identified as being resourceful in the production of biogas that could be used in the production of electricity using various ways of treating and managing wastewater globally.

The integration of natural sciences and engineering in order to achieve a sustainable development of value-added products from wastewater in meeting the needs of an

expanding and increasingly urbanised population in the next millennium will prove that agriculture, fisheries, forestry and industrial sludge are a sustainable way of disposal. Hence, the conversion of waste into renewable energy (such as biogas and bio-fuel) will go a long way in reducing the need to import costly fossil fuel (Sipra et al., 2018; Elum and Momodu, 2017). However, the failure to reuse organic wastes in urban areas would mean a huge loss of resources that could be productively used, but instead, may be discharged into rivers and landfills thereby causing water pollution or leading to air pollution due to greenhouse gas emission.

2.12.1 Development of value-added products from wastewater

It has been established in many fields that waste can be managed and reused as a resource. There are many types of waste. These include waste from agricultural processes, chemical processes, industrial processes domestic and municipal activities. According to McCarty et al. (2011), wastewater is now being conceptualised as a resource rather than waste as it has the potential to address three major resource issues of water, food and energy shortage challenged. The Municipal wastewater, as defined by the United Nations (2003), is the combination of liquid or water-carried wastes that originates in the sanitary conveniences of dwellings, industrial and commercial facilities and establishments. Surface water, ground water and storm water may also be considered as wastewater (United Nations, 2003). Waste from wastewater treatment processes has the potential to produce fertilising nutrients that contribute to food security. Treated wastewater can be discharged back to the environment and renewable energy can be produced to contribute to electricity generation (Rulkens, 2008; Maktabifard et al., 2018).

South Africa currently disposes off large amounts of wastewater into rivers, lakes and estuaries that eventually runs into the ocean. This is detrimental to the vital fresh water resources (Nilsson et al., 2008; Sedlak, 2014; Pimentel et al., 2004; Loucks and Van Beek, 2017). South Africa is becoming a water-stressed country and this is likely to increase, thereby aggravating the growing demand for fresh water across all sectors. Hence, the process of recycling water and wastewater appears to be beneficial, important and critical to meet the growing demands of fresh, clean and drinkable water. In addition to the water being recycled, pathogens (disease organisms), nutrients (e.g. nitrogen and phosphorus),

chemicals from cleaners, disinfectants and even hazardous substances were found in wastewater (Ding, 2017; Lusk et al., 2017). Given the variety of substances found in wastewater, it therefore becomes apparent and imperative to treat wastewater, not only to recycle the water and extract nutrients, but also to protect human life and sustainability as well as the environmental health (Affairs, 2012; Michael-Kordatou et al., 2015; Gude, 2015).

2.13 CONCLUSION

This chapter engaged with a literature review that frames the study focus. More specifically, it contextualised the need for wastewater treatment and the benefits associated with such treatments. Noting that there is a scarcity of natural resources and an increase in demand for such resources, optimisation of processes to extract useful material from wastewater treatment has now become an essential need. This chapter, therefore, presented the various aspects related to structural and process related optimisation possibilities in the treatment of wastewater for extraction. The chapter also presented computational processes as a further evaluation in the optimisation of wastewater treatment. The next chapter presents aspects of methodology as key consideration in the optimisation of wastewater treatment process with a specific focus on the production of biogas for electricity generation.

CHAPTER 3

MULTIVARIATE ANALYSIS OF CORRELATED VARIABLES USING PARTIAL LEAST SQUARES (PLS) REGRESSION MODEL AND PRINCIPAL COMPONENT ANALYSIS (PCA)

3.1 INTRODUCTION

Chen (2019) suggests that inadequate and lack of quality data are a common phenomenon in most hydrologic archives. The author further argues that these may be due to human error, faulty equipment, data corruption or misjudgment in machine processes in storming weather condition. The author concludes that these limited or no datasets often leads to unrealistic and biased assessment (Chen et al., 2019). Noting the above concerns about data quality, qualitative and quantitative authentication of data correctness or improvement towards minimisation of prediction error using advance technological and computation intelligent approach are, therefore, becoming a fast forecasting tool for creative exploitation in data management (Nastac et al., 2018).

Data pre-processing are meant to reproduce the endogenous trends in data observation, while post-processing reveals hidden meaning that are present in the data over time (Taber, 2018). The quality of the available database influences estimation accuracy regardless of the method used (Pospieszny et al., 2018). As reported by Metcalf and Eddy (2014), infrastructural support needs an adoption of best practices through the optimisation of the various process units, identification of the operational parameters limitations confronted by the wastewater treatment plant, and in enhancing and converting biogas generation from these digesters to its energy potential. Most of the primary data measured in wastewater treatment plants must be pre-processed and subjected to a rigorous statistical analysis to test their accuracy, homogeneity, consistency and localisation gaps using different intuitive statistical methods before the application of CIA (Gibert et al., 2016).

In this study, PLS was adopted to pre-process the collected data before the optimisation process takes place. The PLS method developed in this research study was adopted to conduct a regression analysis between the various parameters from the datasets obtained

from the study site. The PLS technique is a multivariate statistical technique that allows comparison between multiple response variables and multiple explanatory variables (Mertler and Reinhart, 2016; Peres and Fogliatto, 2018). It is one of the diverse covariance-based statistical methods, which are often referred to as structural equation modeling (SEM) and the regression models have been demonstrated on both real data and simulations (Hair Jr et al., 2017; Steinberg et al., 2016). PLS has been popular in the physical sciences, where there is a significant problem with a high number of correlated variables and a limited number of observations. PLS was also used within the marketing discipline with similar scope of use and similar problems (Ryan, Rayner, & Morrison, 1999). PLS was also designed to be used when datasets are problematic in the sense of having missing values or incorrect recordings of values and sometimes with smaller data sets (Pirouz and Rodriguez, 2006; Lee et al., 2018). PLS is used in this study because of small dataset and missing values within the dataset. This chapter therefore focuses on data collection, data quality, management of datasets and related issues that influences the computational analysis during evaluation and optimisation of biogas generation from the municipal wastes treatment anaerobic digester. It involves the use of PLS for pre-processing of the egg-shaped digester datasets collected from the study site.

3.2 METHODOLOGY

The subsequent sections illustrate the procedural steps employed in the methodology for the pre-data analysis. It started with the description of Partial Least Square regression method adopted in this chapter. It is followed by the method of data collection, the sampling size design and validity. Thereafter, the section continues with data cleaning through observation and correction of missing data. The data integration and reduction were also achieved by statistics description summary and inferential statistical deduction. Among the descriptive statistical techniques employed are variance frequencies, mean, median, and standard deviation, which was used to describe the observations while the data transformation of the collected dataset was achieved through the use of different multivariate statistical tools. The general steps of the pre-data processing have been mentioned in Chapter Two, section 2.9.4. However, these are not limited to the treatment of missing values, need for outlier's elimination, correlations and regression analysis for the relationship among variable; significant test for the consistency analysis. Further

investigation into data mining; reveal the need for reliability test which consists of the use of Cronbach's alpha and Guttman's reliability test, principal component analysis (PCA) and the factor analysis (FA) which helps to extract the relevant information that appeared noisy. The Eigen value/Eigenvector presented rotated matrix approach, which was used for the data analysis. Factor analysis was used for the data transformation in revealing their hidden meaning and making an inferential deduction from the data.

3.2.1 Partial Least Square (PLS) method

The PLS method developed in this research study was adopted to conduct a regression analysis between the various parameters from the datasets obtained from the study site. This method was adopted to determine the extent and effects of the various operational factors which influence biogas production and its optimisation potentials from an anaerobic digester (Faizollahzadeh Ardabili et al., 2018b). By exploring the processes and capacities of the digester, the input variables are normally selected with the purpose of controlling the operation of digesters during the simulation process to enhance biogas production for electricity generation. The pre and post data processes are necessary for determining how well the developed model fits the data during calibration and validation phase as well as to avoid overfitting during the process (Deng et al., 2015). The PLS finds a linear regression model by projecting the predicted variables and the observable variables to a new space. PLS, they argue, is then used to find the fundamental relations between two matrices (X and Y), i.e. a latent variable approach to modeling the covariance structures in these two spaces. A PLS model will try to find the multidimensional direction in the X -space that explains the maximum multidimensional variance direction in the Y -space. PLS regression is particularly suited when the matrix of predictors has more variables than observations, and when there is multicollinearity among X -values. By contrast, standard regression will fail in these cases (unless it is regularised). The general underlying model of multivariate PLS adopted in this study is shown as Equation 3.1 and Equation 3.2.

$$X = TP^T + E$$

(3.1)

$$Y = UQ^T + F$$

(3.2)

Where, X is an $n \times m$ matrix of predictors, Y is an $n \times p$ matrix of responses; T and U are $n \times l$ matrices that are, respectively, projections of X (the X -scores, component or factor matrix) and projections of Y (the Y -scores); P and Q are respectively, $m \times l$ and $p \times l$ orthogonal loading matrices; and matrices E and F are the error terms, assumed to be independent and identically distributed random normal variables. The decompositions of X and Y are made so as to maximise the covariance between T and U . Furthermore, the post processes calibration and validation are required for the developed models to make sure the employed model represents correctly the operational condition given the different constraint consideration and a replicate of the process situation. During a calibration process, model parameters are subjected to adjustments, in order to obtain model results that correspond better to biogas discharge rates observed in the field.

3.2.2 Principal Component Analysis (PCA)

PCA is a powerful tool that has been widely used for the multivariate analysis of correlated variables. This method is used to extract the most important information from the data set and compress the size of the data set by keeping only the important information (Ikudayisi et al., 2018). Principal component analysis was used to rotate the original data space such that the axes of the new coordinates system point into the directions of highest variance of the data. The axes or new variables are termed principal components (PCs) are ordered by variance, while the first principal component (PC1) represents the direction of the highest variance of the data and the second principal component (PC2) accounts for most of the remaining variance under the constraints to be orthogonal to the preceding component, PC1. PCA shows the correlation structure of a data matrix X , approximating it by a matrix product of lower dimension ($T \times P'$), called the principal components (PC), plus a matrix of residuals (E). This is formulated in **Equation 3.3**.

$$X = (\mathbf{1} \times \bar{x}') + (T \times P') + E \quad (3.3)$$

Where, T is a matrix of scores that summarises the X-variables (scores), and P is a matrix of loadings showing the influence of the variables on each score. The term $(\mathbf{1} \times \bar{x}')$ represents the variable averages; the second term, the matrix product $(T \times P')$, models the structure; and the third term, E, contains the deviations between the original values and the projections.

The correlation matrix is calculated from Equation 3.4. Thereafter, the eigenvectors and eigenvalues are estimated, and then the eigenvalues are sorted in descending order. The eigenvector with the highest eigenvalue is the most dominant principle component of the data set i.e. PC1. The second component (PC2) is computed under the constraint of being orthogonal to PC1 and to have the second largest variance. The functions *PCA* and *PCACOV* in MATLAB R2009b was used to perform the PCA and to estimate the variable loadings.

$$r_{x,y} = \frac{\sum_{i=1}^n (x_i - \mu_x)(y_i - \mu_y)}{(n-1)\sigma_x\sigma_y} \quad (3.4)$$

Where, μ_x and μ_y are the sample means of X and Y; σ_x and σ_y are the sample standard deviations of X and Y.

3.2.3 Data sample collection and design

The raw datasets required for the study was obtained from the egg-shaped anaerobic digesters (AD) treating sludge from Darvil Municipal Wastewater Treatment Plant (WWTP) located in the KwaZulu-Natal Province of South Africa. The data collected was edited, transformed and subjected to rigorous scientific analysis. To get the anaerobic operational parameters data, several meetings were held with the staff recording the data at the site to gain a better understanding of the nature and form of data that was recorded.

The collected average daily data was recorded two times a day, once in the morning and once in the evening for the case study area. The data received from the plant was for over a period of five years, post the commencement of the plant upgrade, from 2010 to 2015. However, due to certain limitations and inconsistent record of data, for the purpose of modelling and analysis only, the data recorded during the year 2015 was used with a total of 254 readings. The average of daily recorded data from the selected AD system were normalised and subsequently used for the model development and computational simulation for biogas production.

The typical data composition consists of combined digester volume, digester temperature, digester pH, digester total solid; digester volatile solid VS, with biogas output of methane, CH₄ (50 -70%), Carbon dioxide, CO₂ (20 -40%), Nitrogen, N₂ (0 - 2%), Hydrogen sulphide, H₂S (0 - 3%), Hydrogen, H₂ (0 - 2%) and Oxygen, O₂ (0 - 2%), respectively. Also, the data range between the minimum and maximum value were used as sample design and validity check for the dataset. Table 3.1 depicts a cursory daily summary of the operational data collected.

Table 3.1: Statistical summary of the collected average daily data for the year 2015

Variables	Minimum	Maximum	Mean	Std. Deviation
Both Dig. m ³ /hr	49.00	1067.000	432.598	191.003
Both Dig. Temp.	27.300	37.350	33.818	1.678
Both Dig. PH	6.700	7.535	7.077	0.144
Both Dig. % TS	1.105	5.830	2.639	0.485
Both Dig. % VS	8.765	78.095	47.951	6.555
COD mg O ₂ /L	70.000	950.000	369.213	138.380
Total CH ₄ (%)	48.500	67.700	60.182	3.664

3.2.4 Pre-processing of data for model input analysis

Microsoft Statistical software XLSTAT by Addinsoft version 2019.3.2 was used for all the statistical time series analysis of linear, non-linear and Partial Least Square regression (PLS) models for biogas prediction. The generic XLSTAT statistical software was also used for all the statistical description analysis, including outlier, correlation regression multi factor analysis, and Principal Component Analysis (PCA) for consistency, reliability and normalisation and distribution of variability for the dataset.

The conceptual framework that includes the general steps of the data processing and the major steps for development of the prediction models are described next. The approach used to regard the missing values was to delete the rows (days/dates of the readings that were recorded) where there is at least one missing value. The variables are subsequently summed up to weeks, months and then years. The outlier is an extreme value in a set of data, which is either much higher or lower than the other numbers. The outlier's elimination was made by cross finding with the collected information during the irregular operational conditions of the AD. The usual way of removing outliers was by plotting the dataset into boxplots to eliminate all of the data points that are outside the limits of the boxes of the boxplots (Johnson and Bhattacharyya, 2019). The outlier's analysis was used to correct the weighted average daily measure dataset use. Outlier defect affects the mean value of a data, but has little effect on the median or mode of a given set of data (Xie et al., 2015). All the operational data collected was subjected to homogeneity test. A homogeneity test is used to check whether two samples are from the same population. Non-homogeneity in data often arises from man-made developments (Mentzafou et al., 2018). Given the different collected digester volume and temperature data, the homogeneity test helps in understanding the prevailing underlying physical mechanism occurring in the data (Xie et al., 2016b).

Correlation and regression analysis were used to determine if there is any relationship between the characteristic of the category's digester sample variables and the degree of their relationship respectively. The regression analysis describes the effect of one or more independent variables on a single dependent variable. The factor analysis (FA) is useful to uncover latent structure (dimensions) of an asset of variables. It reduces attribute space

from a larger number of variables to a smaller number of factors through its principal component analysis (Silva, 2015).

Principal component analysis (PCA) was used to extract the most important data, which influence the anaerobic digester operation. The factor analysis (FA) function within PCA indicates the degree of different percentages of each contributing element to the total operation condition analysis known as latent variables. FA partitions the shared variance of a variable from its unique variance of the variable and only the shared variance appears in the analysis findings. However, researchers have identified that PCA does not discriminate between the unique and shared variances of the data variables (He and Zhang, 2018). The correlation relationships between the collected digester's operational data were developed as scatter plots, while regression or log regression analysis was related in order to determine their sensitivity operational significant. Partial Least Square regression (PLSR), an approach of linear regression was used to better understand the behaviour of the data. The PLS approach was used in this thesis and aimed to exploit the merits of PLS regression. This was done by using the following process; the first step was the dimension reduction function, in which the calibration is expected to simplify and reduces the data scope from 254 parameters to a few latent variables.

The next step involved PLS regression to map a latent relationship between two multivariate matrices (input matrix and output matrix) whilst analysing the collinearity between the inputs. Therefore, by specifying the parameters and model outputs as the two matrices, this approach then establishes how each parameter is transformed in order to effect the highest variance in the outputs. This understanding allows parameters to calibrate in a guided/supervised manner and potentially reduce the time required to optimise or recalibrate a model (Xu, 2019). PLS has been found to be an added advantage in investigating data consistency and in revealing other hidden information depending on the sub-subject matter under focus (Shen et al., 2016). This is because regardless of the R-squared valued obtained, it works in conjunction with residual plots, and other statistics model to determine the best fit models from the dataset of interest (Fox & Weisberg, 2018).

3.2.5 Operational Data Used in Model Development

After the pre-data analysis, the data was grouped into digesters, thickening and dehydration variables. The operational parameters for the anaerobic digestion process and the input of the dehydration process was used for model development. These variables include:- Percentage (%) of Total Solids (TS) and % of Volatile Solids (VS). For the digestion process, the following variables were provided: digesters combine volume, pH and the temperature (T) within the digesters, and the percentage of methane from the biogas produced.

3.3 MODELLING USING PARTIAL LEAST SQUARE REGRESSION (PLSR)

The major steps that were involved in the development of PLS regression models include randomise methodology of dividing the initial data (comprising 254 points - without missing values) into a training set (70 % of the initial data) and test set (30 % of the initial data). Then, train the model with the training data, providing both input and output variables (Table 3.2) after which the model is tested with a new training as a tested set that was obtained with a new random split of the initial data and then by cross-validation. The selected best model prediction from the cross-validation process is the model which has higher values of coefficient of determination (R^2) and lower values for the root mean square error (RMSE) (Hair Jr et al., 2017).

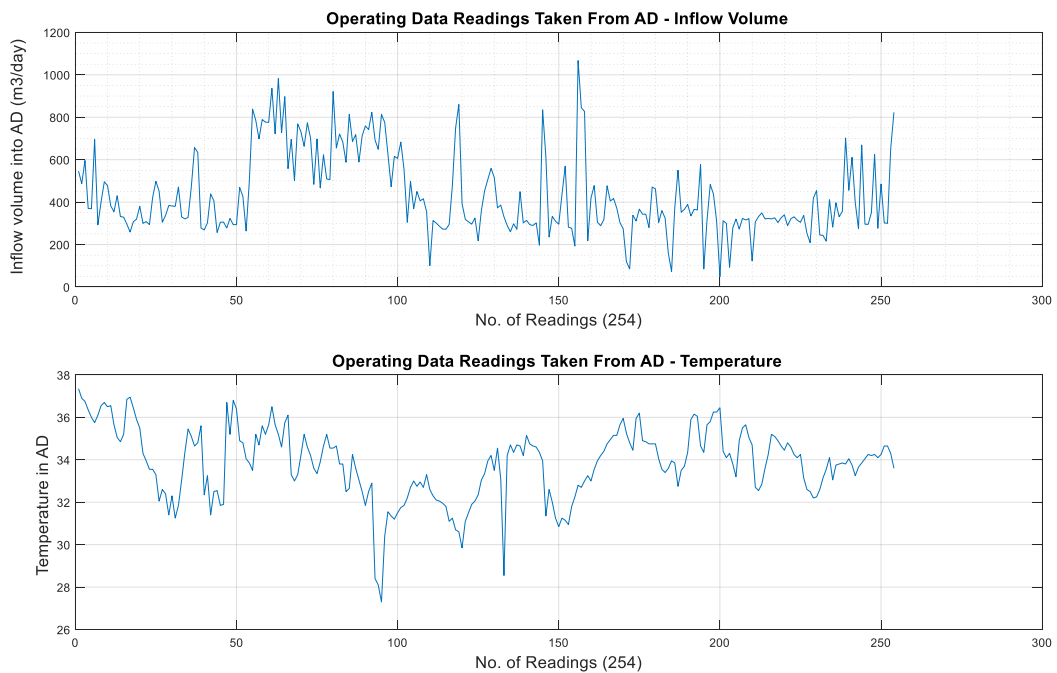
Table 3.2: PLSR input and output variables

Input Variables	Output Variable
Inflow Volume (m ³ /day)	CH ₄ (%)
pH	
Total Solids (%)	
Volatile Solids (%)	
Temperature (°C)	
COD (O ₂ mg/L)	

3.4 RESULTS AND DISCUSSION

3.4.1 Plants performance of the anaerobic digester in producing biogas

Raw data was collected from the Darvill Municipal Wastewater Treatment Plant in South Africa. A total of 254 datasets were screened and selected for the modelling analysis. Prior to processing the data for PLSR modelling, the selected raw data used for this study is presented graphically to illustrate the current performance of the anaerobic digesters in producing biogas (refer to Figure 3.1). Figure 3.1 graphically shows the operation data and parameters used from the Darvill site for the evaluation and optimisation of the biogas production. The 254 datasets plotted graphically in Figure 3.1 is over a period of 1 year taken from January to December 2019. As shown below in Figure 3.1 the ranges of the input and output parameters are as follows: Inflow volume (82.00 – 197.00) m³/d, Temperature (27.30 – 37.35) °C, pH (6.70 – 7.54), Total Solids % (1.11 – 5.83), Volatile Solids % (8.77 -78.10), COD (70.00 - 950.00) mg/L, Methane % (48.5 – 67.70).



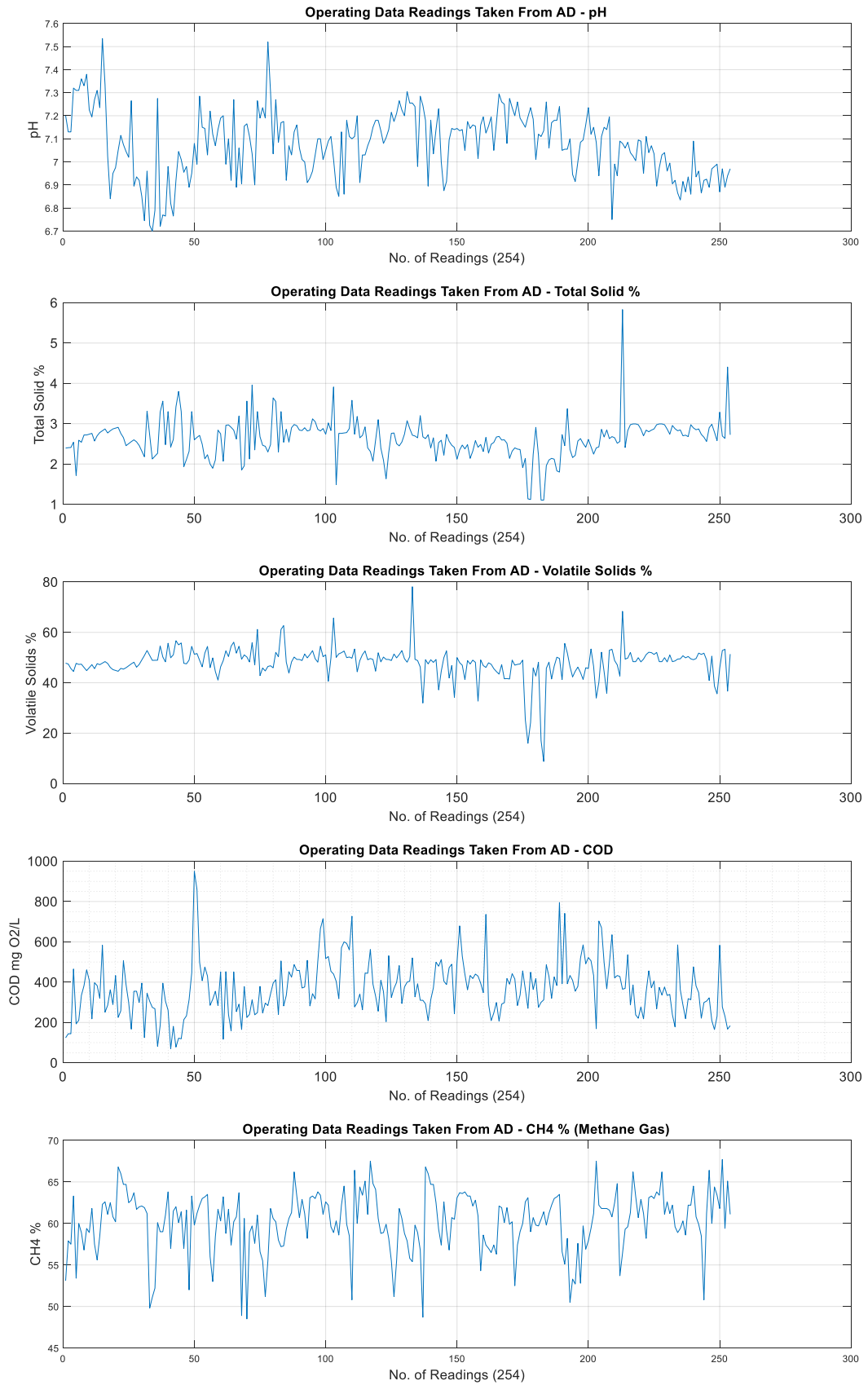


Figure 3.1 Raw data from operating wastewater treatment plant prior to normalisation and removal of outliers

3.4.2 Removal of Outliers and Standardisation of model inputs data

Outlier's analysis was necessary to correct the range of weighted average discrepancy noted in the observed daily datasets used (Figure 3.1). They may be due to variability in the measurement or may indicate an experimental error in the dataset collection. Outlier affects the mean value of the data but has little effect on the median or mode of a given set of data. A minor outlier is classified as a point that falls outside the data set's inner fences, whilst a point that falls outside the outer fences is classified as a major outlier. Figure 3.2 and Figure 3.3 illustrate the outlier's analysis for **input** and output variables. The XLSTAT software was used for the analysis and removal of outliers using PLSR function.

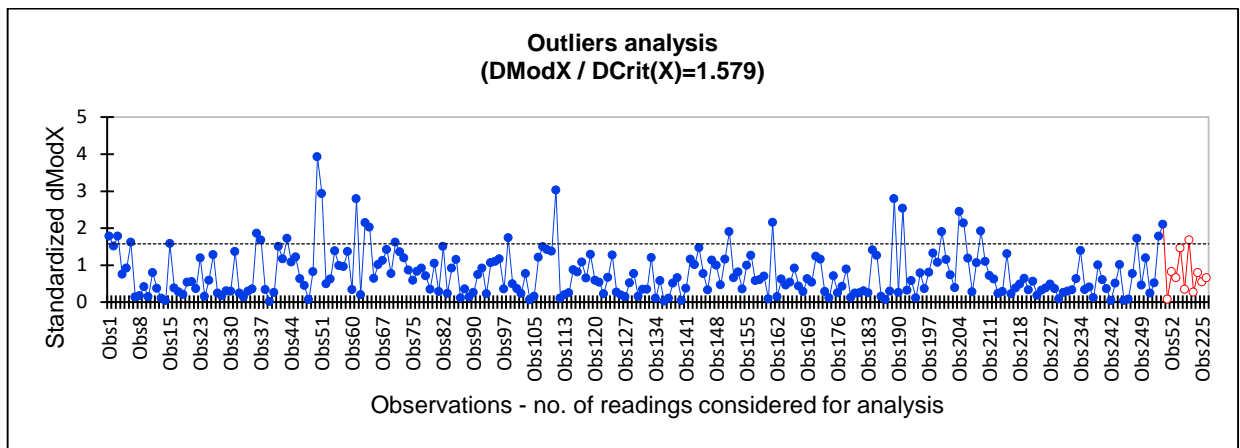


Figure 3.2 Outlier's analysis - X variables (input data) based on the collected raw data from the wastewater treatment plant

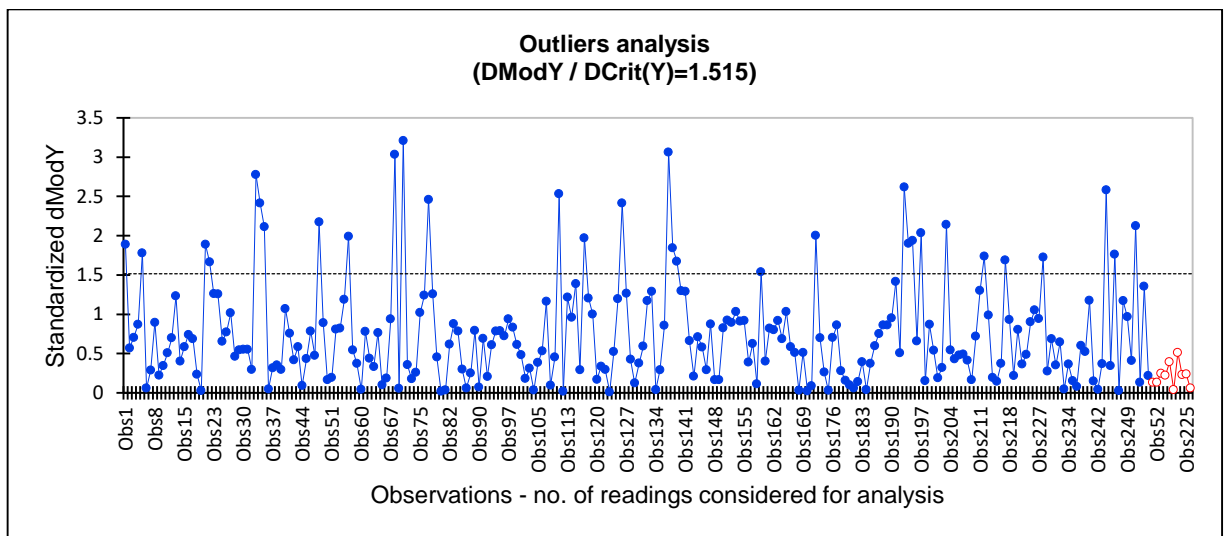


Figure 3.3 Outlier's analysis - CH₄ (output data) based on the collected raw data from the wastewater treatment plant

DModX is the distances from each observation to the model in the space of the X variables and allows for the identification of the outliers for the explanatory (Input) variables: Inflow volume, pH, total solids, volatile solids, temperature and COD. While the DModY is the distances from each observation to the model in the space of the Y variable and allows for the identification of the outliers for the dependent (output) variable (CH₄). The X and Y parameters represents the input and out variables as listed in Table 3.2. The outlier information corresponding to the validation sets are displayed in the observations above the line corresponding to ratio of DModX/DCrit & DModY/DCrit where DCrit is the critical distance derived. As the classical statistics was used, the model finds a relationship between all the X variables together. Hence, DModX is representation of all the input variables, while the moderate outliers shown in Figures 3.2 and 3.3 was $DModX/DCrit(X) = 1.579$ and $DModY/DCrit(Y) = 1.515$ for inputs and output respectively.

Since the studied variables have different variances and units of measurements as shown in Figure 3.1, the data set was standardised (Figure 3.4). This step was done by subtracting off the mean and dividing by the standard deviation (Ikudayisi and Adeyemo, 2016). At the end of the standardisation process, each variable in the dataset is converted into a new variable with zero mean and unit standard deviation. Standardisation of inputs data (normalisation) help to minimise bias and accumulation of predicted error from the observed data during model development and optimisation.

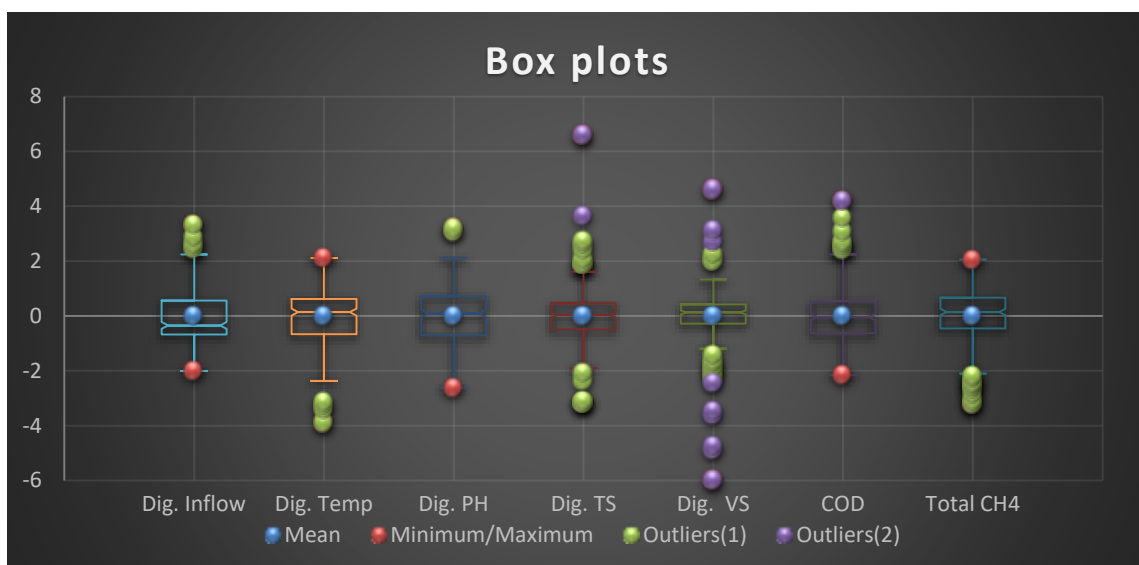


Figure 3.4 Removal of outliers and normalisation of input data to minimise bias and accumulation of predicted error

The Cronbach's Alphas test is commonly used for determining the internal consistency of the data/measurements. The result from alpha coefficient is greater than ± 0.607 , suggesting that the measurements do not have relatively high internal consistency. According to literature Cronbach alpha value of ≥ 0.70 reflects good reliability (Arafat, 2016). On the other hand, Guttman Reliability test publishes six measures based on a split-half method, which studies show to produce generally a higher value than the Cronbach's Alpha. The lambda (L) results in Table 3.3 shows $L1 = 0.373$, $L5 = 0.703$ and $L6 = 0.695$ which shows that $L5$ and $L6$ are within the acceptable level based on the literature. However, good Guttman's reliability values are > 0.80 and sample sizes that are considerably larger, such as $L > 0.6$ is sufficient and considered as a moderate reliability value (Benton, 2015). Both Cronbach's alpha and Guttman's reliability results suggest moderate reliability at an acceptable level (Bolarinwa, 2015).

3.4.3 Impact of Digester Operational Conditions on Biogas Production as Determined by Principal Component Analysis (PCA)

The interaction between the AD chemical, physical and operational parameters with methane production was performed using the application of PCA. This is done to understand the effect of the parameters on methane production. The positive and negative correlations with r values > 0.6 illustrate significant relationship between the measured parameters and methane when Pearson correlation coefficient (r) was applied (Table 3.3). The correlation matrix showed the association between the AD variables and methane production. The correlation matrix (Table 3.3) indicates that pH has a negative impact on methane production, TS % has a positive impact on methane production, temperature has negative impact on methane production and COD has a positive impact on methane production.

Table 3.3: The anaerobic digester datasets correlation matrix (Pearson(n))

Variables	Dig. Inflow	Dig. Temp	Dig. PH	Dig. TS	Dig. VS	COD	Total CH ₄
Dig. Inflow	1	-0.101	0.017	0.104	0.105	-0.037	0.108
Dig. Temp	-0.101	1	0.208	-0.082	-0.204	-0.083	-0.494
Dig. PH	0.017	0.208	1	-0.158	-0.142	0.130	-0.670
Dig. TS	0.104	-0.082	-0.158	1	0.469	-0.012	0.465
Dig. VS	0.105	-0.204	-0.142	0.469	1	0.064	-0.147
COD	-0.037	-0.083	0.130	-0.012	0.064	1	0.351
Total CH ₄	0.108	-0.494	-0.670	0.465	-0.147	0.351	1

Values in bold are different from 0 with a significance level $\alpha=0.05$ and correspond to the factor for which the squared cosine is the largest

The PCA employed to depict the relationship and impact of the AD conditions on the methane gas production generated 3 significant factors (F's) with total variance of 58.26% (eigenvalue of > 1 for each factor) using the mean values of the 7 variables and 254 readings collected from the treatment plant (see Figure 3.5). From the 3 factors generated, the relationship between F2 and F3 (58.26%) have shown to have a greater variance than that of F1 and F2 (53.087%) (Table 3.4). Factor F3 and F2 contribute 29.717% and 28.544% respectively to the total variables with the positive and negative loadings values (Table 3.5), as graphically represented in Figure 3.5. Figure 3.5 shows the effect of the digester conditions on the conversion of MWWTW wastes to methane during anaerobic digestion of municipal wastewater. Similar findings by Enitan et al. (2018) on the effect of pH, temperature among other parameters that affects methane production during anaerobic digestion was identified using PCA (Gaby et al., 2017; Gottardo et al., 2017; Senthilkumar et al., 2016).

Table 3.4: Eigenvalues, measure of variance of observed variables for multi-factor analysis

	F1	F2	F3
Eigenvalue	1.718	1.166	1.104
Variability (%)	24.543	28.544	29.717
Cumulative %	24.543	41.204	56.970

Table 3.5: Factor analysis correlation pattern - measure of association between the variables

	F1	F2	F3
Dig. Inflow	-0.052	0.297	-0.092
Dig. Temp	0.027	-0.537	-0.537
Dig. PH	0.566	-0.475	-0.127
Dig. TS	0.134	0.716	-0.438
Dig. VS	0.268	0.745	-0.429
COD	0.828	0.022	0.322
CH₄	-0.071	0.219	0.726

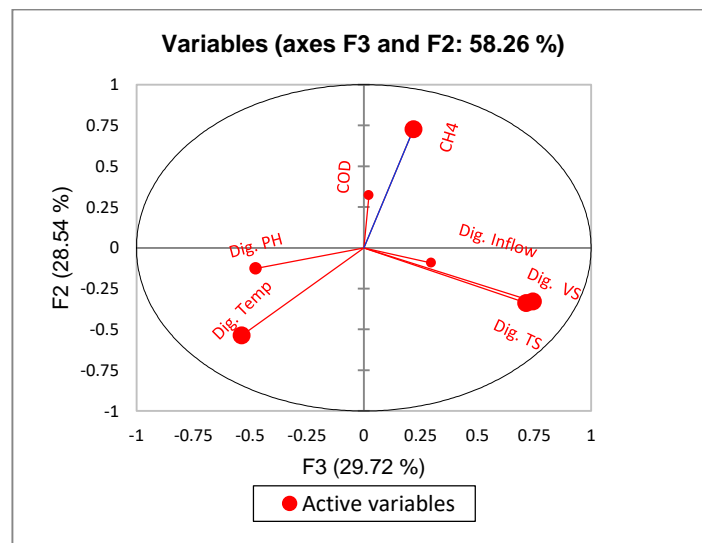


Figure 3.5 Relationship between the digester operational parameters and methane production as determined by principal component analysis

It can be observed that from PCA temperature, pH, TS% and COD are important parameters that affect the rate of methane production. A cursory look into the factor loading and variable correlation matrix depicts that CH₄ concentration is positively affected by COD concentration and TS%, negatively affected by pH and Temperature. These observations from PCA corresponds to findings reported in literature (Zhang et al., 2016) whereby lower temperature could result in decreased biological activity, therefore resulting in decrease CH₄ production. Studies by Mao et al. (2015) and Enitan et al. (2018) showed that controlling the pH value is important for achieving optimal alkaline condition which is important within AD process and for the generation of methane gas. Hence, the increase or decrease of pH values and temperature have an impact on achieving optimal production of biogas (CH₄) (Prabhu et al., 2021; Ravi et al., 2018).

3.4.4 The result of the PLS regression model for Predicting CH₄ production

The PLS regression model was constructed for predicting methane production and good operational condition for the anaerobic digesters. The normalised, outlier removed, homogeneous, and reliable data are subsequently used to develop PLS model to predict biogas generation. With the input variables listed in Table 3.2, the best-obtained model from the PLS regression analysis serve as a preliminary indication for either a good or bad dataset/operational conditions. After a 500 iterations processes, the predicted performance of PLS follows re-training and testing of the new model before it was validated with a new dataset. From the PLSR analysis, the model equation generated is shown in **equation 3.5** and the results of PLS log – regression is presented in Figure 3.6. The figure shows a cluster of captured data are in good proportion with least residual error to give a fair representation for methane predictive as depicted in the goodness of fit statistics (Table 3.9).

$$\text{Total CH}_4 = [((83.711 - 1.614\text{E-}03) * \text{Dig. Inflow}) - (0.522 * \text{Dig. Temp}) - (1.193 * \text{Dig. PH}) + (1.208 * \text{Dig. TS}) - (2.320\text{E-}02 * \text{Dig. VS}) + (1.610\text{E-}03 * \text{COD})]$$

(3.5)

Figure 3.7 displays the variable importance for the projection (VIPs) for each input variable, for an increasing number of components. This allows one to identify the input variables that contribute the most to the PLS regression model. As shown in Table 3.6 and Figure 3.7, temperature, pH, TS and COD have a greater influence in the projection/prediction of methane gas when compared to other parameters. This correlates with the PCA and factor analysis results.

Table 3.6: Variable importance in the projection (VIP) for input variables used in this study

Variable	VIP	Standard deviation	Lower bound (95%)	Upper bound (95%)
Dig. Temp	2.094	0.264	1.448	2.740
Dig. TS	0.730	0.504	-0.504	1.964
Dig. PH	0.718	0.717	-1.036	2.471
COD	0.547	0.299	-0.185	1.279
Dig. VS	0.518	0.537	-0.796	1.831
Dig. Inflow	0.028	0.434	-1.035	1.091

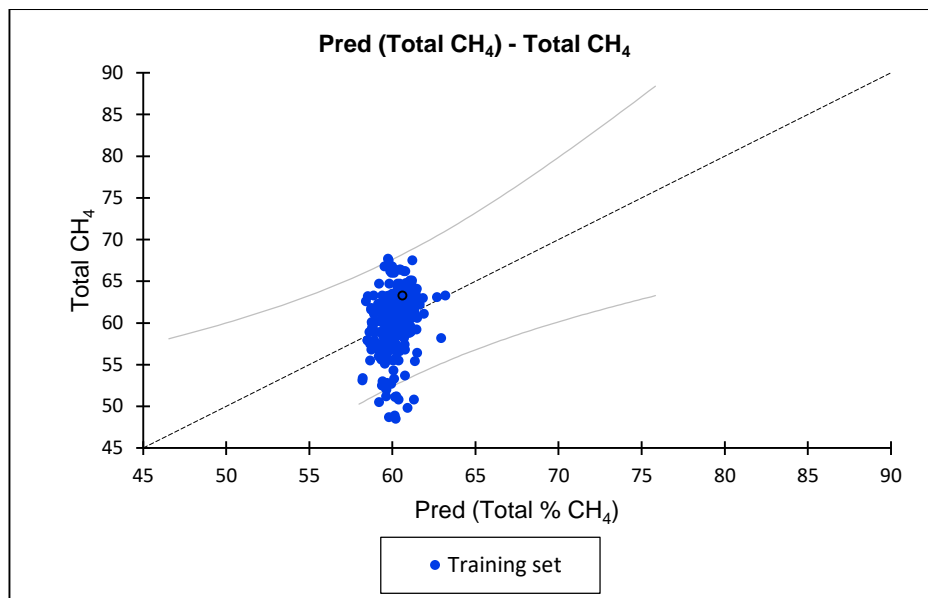


Figure 3.6 The PLS log – regression for CH₄ prediction as compared to the actual values

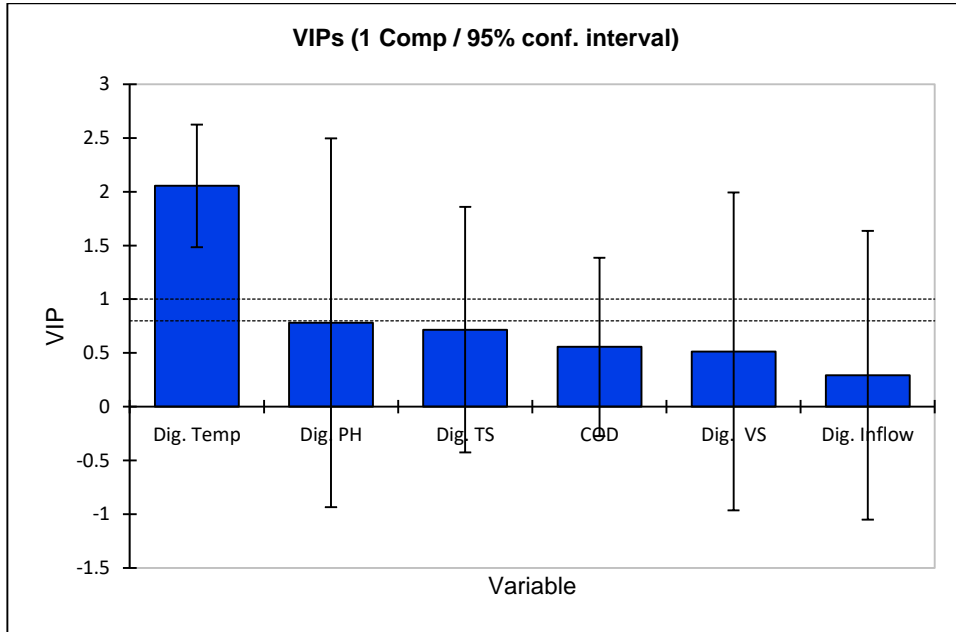


Figure 3.7 Variable Importance in the Projection (VIP) of CH₄ yield

The goodness of fit statistics (Table 3.7) with R^2 value 0.535 and RMSE value of 3.594 for the predicted methane shows fairly good results considering the trained predicted standardised residuals error for methane (Figure 3.12). Regardless of the R -squared value obtained, it works in conjunction with residual plots, and other statistics model in determining the best fit models to the dataset. The other means to assess the PLS predictive accuracy is by calculating the Q^2 value. This metric (Q^2 value) works with the mean values and estimates the model's parameters, it combines aspects of the in-sample explanatory power and the out-sample prediction. As indicated in some studies, Q^2 values that range from 0, 0.25 and 0.5 describe small, medium and large predictive relevance respectively (Hair et al., 2019). Table 3.7 shows a Q^2 value of 0.451, which explains that the model falls between the range of 0.25 and 0.5, suggesting an acceptable and adequate tool for prediction of biogas gas production.

Table 3.7: Goodness of fit statistics of a linear regression for total CH₄ dataset

<u>Goodness of fit statistics (CH₄):</u>	
Observations	254
Sum of weights	254
DF	251
R ²	0.535
Adjusted R ²	0.579
MSE	12.913
RMSE	3.594
MAPE	4.610
DW	1.363
C _p	2.638
AIC	652.781
SBC	663.393
PC	0.977
Press	3310.437
Q ²	0.451

The predictions obtained from the PLS model is shown in Table 3.8. Table 3.8 only shows 19 points out of the 254 observations that was analysed. All 254 observations were analysed and the findings are based on the analyses of all 254 observations. In terms of the scope of this study only 19 results were presented in Table 3.8 out of the 254 results that was analysed, this was to avoid repetitive discussion. This table compares the predicted CH₄ and actual plant produced methane. Although few observed data show minor deviation from the predicted value such as observation 9 where the actual was 59.40% and the predicted is 60.22% resulting in a residual value of 0.82%. From the 254 observations, there is an average of 2% residual difference from the actual recorded dataset to the predicted values obtained from the model. As per Table 3.7 and Table 3.8 with an average 2% residual difference, there is indication of good fitting degree thereby proving the PLSR model good prediction ability.

Table 3.8: The PLS predicted total CH₄ vs actual total CH₄

Observation	Total CH ₄ (%Actual)	Predicted (Total % CH ₄)	Residual
1	53.100	60.017	-6.917
2	57.900	59.981	-2.081
3	57.500	60.075	-2.575
4	63.300	60.115	3.185
5	53.400	59.915	-6.515
6	60.000	60.209	-0.209
7	58.900	59.952	-1.052
8	56.800	60.081	-3.281
9	59.400	60.220	-0.820
10	58.900	60.167	-1.267
11	61.800	59.945	1.855
12	57.500	60.052	-2.552
13	55.600	60.106	-4.506
14	58.500	59.976	-1.476
15	61.200	61.329	-0.129
16	51.100	59.126	-8.026
17	59.000	59.535	-0.535
18	59.000	60.195	-1.195
19	60.100	61.383	-1.283

3.5 CONCLUSION

In this study, data pre-processing was carried out using PLS and PCA techniques. These are regression models that were used to statistically perform multivariate analysis of correlated variables on the datasets from the municipal wastewater treatment plant. Statistical techniques such as correlation, regression analysis, a test of significance, reliability and factor analysis were employed to determine the relationship among the clusters of interrelated variables and their significant factors influencing the optimisation of biogas production among the operational conditions set.

From the results of the statistical analysis, it was discovered that a combination of PLS and PCA makes it possible to analyse and achieve the objective of this chapter, being the management of the data set for quality and appropriateness in the computational analysis process. In managing the quality of the dataset, the outliers were identified and removed. Standardisation of the dataset was applied for input into the modelling process. The dataset was subjected to reliability testing with the alpha coefficient of 0.607 and 0.703 and 0.695

lambda coefficients established. This suggests that internal validity and reliability was acceptable. The PCA was used to establish the correlation matrices and variables that have a greater influence on the methane production. The variables identified were pH and temperature, TS and COD. The PLSR was applied for the prediction of the biogas production, the results of this was established and presented at an average residual of 2% across the 254 observations suggesting that the predicted values were close to the actual observed CH₄ production. The discrepancies identified could be attributed to the quality of data capturing at the plant site as well the management of the plant operations. Looking at the data obtained using PLS analysis, it is recommended that advanced computational tool that will be more accurate with better prediction should be employed as an efficient prediction tool for methane generation.

CHAPTER 4

OPTIMISATION OF BIOGAS GENERATION FROM AN ANAEROBIC DIGESTER USING FUZZY LOGIC

4.1 PREFACE

Noting that the intent of this study is on the evaluation and optimisation of operations at the case study site for the production of biogas to generate electricity, this chapter extends on the previous chapter that focused largely on the evaluation process. Hence, this chapter focused on the optimisation of biogas generation from an anaerobic digester using Fuzzy Logic while the next chapter will provide the backdrop to possibilities of electricity generation based on the case study site.

4.1.1 INTRODUCTION

Digester parameters commonly determine biogas production and its composition, however, the individual parameters that will enhance the production requires elaborate optimisation. Sometimes, evaluation of individual parameters is not efficient to indicate the disturbances affecting the anaerobic digester process. Hence, the application of computational intelligence (CI) using different model-based systems such as neuron networks, proportional-integral-derivative (PID) control, Fuzzy Logic and adaptive neuro-fuzzy interference system (ANFIS) has been proven to be effective for modelling and controlling different aspects of anaerobic digestion (AD) process for biogas production (Oluwaseun et al., 2018; Olabi et al., 2020).

Fuzzy Logic as an optimisation tool has a unique and robust characteristic. It has the ability to track data trends even with all the noise and uncertainty of complexity system such as anaerobic digester. Fuzzy Logic can model and control non-linear functions of subjective complex processes or systems under dynamic conditions by applying valuable expert knowledge (de Salles et al., 2016; Feng, 2018). Noting that there were challenges with the data set obtained at the Darvill Wastewater Treatment Plant (WWTP) and the computational process of cleaning the data for computational analysis, Fuzzy Logic was

deemed most appropriate for this modelling. The decision to use Fuzzy Logic is based on two reasons. The first is that it is used in computer simulation for modelling of complex system behaviours using simple logic rules (Zhang and Tao, 2017). Anaerobic treatment of wastewater is a key process for biogas production. Hence, level of complexity of anaerobic digester contributes to the decision to use Fuzzy Logic as the computational model. Secondly, Fuzzy Logic simulation best fits the study scenario because of the nature of digester and the available variable dataset to achieve the desirable outcome of biogas optimisation. To this end, this section of the study aims to evaluate and optimise the production of biogas from egg-shaped digesters treating municipal wastes sludge using Fuzzy Logic. It explores the use of Fuzzy Logic to estimate the optimal methane generation. The subtractive clustering of the dataset in Fuzzy Logic interphase in MATLAB R2020a environment was used in this section as a viable computational intelligence approach method for anaerobic digester.

4.2 METHODS AND MATERIALS

4.2.1 Operational setup at the case study site for biogas production

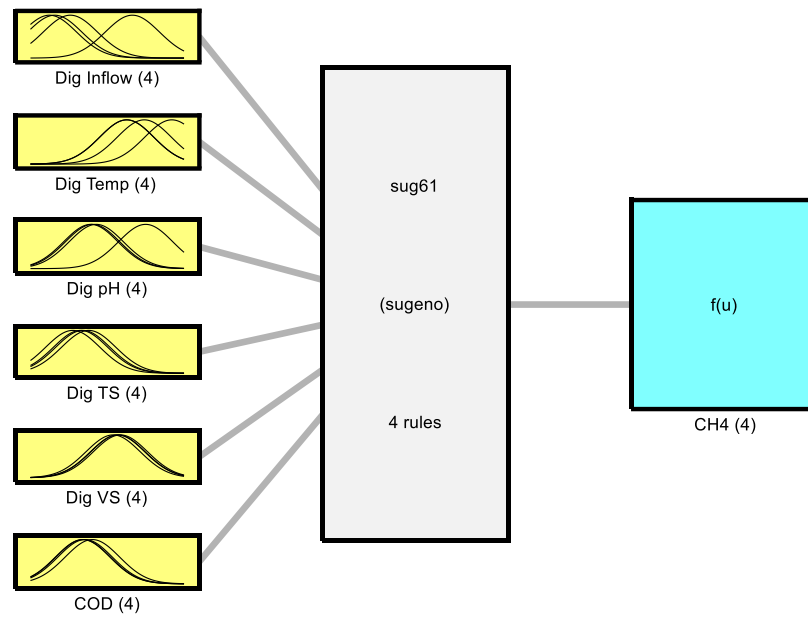
The selected Darvill Municipal Water Treatment Plant (MWWTP) is a biological nutrient removal system. The type of the wastewater that is being treated at this plant is domestic, industrial, agricultural as well as the storm water runoff from the neighbouring township. This treatment plant's current capacity is at 65 MI/day with future plans to upgrade to a treatment capacity of 200 MI/day. The wastewater in this plant is pre-treated by two 28 m diameter and one 40 m diameter primary settling tanks. The sludge from these tanks is gravity fed to the digester feed pump station (DFPS). The DFPS pumps feed predetermined volume of blended, thick primary sludge and conditioned waste activated sludge into two egg-shaped anaerobic digesters with dimensions of 18 m diameter, 32.9 m in height and volume of 4504 m³ per digester.

The mixing and heating of the digested sludge is actuated by the continual operation of the vertical linear mixer (VLM) and a sequential sludge circulation by common standby pumps. The digesters produce biogas mostly, CH₄, CO₂, N₂, H₂ and H₂S during anaerobic biological treatment process under controlled operational conditions. Some of the

controlled and influential parameters include temperature, volume of sludge, pH, total solid content, volatile solids content and chemical oxygen demand (COD) content. Data was obtained from this setup for evaluation and optimisation of biogas generation. In total, 254 observed datasets were used for the modelling and optimisation of CH₄ %. The collected data from the digester was divided into two categories: input and output variables. The inputs consist of temperature, sludge volume, pH, total solids (TS), volatile solids (VS) and COD, while the output variable is percentage of methane (%CH₄).

4.2.2 Detailing how the Fuzzy Logic works, model simulation and evaluation

Fuzzy Logic Toolbox™ in MATLAB R2020a software was employed for the optimisation, due to its genuine graphical interface system and overall simple application. The six input parameters used for Fuzzy Logic include; Inflow(m³/day), Temp(°C), pH, TS (%), VS (%) and COD (O₂mg/L) while the output variable is the percentage of CH₄ in the biogas produced from the egg-shaped digester (Figure 3.1). The inputs were connected to the outputs through a rule-base of Sugeno-type, where the overall output is computed by a weighted average of the crisp output of each “if-then” rule (Alalm et al., 2016). Figure 4.1 illustrates the FIS model used for prediction and optimisation of CH₄ (%). The processes involved in developing the Fuzzy Logic model includes, building a fuzzy inference system, data clustering, generation of rules and member functions. Building a fuzzy inference system (FIS) involved the formulation of a map from the given input variables (e.g. digester inflow) to the output variable (e.g. %CH₄) as shown in Figure 4.2. This mapping then provides the basis from which the model decisions can be made. The data clustering of Fuzzy Logic model was used to introduce the input and output dataset in order to train the datasets, using rules generated from the subtractive clustering, as well as identifying the natural grouping of large datasets for the FIS. The rules dictate the behaviour of the FIS based on the input and output data set and the membership functions (MATLAB user guide). The final stage was used to generate and evaluate the FIS while the model identified the membership functions, parameter, specifies the applied Fuzzy rules and the optimal output in respect to the input variable at specific intervals. The model was structured to assess the input parameters (Inflow, Temperature, pH, TS, VS and COD) in relation to the CH₄ produced and establish the optimum operating conditions for an optimised CH₄ production.



System sug61: 6 inputs, 1 outputs, 4 rules

Figure 4.1 Sugeno Fuzzy Inference System (FIS) model built for the prediction and optimisation of CH₄ (%)

4.3 RESULTS AND DISCUSSION

There are a considerable number of factors, complexity and instabilities of the AD processes that affect the anaerobic degradation of biomass. Like other digesters, the egg-shaped digester used in this study is not a linear process where a single input will determine the single output. There are various operational parameters and factors considered for a successful methane production in an anaerobic digester. Hence, the designed Fuzzy Logic model dealt with the uncertainties of data and allowed the multiple input and output variables. This was used to analyse the nonlinear processes and information.

4.3.1 In Designing the Fuzzy Logic Model for Analysis, subtractive clustering of the dataset

Firstly, a subtractive clustering was performed to obtain crisp and concise correlations between the input and output variables, and to categorise natural groupings in the large dataset. Each data point in subtractive clustering is a potential cluster centre that can be

used as an origin to describe the fuzzy system. Using the data set for this study, and as observed in Eq. 4.1, the matrix, $C_{(4 \times 7)}$, contains four rows (indicating four clusters in the input-output dataset), with seven columns (equivalent to the locations of clusters in each dimension). This result demonstrated that subtractive clustering identified four natural groupings in the studied input-output dataset. As seen in Eq. 4.2, the matrix “ $S_{(1 \times 7)}$ ” had seven columns describing the sigma results that identified the influence range of the cluster centre in each data dimension.

$$C_{(4 \times 7)} = \begin{bmatrix} 321.00 & 33.60 & 7.06 & 2.41 & 49.40 & 369.00 & 59.30 \\ 294.00 & 34.75 & 7.04 & 2.65 & 48.09 & 372.00 & 64.70 \\ 718.00 & 33.60 & 7.03 & 2.90 & 48.29 & 425.00 & 61.30 \\ 401.00 & 36.55 & 7.33 & 2.72 & 46.08 & 383.00 & 56.80 \end{bmatrix} \quad (4.1)$$

$$S_{(1 \times 7)} = [138.77 \quad 1.78 \quad 0.15 \quad 0.83 \quad 12.26 \quad 155.56 \quad 3.39] \quad (4.2)$$

4.3.2 Generating fuzzy inference system

The subtractive clustering identified four basic groupings, and thus, each input and output was described by four membership functions (Gupta et al., 2017). Figure 4.2 shows the number of fuzzy rules generated as a result of the number of clusters from the subtractive clustering function. In addition, the subtractive clusters identify the membership functions for each input, hence each input will have 4 membership functions. The properties of membership functions for the input attributes are listed in Table 4.1. The universes of discourse for the input ranges were; Inflow [197 - 982m³/d], Temp [27.3°C - 37.35°C], pH [6.70 - 7.54], TS [1.11% - 5.83%], and VS [8.77% - 78.1%].

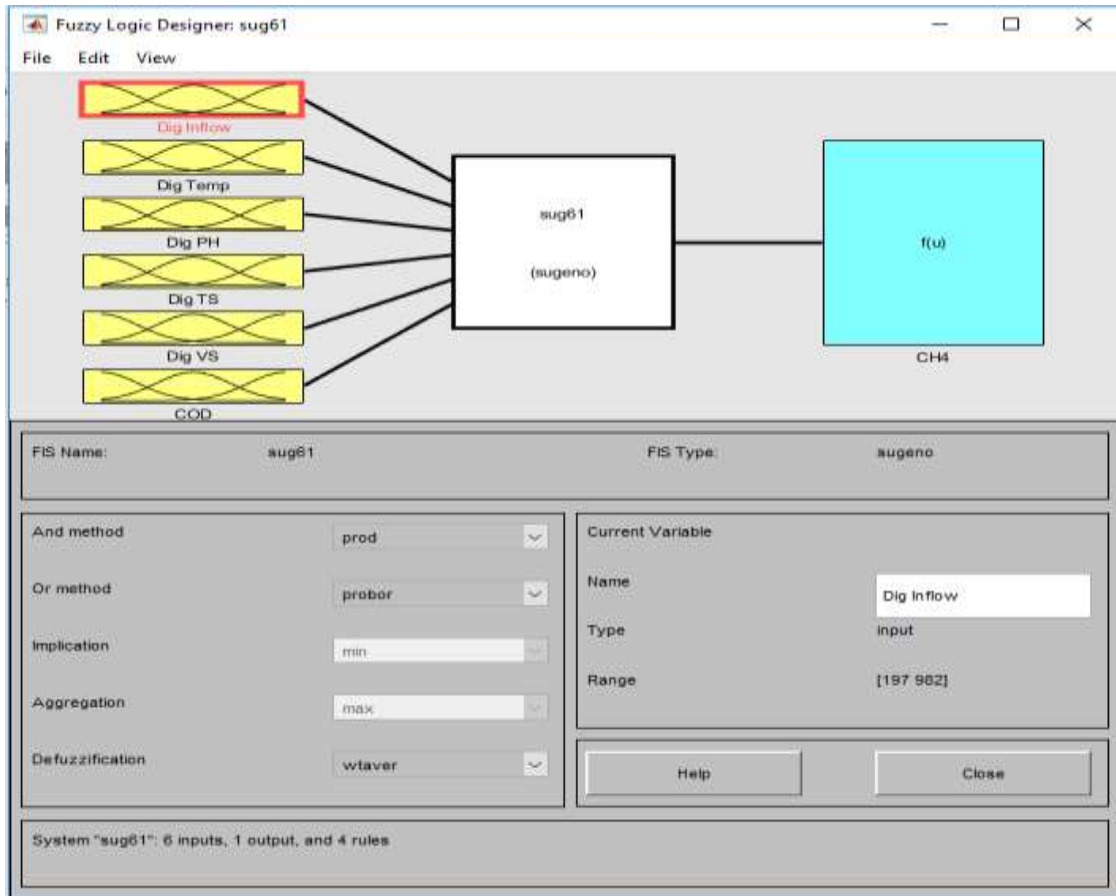


Figure 4.2 Generation of the FIS model for the prediction and optimisation of CH₄ (%)

Variable	Name	MF Range	MF Type	MF Parameters			
				Cluster-1	Cluster-2	Cluster-3	Cluster-4
Input ₁	Inflow (m ³ /d)	[197.00-82.00]	Gaussian	[138.77-321.00]	[138.77-294.00]	[138.77-718.00]	[138.77-401.00]
Input ₂	Temp (°C)	[27.30-37.35]	Gaussian	[1.78-33.60]	[1.78-34.75]	[1.78-33.60]	[1.78-36.55]
Input ₃	pH	[6.70-7.54]	Gaussian	[0.15-7.06]	[0.15-7.04]	[0.15-7.03]	[0.15-7.33]
Input ₄	TS (%)	[1.11-5.83]	Gaussian	[0.83-2.41]	[0.83-2.65]	[0.83-2.90]	[0.83-2.72]
Input ₅	VS (%)	[8.77-78.10]	Gaussian	[12.26-49.40]	[12.26-48.09]	[12.26-48.29]	[12.26-46.08]
Input ₆	COD (mg/L)	[70.00-950.00]	Gaussian	[155.57-369.00]	[155.57-372.00]	[155.57-425.00]	[155.57-383.00]
Output	CH ₄ (%)	[48.5-67.70]	Linear	[0.00 -92.08]	[0.00-157.17]	[0 0 0-76.17]	[0.00-5.02]

The membership function of the first input “Inflow” namely “MFin1, 1” was Gaussian type “gaussmf” having the parameters [138.77 321.00]: where, 138.77 is the spreading coefficient [$S(1, 1) = 138.77$; see eq. 4.2], and 321.00 is the centre of the Gaussian curve

[C (1, 1) = 321.00; see eq. 4.1] as shown in Figure 4.3. The other five input attributes followed the same configuration representing the position and influence of the cluster along their relevant dimensions in the dataset. The output “CH₄ (%)” showed a universe of discourse [48.5 - 67.70].

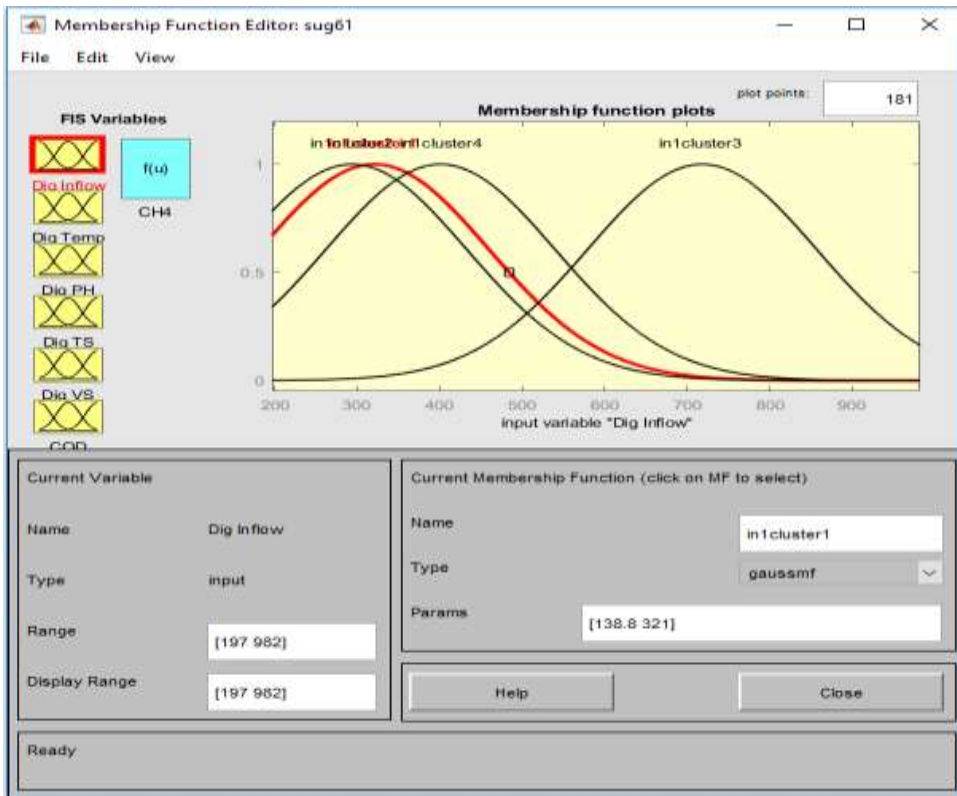


Figure 4.3 FIS Membership Function generated for each input and respective cluster

As listed in Table 4.1, the output of the FIS had four membership functions mimicking the clusters specified during the subtractive clustering procedure. The coefficients of the membership function were computed using the least squares estimation method. In the FIS implementation, Gaussian membership functions were used for the input variables and linear shaped membership function for the output variable. The Gaussian membership function determines the value of membership between 0 and 1 as can be seen in Figure 4.4. The membership functions are constructed giving them ranges respectively and map the non-fuzzy inputs to fuzzy values, which are then inferred according to the rule base (Buriboev et al., 2019; Zurek et al., 2013).

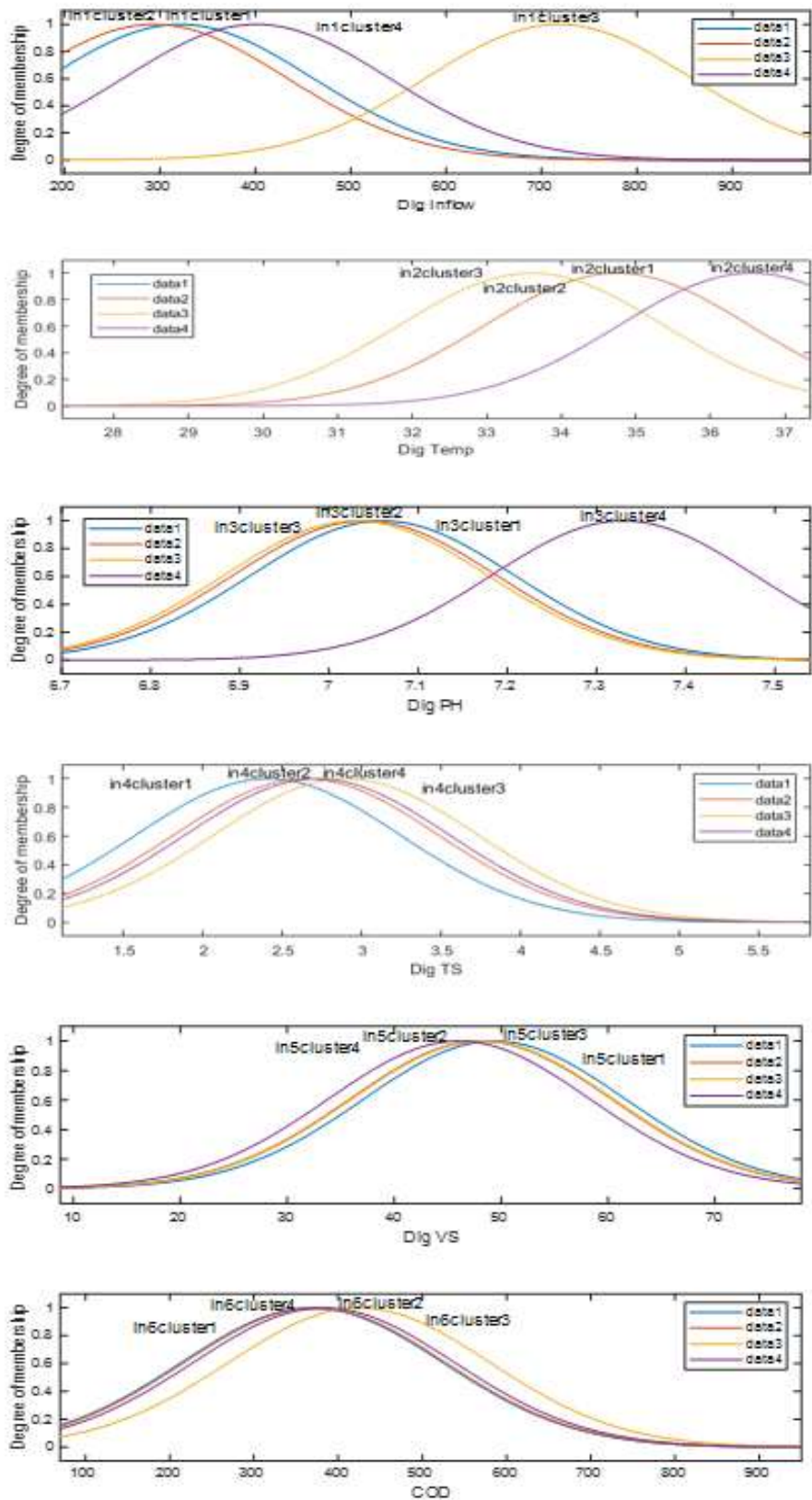


Figure 4.4 Degree of membership functions of the six inputs used for the prediction of CH₄ (%)

4.3.3 Generating fuzzy rules

The FIS rules editor as shown in Figure 4.5 is used to define the rules for the parameters being tested. The input and output membership functions used in the output process are defined by the rules. The FIS has identified by subtractive clustering the 6 inputs and 1 output with the inputs mapped to the output through a rule base (see Figure 4.5). The “if-then” rules are linguistic and describe the fuzzy system’s configuration in terms of inputs, outputs and membership functions (Buriboev et al., 2019; Zurek et al., 2013). This study recognised four rules (i.e., because four clusters were selected), which concisely mapped the cluster in the input space to that in the output space. These rules can be described as follows (the weight of each rule was equal to one):

Rule-1: If (Inflow is MF_{in1} , 1) and (Temp is MF_{in2} , 1) and (pH is MF_{in3} , 1) and (TS is MF_{in4} , 1) and (VS is MF_{in5} , 1) and (COD is MF_{in6} , 1) then (CH_4 is MF_{out1} , 1)

Rule-2: If (Inflow is MF_{in1} , 2) and (Temp is MF_{in2} , 2) and (pH is MF_{in3} , 2) and (TS is MF_{in4} , 2) and (VS is MF_{in5} , 2) and (COD is MF_{in6} , 2) then (CH_4 is MF_{out1} , 2)

Rule-3: If (Inflow is MF_{in1} , 3) and (Temp is MF_{in2} , 3) and (pH is MF_{in3} , 3) and (TS is MF_{in4} , 3) and (VS is MF_{in5} , 3) and (COD is MF_{in6} , 3) then (CH_4 is MF_{out1} , 3)

Rule-4: If (Inflow is MF_{in1} , 4) and (Temp is MF_{in2} , 4) and (pH is MF_{in3} , 4) and (TS is MF_{in4} , 4) and (VS is MF_{in5} , 4) and (COD is MF_{in6} , 4) then (CH_4 is MF_{out1} , 4)

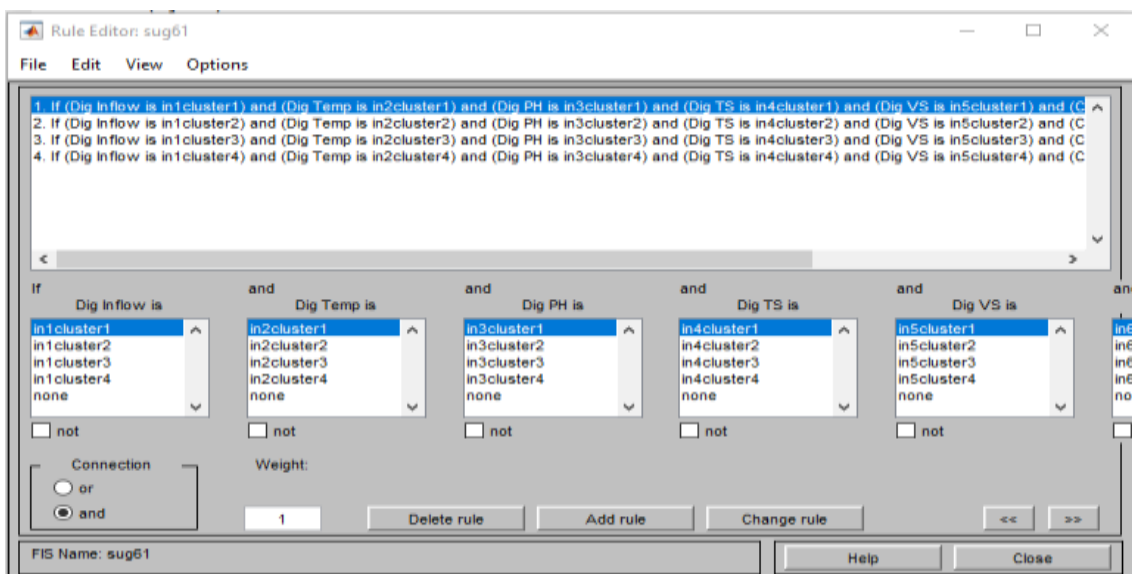


Figure 4.5 Defining rules for CH_4 optimisation – by training the dataset for the Sugeno FIS

4.3.4 Results of the evaluation of the operating conditions at the case study wastewater treatment plant: A surface viewer for data exploration

The surface viewer process creates a graphical representation of the relationships between the output CH₄ and any two of the input variables (Temperature, PH, COD, VS & TS). Figure 4.6 shows the correlation between the input-output model surface, the dependency and interrelations of CH₄ production on one or two of the input variables, as well as the combination of the input variables. The output “CH₄ (%)” of the FIS was plotted against the inputs “Inflow, Temp, pH, TS, VS and COD” as a surface viewer. Taking the first scenario as an example, the surface viewer as seen in Figure 4.6a shows that the output CH₄ increases with an increase in the Dig. TS and Dig. VS. The second Figure 4.6b illustrates that as the VS increases CH₄ increases, however as the temperature increases the CH₄ decreases. Figure 4.6c shows a positive relationship between COD, TS and CH₄, the higher these parameters the more the production of CH₄. The 4th scenario in figure 4.6d, illustrates that pH has a greater influence and impact on methane than inflow. pH greater than 7.2 or less than 7 will have a negative impact on CH₄ production. Hence, the visualisation of the relationships and interaction of the inputs with the output help to understand how the FIS is going to behave within the input space (Taghavifar et al., 2016).

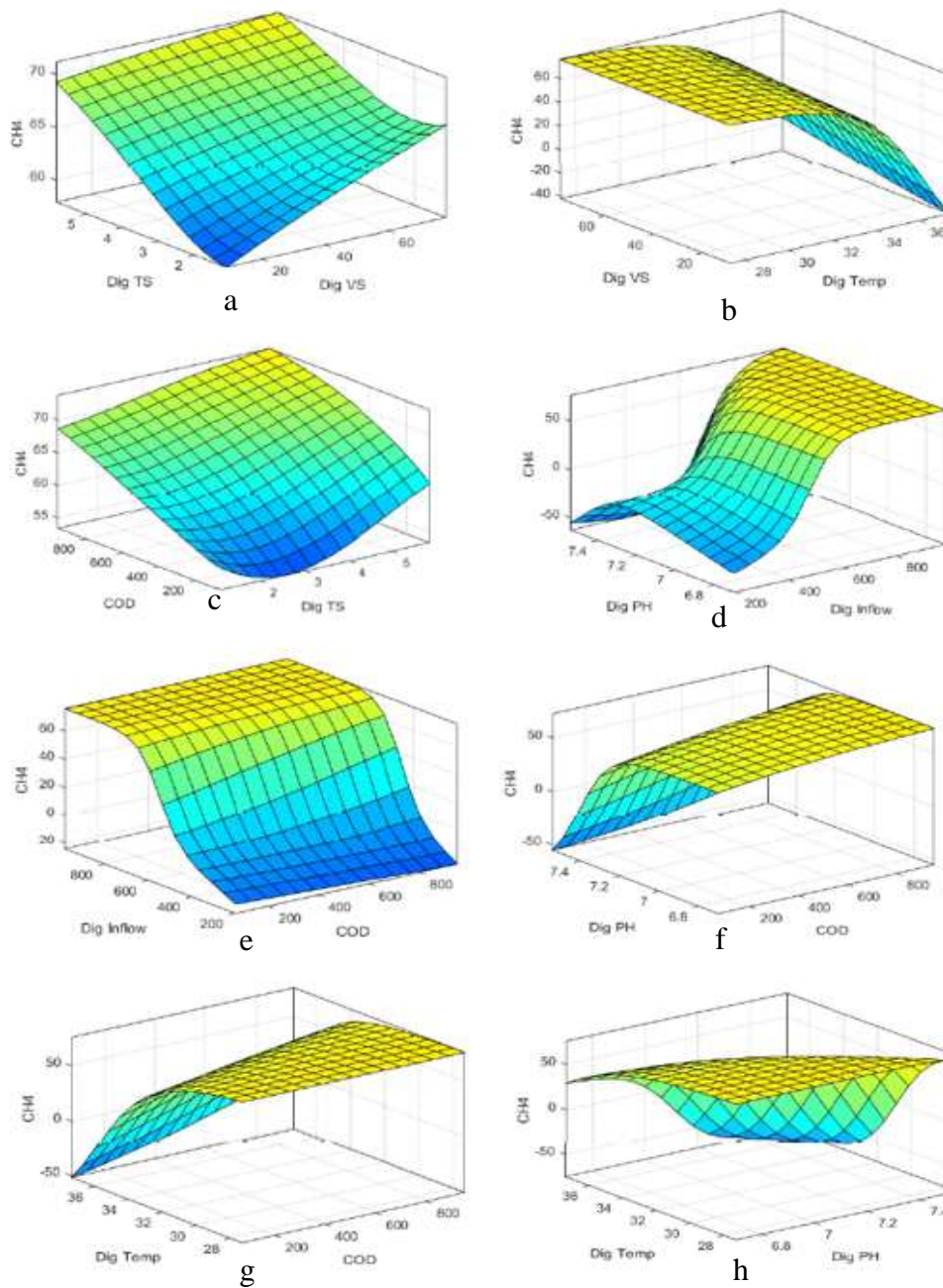


Figure 4.6 The FIS surface viewer – graphical representation of the relationship between the output variable CH₄ and two of the input’s variables (Temperature, pH, COD, VS and TS)

Several studies have shown that TS could range between 5% to 7.5% in the organic wastes and this enhances CH₄ production (Deepanraj et al., 2014; Yi et al., 2014; Lee et al., 2015). The dataset and membership range identified in this study shows that maximum TS% is 5.83% (Table 4.1). The evaluation of CH₄ production at the case study site is consistent with the range value suggested in literature.

The VS is identified as the concentration of biodegradable solids within the total solid composition (Yi et al., 2014; Deepanraj et al., 2014; Makhura et al., 2019). It was found that high VS% due to a high organic matter results in high CH₄ production which is in line with a study conducted in South Korea on the effect of volatile fatty acid concentration on anaerobic degradation rate from field anaerobic digestion facilities treating food waste leachate (Lee et al., 2015; Lee et al., 2017a).

4.3.5 Optimal output of CH₄: Rule reviewer for graphical simulator

The rule viewer was developed to simulate the entire FIS (Figure 4.7). The rows in the plot express the “if-then” rules with six inputs as the first 6-columns and one output as the last column. The vertical red line passing through each input defines the grade of membership in the rule. The box in the lower right corner of the last column represents the aggregate weighted decision, in which a bold vertical line is used to determine the defuzzified output.

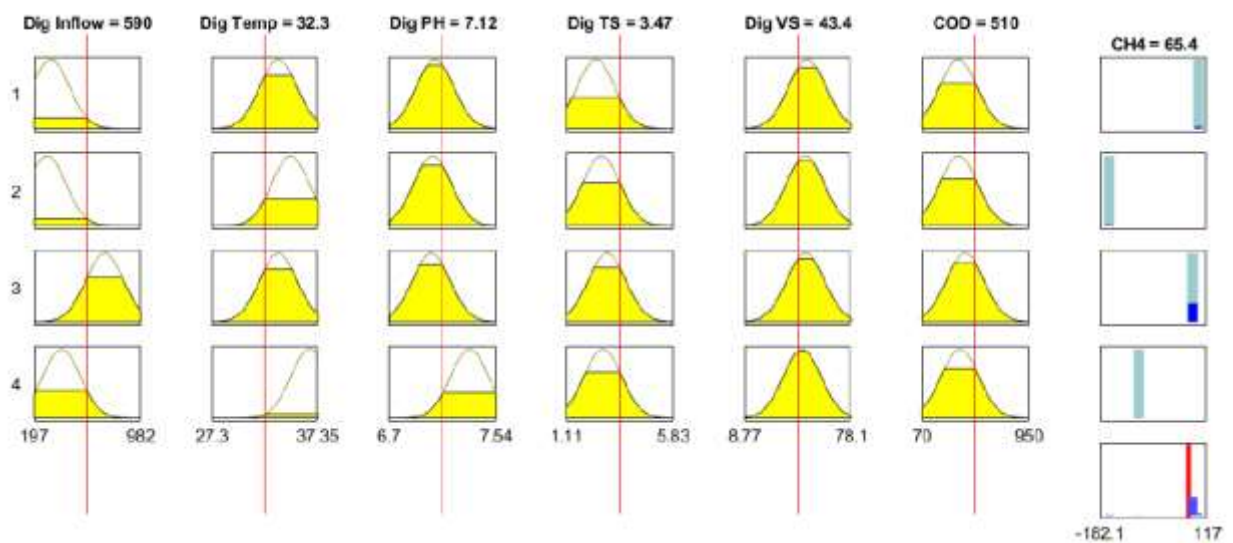


Figure 4.7 The Rule viewer showing the defuzzified form of parameters – FIS optimal CH₄% at the specific values of the input data set

Results indicated that the coefficient of determination (r^2 -value) was 0.926, demonstrating that 92.6 % of the variations in CH₄ (%) were explained by the fuzzy inference model. However, the model did not explain 7.40% of the total variability in the response.

Currently, the rule viewer can simulate the FIS to predict CH₄ (%) at particular experimental factors. Figure 4.8 shows the optimisation of the input factors. The rules were then applied to the data set to generate and identify the optimal CH₄ output. In this case study, the maximum CH₄ (%) of 65.4% was predicted at the following operating parameters; Inflow = 590m³/day, Temp = 32.3°C, pH = 7.12, TS = 3.47%, VS = 43.4% and COD = 510 mg O₂/l. The original data from the Darvill site presents an average of 59.56% of CH₄ generated from the Inflow = 432.59 m³/day, Temp = 33.81°C, pH = 7.08, TS = 2.64%, VS = 47.95% and COD = 369.21mg O₂/l. The difference of 5.84% in the percentage of CH₄ suggests that there are opportunities to enhance the capacity of anaerobic digester treating sludge from Darvill MWWTP.

4.3.6 Discussion

The Fuzzy Logic model was developed based on 4 rules in the IF-THEN format through subtractive clustering and training of data with 254 available observations. The TS in the treated sludge is within the range that can produce maximum concentration of CH₄ if the digester conditions are properly maximise. The attempt to enhance CH₄ by the Fuzzy Logic optimisation confirms the potential and the capacity of the study case digester could be maximised. The optimisation process reveals a potential to produce 65.4% CH₄. This potential percentage is slightly higher than the current operational output of CH₄. The small difference between the modelled output and the operational output may not be considered significant due to several reasons. These reasons include the poor quality of data capture and operational management of the plant. These reasons are well established in the literature (Jonker, 2007; Dai, 2013; Hove et al., 2013; Lee et al., 2017b). Below are some studies that shows the impact of operational conditions on the production of methane gas.

In line with the findings of this study, literature supports the optimisation of biogas production through the manipulation of number of input variables. For example, Bioelectrochemical CO₂ reduction to methane plant was possible through the manipulation of pH levels (Nelabhotla and Dinamarca, 2019). It was shown that adjustment of pH levels affects methane production with a decrease in concentration due to an increase in pH from 8.2 to 8.7. Whilst when at the optimum methane concentration production 91.4%, pH was found to be at approximately 7.8. This study, therefore, shows that when pH is about a

threshold range level, the efficiency of methane gas production diminishes, suggesting that high ranges of pH reduces methanogenesis activity resulting in lower methane production.

In another study conducted by Tsiakiri, et al. (2021) where 1kg samples of sludge were collected from 4 different WWTP's for the analysis of biogas production through experimenting with a set temperature but different total solids percentages, volatile solids percentages and COD levels. The methane gas potential production was determined by the AD treatment performed in batch reactors. The duration of the experiment was for 80 days at a temperature of 37°C. The production of methane gas was measured by a gas chromatographer. The optimum methane gas produced was 80%, all samples reached the optimum at different retention times and at different levels of COD, TS% and VS%. The study had showed that the fastest sample to achieve 80% methane concentration within a 10 to 30 day retention time frame contained COD ranging between 400 - 600mg/l, TS% ranging between 90 - 100% and VS% ranging between 20-30%. This study shows the potential to achieve an optimum methane gas production of 80% and that accuracy in recording of data and ongoing observations are necessary to establish the optimum operating conditions to extract the optimal methane gas from a wastewater treatment plant.

Bolarinwa (2015) confirms the need for rigor in ongoing recording and observing of data in the operating processes within a plant that could inform the operating conditions for optimal outputs that can be of benefit. Due to complexity of the plant and its operations, regular evaluation of its processes and recording of the results and performance deficiencies need to be recorded to identify areas for improvement and optimisation possibilities. Bolarinwa (2015) also recommends that the optimisation of WWTP's is a continuous process which requires a dedicated and focused operating team with continuous education and experience exchange to maintain an optimised operational condition of the plant to generate the maximum CH₄ output possibilities that can be realised from the plant. Based on the optimisation parameters generated using Fuzzy Logic, egg-shaped digester in Darvill WTTW could produce more methane under controlled operational conditions to increase methane gas production.

4.4 CONCLUSION

This chapter used Fuzzy Logic to optimise the production of CH₄ using the actual dataset obtained from the Darvill Municipal Wastewater Treatment Plant digester. The Fuzzy Logic was argued for as the most appropriate model for the optimisation process based on the data available from the Darvill site. The Fuzzy Logic model was able to analyse and identify the parameters that could lead to the optimisation of the CH₄ production output at this case study site. The analysis based on the computational model used reveals an optimisation of 65.4% CH₄ production. Drawing from literature it is possible to optimise CH₄ production up to 80% if rigorous data capturing and monitoring of the operational conditions of the plants is in place and maintained to allow for adjustments of the variables that influence methane gas production from wastewater treatment. The chapter therefore suggests that data management is key to plant operations to realise the optimal potential that can be derived from the AD process. The study recommends the estimation of potential electricity generation based on the actual and optimised output of methane gas from the case study plant.

CHAPTER 5

ESTIMATION OF POTENTIAL BIOGAS TO ELECTRICITY GENERATION USING MUNICIPAL EGG-SHAPED ANAEROBIC DIGESTER

5.1 INTRODUCTION

In the previous chapter, the optimisation of biogas production from an egg-shaped digester located in the Darvill Wastewater Treatment Plant (WWTP) was presented using the data supplied by the plant record keepers with the use of Fuzzy Logic model. Noting that the major focus of the study was on the optimisation of biogas production for the generation of electricity, it is therefore necessary to establish how much electricity can be produced from the optimised production process. Hence, this chapter presents the estimated electricity that could be generated from the optimised biogas plant. The chapter commences with literature on the production of electricity from biogas to show the various processes and outcomes in the electricity generation and the assumptions made that would influence the output values of generated electricity. Noting that there are several methodologies used in the generation of electricity from biogas, the chapter makes a case for a particular methodology by Metcalf and Eddy (2014) selected for this study to calculate the electricity output from the optimised values. Using this methodology, the electricity generated from the optimised biogas is calculated and discussed. The chapter concludes with a summary of the intent of this study, the process followed in establishing the optimised biogas production and the significance of this study and recommendations made from this study.

5.2 CONTEXTUALISING ELECTRICITY GENERATION FROM BIOGAS

Production of electricity from biogas has been in existence for several decades usually in remote areas where the cost of electricity transmission and the instability of continuous supply has become unsustainable and unreliable (Mukumba et al., 2013; Joshi et al., 2018). Biogas produced through wastewater treatment can be used directly (e.g. cooking) or it can be transformed into thermal, electrical or mechanical energy (Joshi et al., 2018). The most

important elements in biogas are methane and carbon dioxide. These two components are used to determine the amount of electricity that can be generated from biogas. Irrespective of the process used for generating electricity, the biogas stored or piped must be dehumidified and purified before its combustion (Joshi et al., 2018). This suggests that there are additional processes required in the value chain during the conversion of biogas to electricity.

There are various technologies available to generate electricity from biogas. These include heat engines, gas turbines and combustion engines (Muthu et al., 2017). According to Joshi et al. (2018) the most common technologies in generating electricity from biogas are gas turbines and combustion engines. Combustion engines can be either internal combustion engine or external combustion engine. More recently, fuel cells, for example Solid Oxide Fuel Cells, are increasingly being considered, because of their high fuel flexibility and high operative temperature that enables combined heat and power generation (Baldinelli et al., 2018). The basic principle behind the generation of electricity from biogas is that the chemical energy of the combustible gases is converted to mechanical energy within a combustion system that is highly controlled. Then, the mechanical energy is used to drive a generator (e.g. a dynamo) to produce electrical power (Omer, 2017).

As indicated earlier, there are several usages in the generation of electricity from biogas with many studies reported on the small-scale energy production (Salerno et al., 2017; Ahammad and Sreekrishnan, 2016; Eggemann et al., 2020). For example, Mukumba et al., (2013) reported a case study of biogas generation from cow dung, chicken manure and human wastes in Zimbabwe. The authors proposed possible design for electricity plant that is needed in a school. Based on the assumption that 1m^3 of gas produces 9 kWh of energy, they showed that 50m^3 of biogas could produce 450 kWh/day of energy from the cattle, chicken and human wastes. Based on these assumptions, they suggested that three generators at the high school would be used to harness the biogas for the electricity generation that the school could use. Of note in this case example is the assumption made about the amount of electricity that could be generated from biogas. The assumptions made in terms of generation capacity is therefore dependent upon the process of biogas production (Scarlat et al., 2018). The constituent components of biogas (e.g. methane and

oxygen) in effect is another layer of concern when considering the generation capabilities of a plant for electricity production in WWTP.

In another small-scale operation of generating electricity, Joshi et al. (2018) suggested that most generators produce alternating AC electricity with the assumption that 1m³ biogas produces 2.14kWh of electricity. Using a method where the biomass in a gas generator is not subjected to a wet scrubbing step, the authors Joshi et al. (2018) showed that biogas, after treatment according to their suggested process may be directly charged to an electric power producing combustion turbine which could be more efficient when operating in a cogeneration cycle producing heat and electricity. Cogeneration or Combined Heat and Power (CHP) describe the simultaneous generation of both electricity and useful heat. They further argued that heat engines in general do not convert all their thermal energy into electricity, suggesting that as much as a bit more than half is lost as excess heat. They argue that by capturing the excess heat, CHP use heat that would be wasted in a conventional power plant, potentially reaching an efficiency of up to 89%, compared with 55% for the best conventional plants. In this example of an alternate method of producing electricity from biogas, efficiency was the focus. This means that in generating electricity from biogas, the amount of electricity generated would also depend upon the method employed in the process of generation.

In larger scale operations, (Karapidakis et al., 2010) Karapidakis and Tsave (2010) explored the generation of electricity in a landfill site in Greece for either the needs of the site or to export to the electricity grid (Vourdoubas and Skoulou, 2016). Based on the average recuperated quantity of biogas which was found to be equal to 462 m³/h for 14 year-long, they argued that the landfill site in the case study in Greece has the potential to export electricity onto the grid. Germany has proven that sustainable energy can be produced from biogas, nearly 800 WWTPs produce electric energy from biogas generating on average of 1800GWh/year (dos Santos et al., 2016). The case examples from Germany illustrate that large-scale electricity generation is possible and can be beneficial to a nation.

5.3 METHODOLOGY EMPLOYED FOR THE ESTIMATION OF POTENTIAL ELECTRICITY GENERATION FROM THE OPTIMISED BIOGAS PRODUCED FROM THE MUNICIPAL WASTEWATER TREATMENT WORKS (MWWTW)

The methodology employed to calculate the amount of electricity that can be generated from biogas is based on Metcalf and Eddy Wastewater Engineering: Treatment and Resource Recovery 5th Edition (2014). This methodology is commonly used in WWTPs where electricity generation is operationalised. This textbook is also used for training purposes and as such is considered most appropriate for this study for the purposes of illustration of potential electricity production from the egg-shaped digester located in Darvill MWWTP. The potential electricity output was calculated, using the case site and optimised biogas data (See Chapter four, section 4.3.5 & 4.3.6). In order to calculate the amount of electricity that can be generated, equations 5.1 to 5.4 were used:

Total mass VSS destroyed = Total VSS before digestion – VSS after digestion

(5.1)

Lower Heating Value (CH_4) = $\frac{CH_4 \times \text{Theoretical Calorific value}}{CH_4 \%}$

(5.2)

Flow of biogas = VSS converted to methane × Mass VSS destroyed

(5.3)

Energy = Flow of biogas × Lower Heating Value (CH_4)

(5.4)

5.4 RESULTS AND DISCUSSIONS

To achieve the aim of the study, the data collected from an egg-shaped digester was used to optimise electricity potential of biogas produced from the digester. The electricity potential was calculated for both actual and the predicted biogas (as already established in the previous chapters). The different inputs used to calculate and determine the electrical outputs are shown in Table 5.1 while Table 5.2 shows the results obtained for the potential electricity that can be generated from the produced methane.

Table 5.1: Operational parameters used to estimate potential electricity generation using biogas produced from anaerobic egg-shaped digester

Input	Value	Unit
Total volume of digester	4505	m ³
% of average total solids	2.64	%
% of average volatile solids	47.95	%
Retention time	20	Day(d)
% of methane gas (CH ₄)	50-65	%
% of carbon dioxide (CO ₂)	15-20	%
Density of methane gas	0.63	kg/m ³
Density of carbon dioxide gas	1.97	kg/m ³
Lower heating value @ 65% CH ₄	22 400	m ³ /kg
Specific gravity of sludge	1.02	Kg/m ³

Table 5.2: The actual versus predicted biogas content used for the estimation of electricity potential generated per digester

	Actual	Predicted Optimised	Potential Optimised	Units
<i>Biogas composition CH₄</i>	0.596	0.654	0.800	fraction
<i>Gas density@ 35°C Methane</i>	0.63	0.63	0.63	kg/m ³
Total mass VSS destroyed	1,070.5	1,070.5	1,070.5	kg VSS/d
VSS converted to Methane	0.8	0.8	0.8	m ³ /kg
For 65% CH ₄ , digester gas calorific value (Metcalf & Eddy 2014)	22,400.0	22,400.0	22,400.0	kJ/m ³
Heating value for methane gas (corrected for actual CH ₄ comp.)	20,539.1	22537.85	27569.23	kJ/m ³
Theoretical CH ₄ biogas production volumetric flow	802.8	802.8	802.8	m ³ /d
Energy generated per digester	16,488.8	18,093.4	22,132.6	MJ/d
	4,580.2	5,025.9	6147.9	Kwh/d

Table 5.3: Potential bio-economic saving predicted in this study

Potential bioenergy saving per digester	kWh/d	Rate/kWh	Cost/d
Actual biogas production	4580.2	R1.90	R8702.38
Predicted optimised biogas production	5025.9	R1.90	R9549.29
Potential optimised biogas production	6147.9	R1.90	R11681.08

Based on the current operation conditions at Darvill site at the time of collection, CH₄ content was 59.6%. The potential electricity generation calculated using the actual value of biogas produced from the digester is approximately 4580.2 Kwh/d (Section 5.3). If the MWWTW's works operate the anaerobic digester with the predicted parameter to generate the methane content, then the potential electricity that could be generated is approximately 5025.9 Kwh/d, working on the basis of an optimised value of CH₄ at 65.4%. The potential optimised biogas production based on possibilities evident in the literature (Nelabhotla and Dinamarca, 2019; Tsiakiri et al., 2021), the enhanced electricity generation would be 6147.9 Kwh/d (See Table 5.2). The bio-economic benefit in terms of electricity saving and potential cost represented in Table 5.3 indicates that optimisation of biogas could enhance electricity production from anaerobic digester. This study further shows that sludge treatment using egg-shaped anaerobic digester in Darvill MWWTP would have more economical value if the full potential of the digester for electricity generation through biogas conversion is considered by the municipality.

Calculation of electricity potential from anaerobically produced biogas (Tables 5.1, 5.2 and 5.3) could serve as a guideline or baseline for MWWTW that treat on average 100 ML/d of wastewater with tons of sludges as wastes. The current selected digester used as case study has the potential to be optimised for further biogas production, hence could be used to leverage the current electricity shortage. The electricity generated from the anaerobic digesters can be used within the MWWTW to offset the current electricity usage and help in reducing the use of coal for electricity generation. Therefore, this exploration will involve further investigation and management of MWWTW. Thus, this study shows that both MWWTW and the government can benefit from the potential biogas-electrical generation, as the supply and demand as well as the costs could be substantially reduced.

5.5 CONCLUSION

South Africa is a water stressed country with a depletion of natural resources, the use of bio resources from wastewater treatment works is explored in this study. The study focused on the optimisation of biogas production at Darvill Wastewater Treatment Plant with a view to electricity generation. Egg-shaped digester in Darvill WWTP was used as case study and the obtained results showed that biogas for electricity generation can be

optimised as a way to contribute to the green economy. Using the data generation over a period of time at the plant, the process of optimisation of biogas production was established, through which optimised values were predicted using the Fuzzy-Logic model. The study concluded with an illustration of the variance in electricity production between the biogas normally produced at the site and the predicted values. The outcome of the study is that there is a potential to optimise biogas production using the selected digester in order to increase electricity generation. The study is significant as it contributes to the global agenda of reducing reliance on the natural resources with a view to preserving the natural resources for future generations. It further provides a scope to optimise operations of WWTPs for electricity generation which could serve both the needs of WWTP as well as contribute to societal electricity demands within the municipalities. Design engineers would likewise benefit from this study as it will contribute to optimisation insights on waste treatment and biogas production.

CHAPTER 6

GENERAL CONCLUSIONS AND RECOMMENDATION

6.1 INTRODUCTION

Having located the study within a broader field of the diminishing of natural resources that necessitated a review of how secondary sources of resources could be harnessed to meet rising societal demands, this study explored a case study of wastewater treatment at a site that has egg-shaped digesters. The Darvill site for the treatment of wastewater was undergoing an upgrade to increase its treatment capacity, at the time of this study, to handle the increase in the amount of wastewater channelled to this site. This site had two egg-shaped digesters and the upgrade included the construction of four more egg-shaped digesters. While this study did not focus on the influence of the egg-shaped digesters, nor on the additional capacity that was being constructed, the potential to optimise the electricity generation could also be enhanced by this structural enhancement at this site and could be the focus of future studies.

In attempting to optimally harness benefits from wastewater treatment, as indicated in chapter 1, the study focused on the treatment efficiency of the anaerobic digester treating sludge produced from Darvill Wastewater Treatment Plant (DWWTP) as well as the optimisation of biogas production using computational intelligence with the potential for sustainable energy policy implementation. In this study, the data generated over a period of time from AD processes at Darvill was used for the evaluation and optimisation processes for the production of CH₄ that would then be used for the generation of electricity at this case study site. This chapter presents the general conclusions with recommendation. Research objectives achieved in the study include; (1) The prediction of biogas production (methane produced) in an anaerobic digester treating sludge produced from a municipal wastewater treatment plant. (2) The study also developed and simulates biogas production from the anaerobic digester processes using computational intelligence techniques for optimisation. (3) And lastly, the potential electricity that could be generated from biogas produced from the egg-shaped digester was estimated.

This study sought to do the following:

- To develop and calibrate a Partial least squares (PLS) regression model to determine confidence in the data that were used in the prediction process using computational analysis. The key reasons for developing and calibrating the PLS regression model was in response to the issue of data quality in computational analysis and of the multivariable processes involved in the production of bio-gas that would be used in the generation of electricity.

The finding revealed that PLS log-regression and linear regression is a good predictive model for biogas production. This finding is necessary to continue with the next phase of the optimisation process which involves the use of Fuzzy Logic modelling.

- To optimise biogas generation from the egg-shaped anaerobic digester used at the research site for AD. This optimisation process involved the use of Fuzzy Logic modelling. Fuzzy Logic works with uncertainty in the definitions of concepts rather than the frequency of occurrence of a phenomenon (Sari et al., 2013) and the concept was derived from its ability to accurately describe imprecise values of variables such as inflow, temperature and pH values.

The findings from the Fuzzy Logic computational process revealed that the subtractive clustering of the modelling process revealed four groups, which identified membership functions and its associated rules. The rules were then applied to the data set to generate the optimal CH₄ output and identified the defuzzified outputs. In this case study, the output was considered across a range from 48.5 to 67.70 and it was found that the optimal output of 65.4% of CH₄, using the rules generated for the optimising process on the fuzzy inference system (FIS) is possible.

- To estimate the amount of electricity that could be generated from the optimised biogas produced from the egg-shaped digester. To establish any significant gains, electricity production is calculated using both the predicted and the actual biogas produced from the plant. The potential electricity that can be generated using the actual biogas production is approximately 4580.5 Kwh/d. If the MWWTW's works

on the predicted biogas value, the potential electricity that can be generated would be approximately 5118.4Kwh/d. From these calculations, the enhancement of electricity generation from fermenting the sludge produce from wastewater treatment process for biogas production is established.

The conclusion drawn from this process is that optimisation of biogas would lead to an increased electricity generation if the MWWTP wastes is properly maximised.

6.2 GENERAL CONCLUSIONS DRAWN FROM THE FINDINGS OF THE STUDY

The following general conclusions can be drawn from the study:

- i. The potential to exploit the re-use of wastes within municipal wastewater treatment site is possible and would include structural, process and computational intelligence opportunities to achieve optimal benefits. It was found that electricity generation through the optimisation process can be enhanced.
- ii. The quality of data collected at WWTPs may compromise optimisation processes using computational analysis, the exploration of appropriate computer intelligence models to manage the low quality of data available at the treatment plants is possible. The Fuzzy Logic regression model was found to be most appropriate to work with low quality data sets.
- iii. The optimisation of outputs from WWTP is a lengthy process and involves various steps from cleaning the data sets to the selection of appropriate modelling technique for optimisation.

6.3 CONTRIBUTIONS TO THE BODY OF KNOWLEDGE ON BIOGAS PRODUCTION

The egg-shaped digester in Darvill WWTP was used as the case study. The obtained results showed that biogas for electricity generation can be optimised and contributes to the green economy. Using the generated data by egg-shaped digester, the process of optimisation of biogas production was established and predicted using the Fuzzy-Logic model. The study concludes with an illustration of the variance in electricity production between the actual and predicted values of biogas produced by the digester.

The outcome of the study is that there is a potential to:

- Enhance biogas production using the selected digester in order to increase electricity generation.
- The study is significant as it contributes to the UN Sustainable Development Goals (SDGs) 6 to 8 and 13 in the context of clean water and sanitation; affordable and clean energy; decent work and economic growth; and the mitigation of climate change.
- This study also supports the global agenda of reducing reliance on the natural resources with a view to preserving natural resources for future generations through the use of AD technology.
- It further provides a scope to optimisation of WWTPs operation for electricity generation which could serve both the needs of WWTP as well as contribute to societal electricity demands within the municipalities thus, contributes to human empowerment and energy security.
- Application of anaerobic digester in treatment of municipal sludge treatment is considered economical and socially sustainable for both liquid and solid wastes, which would likewise benefit design engineers, hence contribute to optimisation insights on waste treatment and biogas production.

6.4 RECOMMENDATIONS ARISING FROM THIS STUDY

Drawing from the findings of the study and from the general conclusions reached through the study, the following recommendations are made:

- i. The quest for optimisation of the process involved in wastewater treatment must be an on-going quest. Hence, it is recommended that WWTPs continue to be sites of on-going research.
- ii. One of the challenges, which was regarded as limitations in this study is the accurate and on-going record keeping of all variables in the treatment plant. Good quality data would generate good optimisation processes and the results would be accepted with a high degree of confidence. Hence, it is recommended that strict protocols be followed at wastewater treatment plants on data collection, recordings and storage. This would include constant auditing of the data sets collected by the operators and laboratory technicians to generate consistent data.
- iii. It is recommended that the computation intelligence be used in the tracking and optimisation within MWWTW for the optimisation of biogas production in contribution to alternate energy sources.
- iv. The variables inflow volume, TS, VS, pH, temperature & COD within the MWWTW and AD process should be rigorously monitored and controlled for the optimisation of biogas production.
- v. Biogas produced from the MWWTW produced be used to generate electricity for the MWWTW plant's use.

Further research arising out of this project could include:

- A focus on the structural engineering enhances for optimisation of biogas production such the use of egg shaped digesters.

- The sludge from the MWWTW process plays an integral part in the optimisation of biogas, further research is therefore needed in the sludge analysis, treatment and control for the enhancement of CH₄ production for the contribution toward alternate energy resources.

6.5 CONCLUSION

Located within a broader discourse of preservation and management of natural resources with recycling as one of the key strategies, this study sought to explore optimisation in the wastewater treatment process as a possible contributor to this discourse. Using a case study of a wastes from WWTP, this study explored how contributory parameters can be optimised to produce elements that can be used in substantial positive ways that will contribute to the preservation of the natural resources. Using the data from the case study site, optimisation of CH₄ production was explored using Fuzzy Logic as a computational model. The CH₄ optimisation realised through the computational model was subjected to further analysis to show how it can influence electricity generation. The data analysed through the optimisation process and estimation for electricity generation showed that it is possible to increase the electricity generation at the case study plant. Based on this finding, it was concluded that optimisation of processes should be an on-going process to enhance useable bio products from wastes treatment. Such useable outputs can then be used to generate, for example, an increased electricity that can be used by the plant as well as the general community. Some recommendations have been made to strengthen the process of optimisation by the municipal wastewater treatment plants.

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APPENDIX 1: ETHICS CERTIFICATE



APPENDIX 2: TURNITIN SIMILARITY INDEX REPORT

Masters dissertation as at 14 Oct 2021

by Zesha Ramrathan

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RE: EDITING CERTIFICATE

**FOCUS AREA: EVALUATION AND OPTIMISATION OF BIOGAS PRODUCTION IN
MUNICIPAL WASTEWATER TREATMENT PLANT USING
COMPUTATIONAL INTELLIGENCE APPROACH:
POTENTIAL TO GENERATE ELECTRICITY
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This serves to confirm that this research report has been edited for clarity, language and layout.

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