NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DEPARTMENT OF CIVIL ENGINEERING

# COMPARATIVE ANALYSIS OF HYDROPOWER AND NON-HYDROPOWER ELECTRICITY IN AFRICA USING DIFFERENT EMPIRICAL APPROACHES TO EVALUATE CLIMATE PARAMETERS IMPACTS.

M.Sc. THESIS

ABDIMAJID IBRAHIM ALI

NICOSIA

JUNE, 2023

ABDIMAJID IBRAHIM ALI

COMPARATIVE ANALYSIS OF HYDROPOWER AND NON-HYDROPOWER ELECTRICITY IN AFRICA USING DIFFERENT EMPIRICAL APPROACHES MODELS TO EVALUATE CLIMATE PARAMETER IMPACTS.

2023

**NEAR EAST UNIVERSITY**

**INSTITUTE OF GRADUATE STUDIES**

**DEPARTMENT OF CIVIL ENGINEERING**

# COMPARATIVE ANALYSIS OF HYDROPOWER AND NON-HYDROPOWER ELECTRICITY IN AFRICA USING DIFFERENT EMPIRICAL APPROACHES TO EVALUATE CLIMATE PARAMETERS IMPACTS.

**M.Sc. THESIS**

**ABDIMAJID IBRAHIM ALI**

**SUPERVISOR**

**PROF. DR. HÜSEYIN GÖKÇEKUŞ**

**NICOSIA**

**JUNE, 2022**

## Approval

We certify that we have read the thesis submitted by Abdimajid Ibrahim Ali, titled "**comparative analysis of hydropower and non-hydropower electricity in Africa using machine learning, mathematical and statistical models to evaluate climate parameters impacts**" and that in our combined opinion it is fully adequate, in scope and in quality as a thesis for the degree of Master of Civil and Environmental Engineering.

| Examining Committee | Name-Surname | Signature |
|---|---|---|
| Head of the Committee: | Assoc. Prof. Dr. Youssef kassem | |
| Committee Member | Assıst. Prof. Dr. Mustafa Alas | |
| Supervisor: | Prof. Dr. Hüseyin Gökçekuş | |

Approved by the Head of the Department

.03./.08./2023

..............................

Prof. Dr.Kabir Sadeghi

Head of Department

Approved by the Institute of Graduate Studies

17./.8./2023

Prof. Dr. Kemal Hüsnü Can Başer

Head of the Institute

YAKIN DOĞU ÜNİVERSİTESİ SAĞLIK BİLİMLERİ ENSTİTÜSÜ 1988

## Declaration

I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

Abdimajid Ibrahim Ali

…../…../2023

## Acknowledgments

I would like to express my deepest gratitude to Prof. Dr. Hüseyin Gökçekuş and Assoc. Prof. Dr. Youssef Kassem for their tremendous support throughout my accomplishments. Without their encouragement and the dedicated assistance in providing me with ample study hours, I would most certainly not have succeeded in meeting my goals. As my mentors, I cannot express in words how much they have impacted my education and my holistic development. They continually shared their teachings and their priceless wisdom with me, and for that, I am forever grateful.

I am immensely gratified for the collaborative initiatives of those whom I encountered during the completion of this and other projects. Their contribution has had tremendous influence in the successful accomplishment of this endeavor. In addition, my educational advisors at the university have been of great aid in my discovery of scientific inquiry, building up my knowledge and maximizing my personal and professional growth.

My highest appreciation goes out to my family and friends for sticking with me through this undertaking. Their conviction in my capacities has been a steady motivation and push for me to move forward. From the bottom of my heart, I thank my parents for their continuous assistance and lasting affection, without which I would not have had the capacity to achieve so much. Besides, I wish to express gratitude to my elder sibling, whose reliable bolster and Solace consistently drove me to shoot for the stars.

The diligent advice and assistance provided by Prof. Dr. Hüseyin Gökçekuş, Assoc. Prof. Dr. Youssef Kassem, my faculty teachers, family and friends have been crucial for the success of this project. Their dedication to my development and persistence in their encouragement have been invaluable to me during this entire journey.

**Abdimajid Ibrahim Ali**

**Abstract:**

**COMPARATIVE ANALYSIS OF HYDROPOWER AND NON-HYDROPOWER ELECTRICITY IN AFRICA USING DIFFERENT EMPIRICAL APPROACHES TO EVALUATE CLIMATE PARAMETERS IMPACTS.**

**Ali, Abdimajid Ibrahim**
**MA, Department of Civil Engineering**
**June, 2023, 90 pages**

Securing affordable and reliable access to power sources remains an immense challenges for the African continent. Africa depends heavily on both hydropower and non-hydropower energy sources, but these can be affected by the climate. Climate change can significantly impact the availability of water, which endangers the stability of hydropower generation, while solar and wind power are affected by external elements such as wind speed, temperature, and precipitation.

This thesis attempts to analyse the impact of climate parameters on hydropower and non-hydropower electricity production in Africa utilising machine learning models, and comparing their performance with mathematical and statistical models. Relevant data from trusted sources such as the NASA Prediction of Worldwide Energy Resources (POWER) and the U.S. Energy Information Administration (EIA) databases is used to establish correlations between climate parameters and electricity production in Africa.

Machine learning approaches are used to predict electricity generation from different sources of electricity such as hydropower and non-hydropower. In particular, the multilayer perceptron neural network (MLPNN) and the radial basis function neural network (RBFNN) are utilized. Statistical analysis such as the determination coefficient (RSQ) and root mean square error (RMSE) are used to evaluate the accuracy of the machine learning models. As well as multiple linear regression (MLR) model to compare with the machine learning models.

The results shows that hydropower generation is strongly impacted by rainfall and average temperature, while other non-hydropower sources are significantly affected by elements such as wind speed, maximum temperature, and relative humidity.

Obviously, machine learning models show better performance than mathematical models in predicting electricity production from both hydropower and non-hydropower sources. In this context, the MLPNN model demonstrates the highest accuracy in predicting hydro-electricity production, while the RBFNN model is the best performing model for forecasting non-hydropower electricity output.
Consequently, it is recommended to opt for machine learning models to effectively predict electricity production from hydropower and non-hydropower sources. Such an approach would not only create more accurate electricity production predictions, but also support a greener, more sustainable energy mix in Africa.

***Keywords:*** Africa, climate, hydropower, non-hydropower, empirical approaches.

## Table of Contents

# List of Tables

## List of Figures

## List of Abbreviations

**ANN:** Artificial Neural Network

**MLPNN:** Multilayer perceptron Neural Network

**RBF:** Radial Basis Function

**MLR:** Multiple Linear Regression

**RSQ:** R-squared (Coefficient of determination)

**RMSE:** Root Mean Square Error

**H:** Hydropower

**NH:** Non-Hydropower

**LAT:** Latitude

**LONG:** Longitude

**ALT:** Altitude

**EIA:** U.S. Energy Information Administration

**AfDB:** African Development Bank

**UNESCO:** United Nations Educational, Scientific and Cultural Organization

**IEA:** International Energy Agency

**Y:** Year

**TAV:** Temperature Average

**TMAX:** Temperature Maximum

**TMIN:** Temperature Minimum

**NASA-POWER:** NASA Prediction of Worldwide Energy Resources

**IHA:** International Hydropower Association

**GWEC:** Global Wind Energy Council

**WS:** Wind speed

**RH:** Relative Humidity

**UNDESA:** United Nations Department of Economic and Social Affairs

**PRE:** Precipitation

**MW:** Mega Watt

**IPCC:** Intergovernmental Panel on Climate Change

**UN-Habitat:** United Nations Human Settlements Programme

**TWh:** Terawatt Hours

**ITCZ:** Inter-Tropical Convergence Zone

**CSP:** Concentrated Solar Power

**PV:** Photovoltaic

**GDP:** Gross Domestic Product

# CHAPTE I
# Introduction

This chapter includes the general introduction, aims, an overview of electricity, climate of Africa and challenges and opportunities of the hydro and non-hydropower.

## 1.1 Introduction

Access to reliable and affordable energy sources is fundamental for economic growth and poverty reduction in Africa. However, the continent is facing with multiple energy challenges causing its limited energy resources and poor energy infrastructure. According to the International Energy Agency (IEA), African energy demand is predicted to double by 2040 (Africa Energy Outlook, 2019); thus, this imposes a considerable problem for policymakers and energy planners.

Currently, the energy mix in Africa is mostly dependent on hydropower and non-hydropower sources. Hydropower accounts for nearly 20 % of the entire electricity production in Africa (Africa Energy Outlook, 2019). Solar, wind and thermal power encompass the remaining 80 % of the electricity produced (Africa Energy Outlook, 2019). Nonetheless, the production of electricity from these sources is under the influence of climatic factors such as temperature, wind speed, precipitation and humidity. Climate change is likely to exacerbate the challenge of energy production in Africa by diminishing the availability of water resources and decreasing the reliability of hydropower production.

The use of machine learning models has been generating a huge attention in recent times to forecast electrical production. Such machine learning models have demonstrated high efficiency in research and analyzing large datasets in order to predict possible results.

This Master's thesis seeks to evaluate and compare the production of electricity from hydropower and non-hydropower sources in Africa using machine learning models and mathematical/statistical models.

The effects of climate parameters on the production of electricity will be analysed using data obtained from NASA’s Prediction of Worldwide Energy Resources (POWER) and the U.S. Energy Information Administration (EIA) databases. To predict electricity production from hydropower and non-hydropower sources, this study will employ machine learning models such as the multilayer perceptron neural network (MLPNN) and the radial basis function (RBF), while mathematical models like multiple linear regression (MLR) and statistical analysis techniques (i.e. determination coefficient (RSQ) and root mean square error (RMSE)) will be used for comparison purposes with the machine learning models.

This thesis will be divided into three parts. Chapter two will discuss the background information related to energy production, hydropower, non-hydropower sources, climate change, and machine learning models. Chapter three will detail the methodology used, including data collection, pre-processing, and model development. Finally, chapter four will present the results and conclusions of the study. Chapter 4 presents results from this project, featuring the effects of climate parameters on the production of energy from hydraulic and non-hydraulic sources as well as the performance of machine learning models in comparison to mathematical and statistical models. Finally, Chapter 5 concludes the thesis in summarising the key findings and proposing ideas for potential future study.

**1.2 Aim of the Study:**

The aim of this Master's thesis is to conduct a comparative analysis of hydropower and non-hydropower electricity production in Africa using machine learning models and comparison with mathematical and statistical models. Specifically, the study aims to:

- Analyse the relationship between climate parameters and the production of electricity from hydropower and non-hydropower sources in Africa.
- Develop machine learning models to predict the production of electricity from hydropower and non-hydropower sources in Africa.
- Identify the most impactful climate parameters on the production of the electricity in Africa on the face of hydropower and non-hydropower electricity production.
- Evaluate the climate change impact on the electricity generation of the electricity in Africa form hydropower and non-hydropower sources of electricity.
- Comparison the enhancement of the machine learning models with mathematical models and checking the accuracy of the models with different statistical indices in predicting the hydro and non-hydropower electricity generation in Africa.
- Provide recommendations to the energy sectaries such as energy planers and policymakers in Africa to develop sustainable energy mix that considers the impact of the climate change on the production of the electricity.

This study aims to analyse the impact of climate change on the electricity production of from hydropower and non-hydropower sources in Africa. The study will analyse the potential of machine learning models in making predictions in the production of electricity from hydro and non-hydropower sources of electricity, mostly in relation to the effects of climate parameters. By performance so, it will be promising for energy planners and policymakers in Africa to consider the climate impact when creating a sustainable energy mix. The outcome of this analysis can subsidize and help to better understand of how electricity production from the both sources hydro and non-hydropower in African impacted by the changing climate.

This thesis study will examine the electricity production from hydropower and non-hydropower sources in the African continent by analysing the impact of climate parameters on these sources of energy. A different empirical models is to be employed and developed to better understand the efficiency and the limitations of the machine learning and mathematical models in the prediction of the energy production in relation to climate parameters change. The results of this study will help the African policy makers, energy professionals, and other interested parties in Africa who motivated to increase the generation of the energy while mitigation the impact of the climate parameters change.

## 1.3 Electricity in Africa

In Africa electricity generation is the back born of the economic and socoal development of the continent. Although renewable energy sources have a great potential for the continent, many African countries are still heavily dependent on non-hydropower sources of energy. This practice can have adverse environmental effects and make African economies dependent on the global market price of fuel. To counter this issue, diversifying the energy mix in Africa has become a priority for many countries in the region.

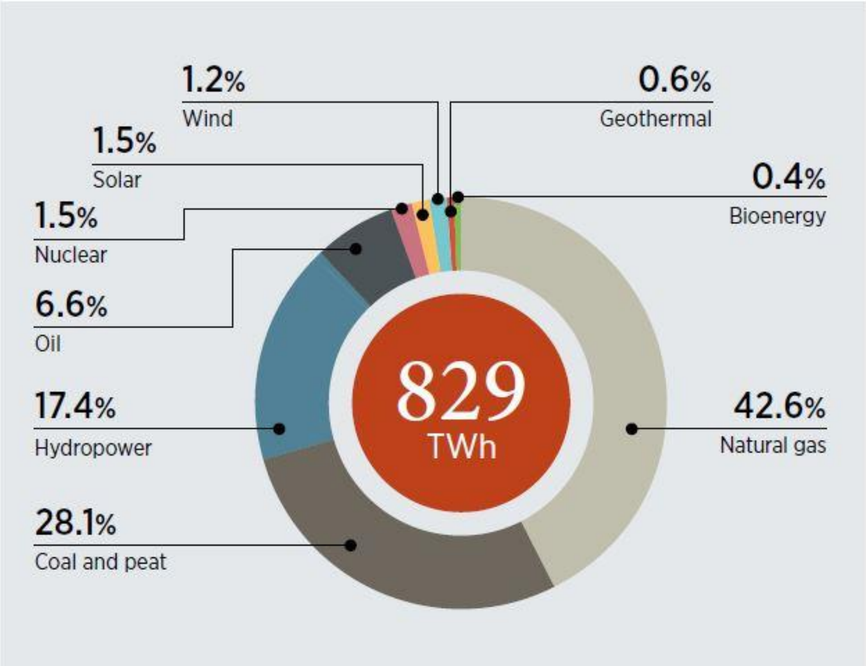
Hydropower is a major electricity contributor in Africa. According to the IHA (International Hydropower Association), African hydropower capacity raised at 36 GW in 2020, which accounts about 17.4% of the continent's entire energy production. East and Southern Africa are regions with the largest number of hydropower installations, and countries such as Ethiopia, Zambia, and Zimbabwe enjoy the highest levels of installed capacity (IHA, 2019).

Non-hydropower-based electricity sources play an important role in fulfilling Africa's energy demand. Containers fuelled by oil, coal, gas, and nuclear energy have all taken the lead in producing a substantial portion of electricity from the continent (Tsige & Ghirmay, 2019).

Despite the need for electricity, such energy sources are problemized due to their environmental & health implications, including air contamination and greenhouse gas emissions.

**Figure 1**

*Electricity generation in Africa, by energy source, 2019 (Source: IHA, 2022)*




Given the disadvantages related to non-renewable energy sources, there is an increased concentration in renewable sources of energy, such as wind, solar and geothermal, plus hydro-electricity. These renewable energy sources can produce a great deal of energy for Africa, since it has a lot of renewable energy resources. For example, the Global Wind Energy Council (GWEC) asserts that the wind energy potential, alone, in Africa stands at 180,000 terawatt hours (TWh) per year. That is incredibly high, and suggestive of the tremendous amount of power the wind can offer to meet Africa's energy requirements, which is more than 250 times over, (World Bank, 2021).

Finally, electricity is necessary for Africa's growth, and a means to broaden the energy mix in order to guarantee a regular, economical and sustainable supply of electricity. Hydro-power supplies a substantial part of electricity production in Africa, but there is need to look into other renewable energy sources such as wind and solar, so as to match the growing demand for energy.

### 1.4 Climate of Africa

Africa is a large continent that is home to an array of climate conditions. Temperatures tend to be warm across the continent, while humidity and precipitation also vary depending on the region. Many factors contribute to the diversity of climate conditions found in Africa such as ocean currents, the lean of the Earth, altitude, and wind patterns. For instance, northern Africa is generally hot and arid, due in large part to the immense Sahara Desert.

Central and eastern Africa, meanwhile, feature tropical climates that are highly influenced by the yearly movements of the inter-tropical convergence zone (ITCZ), a region where the trade winds from the north and south collide and generate a zone of low pressure that can cause heavy rains in the encompassing areas (Higgins et al., 2020).

The southern region of Africa is located further away from the equator and thus experiences a more temperate climate. This climate is characterized by dry winter months, as well as moist and humid summers due to the influence of the South Atlantic high-pressure system (Yahaya, 2018). For those living in Africa's coastal regions, they are subject to a more mild and humid Marine Climate due to the influence of nearby oceans (Agrawal & Ghosh, 2019).

Climate change is having an adverse impact on African climates, drastically altering temperature patterns and rainfall. This has caused decreased agricultural productivity, water scarcity, higher frequencies of extreme weather events, floods and droughts, and rising sea levels, all of which directly threaten the wellbeing of coastal and inland populations (IPCC, 2018).

When considering the relationships between climate and electricity production, it is essential to have a strong understanding of the impact of a variety of climate parameters. Variables such as temperature, precipitation, wind speed, and relative humidity are all required to be taken into account when examining the generation of hydropower and non-hydropower energy. This shall be discussed in further detail in the proceeding section.

## 1.5 Energy state in Africa

Africa is provided with numerous power resources, however, access to advanced energy services, investments, and infrastructures persist to be hard to access in various part of the continent. This limits socio-economic development, particularly in rural regions. Although fossil fuels dominate the African energy mix, renewable sources such as hydropower, solar and wind power are gaining in importance.

This change is driven by increased energy security, climate change mitigation and decreased reliance on non-renewables. Governments and organizations across the continent are recognizing the importance of renewable energy development, and are investing in projects which will help provide Africans with reliable and affordable energy services.

Hydropower is a major source of energy in several African countries such as Ethiopia, Ghana, and Zambia due to the availability of rivers that offer tremendous potential for hydropower generation. Other renewable energy resources, including thermal, solar, and wind power, are also being utilized in different African states such as Morocco, South Africa, and Egypt. Advantages of these non-hydropower alternatives include low operational costs, minimal environmental impact, and quicker launch compared to hydropower.

However, despite these potentials of renewable energy sources, their contribution to African electrical resources overall is still considerably small. The high investment costs and complex technical issues linked with renewable energy projects are two major elements that have limited their development (AER, 2021). Furthermore, limited access to financing and inadequate regulatory structures have hindered investment in the renewable energy sector.

The vigor sector in Africa is imperative to the landmass's advancement, and renewable energy evolution is paramount to accomplishing manageable economic upswing. To accomplish this, African countries must implement laws that exhort renewable energy development, increase venture in the area, and construct an aiding atmosphere for private area contribution. Also, there is a requisite to sink capital into research and expansion to recognize and confront the tribulations confronting renewable energy advance in the continent.

## 1.6 Hydropower and Non-Hydropower of Africa

### *1.6.1 Hydropower in Africa:*

Africa has roughly 17% of the world's population, but remarkably only 4% of global power generation. As a result of this underrepresentation in access to electricity, several countries are seeing a rise in those without electricity in 2021. Hydropower is becoming a more prominent renewable energy source on the continent and several new projects on this front are coming online. The West African Power Pool region is projected to be home to about 1.5 billion people by 2070, accounting for about a third of Africa's population. It is therefore increasingly essential to capitalize on the African continent's vast hydropower potential. Not only can renewable energy be a game-changer for the economic development of Africa but also help meet the UN's Sustainable Development Goals.

The African Development Bank (AfDB) is devoted to providing access to environmentally friendly and dependable sources of energy through its Africa Hydropower Modernization Program. Supported by the International Hydropower Association (IHA), the program concentrates on modernizing existing hydropower operations considered that roughly 60% of all the existing capacity is more than two decades old. It is thought to be one of the inexpensive power sources in comparison to other sources and has a minimal effect on the environment. Despite the fact that Africa makes up an meagre two percent of the world’s carbon dioxide emissions caused by energy generation, the region is severely affected by the effects of climate change, which have a direct impact on its hydropower capabilities, and more significantly, on crucial food production systems and services.

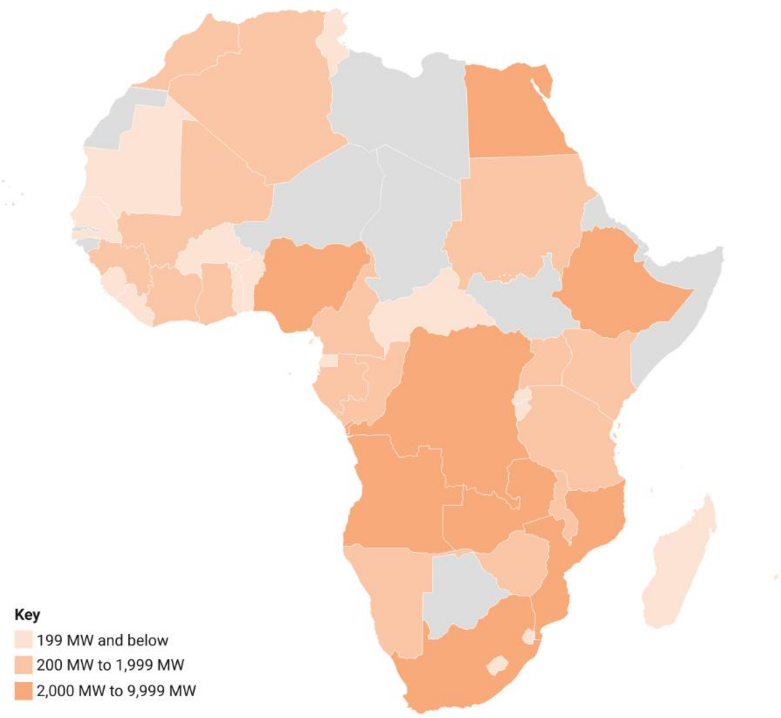
The Grand Ethiopian Renaissance Dam (GERD) is a hydroelectric power station that is being built in Ethiopia, on the Blue Nile. This station is expected to be fully operational in 4-7 years, and is envisioned to be the largest hydroelectric power station in Africa and one of the grandest in the world. The amount of power that the port can generate once it is inaugurated is 5.3GW. Authorities announced that the two turbines that were set up began working in February 2022 and each of them generating 375MW electricity. The concern is that some countries like Egypt, fear that this project may cause adverse effects in terms of water security. In spite of these facts, Ethiopia argues that the infrastructure will bring positive results both to them and to the countries in the zone.

In 2022, the Kikagati Hydropower Plant was launched by Voith Hydro with a capacity of 15.57 MW situated on the Tanzania and Uganda border. During the year prior, Uganda Electricity Generation Company Ltd (UEGCL) solicited bids for the 44.7 MW Muzizi scheme to be built on the Muzizi River. During the same year, the first 150 MW unit of the 750 MW Kafue Gorge Lower Hydropower Station, owned by Zambia Electricity Supply Corp. (ZESCO), was launched with Sinohydro Corporation as the contractor. Additionally, the initial 175 MW unit of Zungeru Hydropower Station in Nigeria was commissioned in the same year.

On completion of every unit, the project is offering 700 MW of electricity to the grid. Recently, to confront the growing energy requirement, Kenya Electricity Generating Company (KenGen) pronounced that they are meeting domestic needs through creation from geothermal, hydro and wind power. This was after the greatest ever electricity demand of 2,036 MW in the country.

**Figure 2**

*Africa's Hydropower Installed capacity 2021 (MW) (Source: IHA, 2022)*




In Mali, the Mariguina hydroelectric station is expected to become active brings its first chunk of power to the grid by March of 2022. The 3 x 49 MW Kaplan generator setup has the power to provide 140 MW and is planning to create 1,000 job opportunities, giving a huge benefit to the locals' economic growth. Burundi's government also gave permission for the Songa Energy Company to construct two hydropower stations on the Mulembwe and Ruvyironza rivers, pumping in 10.65 MW to the grid. In spite of having the same population, African's electricity infrastructure is remarkably behind that of India which consists of roughly 430,000 km of high voltage transmission lines, while the continent's only has 26,000 km. Challenges are sure to arise as predicted demands for electrical power in Africa are expected to triple by 2040. These needs will undoubtedly combine, resulting in the need to improve and spread out electric transmission and distribution networks throughout the continent.

Various African countries are implementing innovations that will lead to progress. In an effort to interconnect the power systems of Kenya and Ethiopia, what is said to be the longest power transmission line between Central and East Africa is being put into place and is prepared to generate as much as 2,000 MW of electricity shortly. Angola is similarly effecting significant improvement to their power network with the completion of a 343 km long wire to link the north and south electricity grids and thus empower 1,000 MW of cost-efficient hydroelectric power for utilization. The African Development Bank has devoted considerable funds to finance the project, purported to bring forth a yearly reduction of 125 Mt of $CO2$ emissions and 46 billion litres of diesel fuel used. Moreover, for a venture that looks to bring the Baynes Hydropower Plant to fruition in 2025, the Southern African Power Pool has been recently provided financing from the African Development Bank through the NEPADIPPF Programme in March 2021.

### *1.6.2 Non-Hydropower Electricity in Africa:*

Recently, there has been a heightened focus on diversifying the energy mix in Africa with the introduction of renewable power sources like solar, wind, and geothermal energy. Solar energy has become one of the most sought out sources of energy due to its abundance in certain parts of the continent, with countries such as Morocco and South Africa both taking steps to develop large-scale solar projects with the use of Concentrated Solar Power (CSP) and photovoltaic (PV) technologies. Wind power is another renewable energy source that has been growing in prominence over the past few years, with countries such as Egypt, Kenya, and Morocco all utilizing their potential to build wind farms and install wind turbines. Geothermal energy is another alternative for those areas that possess volcanic regions, with Kenya and Ethiopia already having built geothermal power plants, where they can collect and utilize the energy from the Earth's heat to generate electricity.

Non-hydropower renewable energy sources furnish many advantages to both the environment and population. Decentralized energy solutions have been gaining traction in recent years due to the environmental and economic benefits they bring. These solutions assist in decreasing the discharge of greenhouse gases into the atmosphere, potentially controlling the effects of climate change. Additionally, these systems provide electricity to remote areas without having to connect to large, centralized power grids. Though the intermittent nature of renewable energy sources can present challenges to providing a continuously reliable supply of power, the development of energy storage solutions and smart grids are providing ways to deal with this issue.

## 1.7 Current State of Hydropower and Non-Hydropower in Africa:

### *1.7.1 Current State of Hydropower in Africa:*

Hydropower has the opportunity to serve as a reliable, renewable, and cost-effective form of power generation across the continent of Africa. This is due to the abundance of rivers, lakes, and other sources of water found there. Estimates of the total hydropower potential of the continent come to 1,750 TWh/year, which is hugely beneficial for Africa's development. Making use of the natural resources in this way could bring about a great surge in the continent's economic prospects, as well as providing an environmentally-friendly source of energy. Hydropower could therefore prove to be a critical part of Africa's future.

Africa has stepped up its commitment to harnessing its plentiful water resources to generate electricity. Ethiopia's Grand Ethiopian Renaissance Dam is a prime example of this, leveraging its sheer magnitude with an estimated 6,450 MW output. Congolese counterparts also boast impressive yields, the Inga Dam building up to the capacity of 40,000 MW, ranked among the largest hydro operations in the world (Walia & Aklilu, 2021). This illustrative example highlights the extent to which Africa is investing in its water resources for the generation of electricity.

Despite its immense hydropower potential, Africa is still lacking when it comes to its overall energy needs. Several issues, such as the scarcity of financial resources, lack of infrastructure, and socio-environmental concerns associated with large-scale dams, are making the development of hydropower projects challenging in certain areas. Nevertheless, there are efforts being carried out to counter these obstacles and make the most of this clean, sustainable energy option.

### *1.7.2 Current State of Non-Hydropower Electricity in Africa:*

The utilization of renewable energy in Africa is on the upswing as its numerous benefits and abated costs become broadly apparent. Solar energy holds unique potential in the continent as it experiences abundant sunshine throughout the year. To capitalize on this, a number of countries have begun to construct large-scale solar projects, such as concentrated solar power (CSP) and photovoltaic (PV) installments. Morocco, with its Noor Solar Complex, is a leader in this area - one of the world's largest CSP plants. South Africa's utility-scale PV projects are another noteworthy advancement, helping to significantly increase the nation's renewable energy capability. Moreover, Egypt, Kenya and Namibia are moving to explore the potential of solar energy, working to diversify their energy sources.

Wind energy is a rapidly increasing source of energy in Africa that does not originate from hydropower. Those nations which have advantageous wind conditions, like Egypt, Ethiopia, Kenya, Morocco and South Africa, have been forming wind farms and constructing wind turbines. An example is the Lake Turkana Wind Power in Kenya, a wind power scheme that can generate up to 310 MW of electricity, making it one of the greatest wind power projects on the continent (Mathebula & Mathebula, 2018).

Although limited to certain volcanic areas, geothermal power has plentiful potential in some African nations. Kenya and Ethiopia are two such countries that have been working thoroughly to optimise their geothermal resources. The Olkaria Geothermal Complex in Kenya is currently estimated to be the largest of its kind in the complete continent. It is stated that this particular energy source has exponentially increased the national share of the renewable energy supply (Kone & Khandi, 2017).

## 1.8 Challenges and Opportunities Facing Hydropower and Non-Hydropower Development in Africa:

In spite of the latent prospective of hydropower and alternate resources of electricity for the African continent, there are certain challenges to their development. For example, funds allocated to the infrastructure and the energy industry in Africa are unsatisfactory, a fact that yields to the insufficiency of electricity for a large portion of the continent’s inhabitants (Ahmed et al., 2018). Moreover, economical inconsistency, dishonesty, and the lack of responsive regulatory mechanisms make it challenging for private investments to flow into the energy industry.

One of the major challenges facing hydropower development is the impact of climate change. The variability in precipitation, increasing temperatures, and the rising necessity for water usage for agricultural and metropolitan activities can affect the provision of water available for powering hydroelectric sources. Also, other renewable energy sources such as wind and solar energy are also prone to climate fluctuations, including those on the velocity of wind and the amount of cloud covering, which can impact their energy production (Akintola & Midzi, 2021). Consequently, it is important to account for potential effects of climate change while planning hydro-power projects, and come up with methods to address their related impacts.

The African continent is overflowing with potential when it comes to the development of its energy sector. With the right strategy and infrastructure, the opportunities that exist in this region are vast and can be harnessed to great effect. While there are current issues to be addressed in terms of limited resources and access, the potential for exponential growth in the sector is undeniable. By taking proper steps to ensure greater accessibility and more efficient usage of resources, African countries can open up pathways to greater economic, social and environmental benefits.

The Congo River basin presents an opportunity for the development of hydropower, while the Sahel region has great potential for solar energy. Although these options may not come without difficulties, the rising demand for energy and the need to reduce energy poverty gives investors an opportunity. With the advancements in technology, clean energy sources are becoming far more affordable and sustainable. This improvement in technology has presented an ideal opportunity for Africans to benefit from clean, cost-effective energy.

Overall, it is essential to approach the struggles highlighted from hydropower and non-hydropower design in Africa to maximize the reasonable starts available. A better understanding of the climate parameters on these energy sources can make indicators for investment choices and policy-making to insure reliable energy growth on the continent. Machine learning, mathematical Models, and statistical indices can compromise support in this understanding, and a comparative analysis of hydropower and non-hydropower origins can benefit distinguish their definite prospect and obstacles.

## 1.9 Energy Demand in Africa

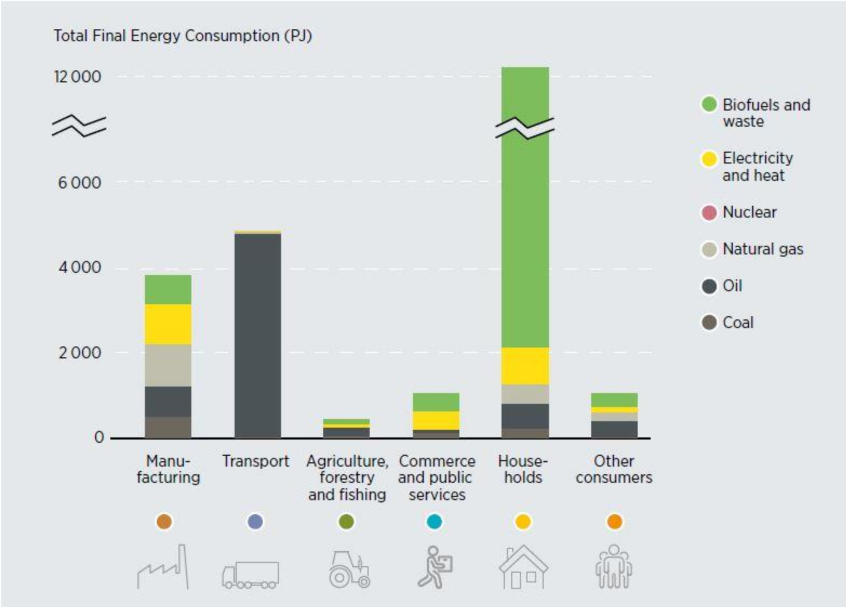
The continent of Africa has witnessed a significant period of economic growth in recent years. This growth is mainly driven by increased demand for energy to fuel industrial, commercial, and residential activities. It is projected that energy demand in the African region is set to increase by around 60% by 2040, mostly attributed to population growth and urbanization (World Bank, 2020). The challenge facing Africa in decreasing the energy production is significant, as a limited and often unreliable electricity supply is accessible in the region.

### *1.9.1 Current State of Energy Demand in Africa:*

The current incompatible state of access to electricity in Africa is a major challenge to economic and societal development. According to a recent measure by the International Energy Agency (IEA), an estimated 600 million people in Africa are in lack access to electricity (IEA, 2017). Moreover, in sub-Saharan Africa, for only 43% of the population has access to electricity (IEA, 2018). This patent variation in access to basic energy resources has substantial implications for the social and economic growth of the continent.

**Figure 3**

*Total final energy consumption in Africa by sector and source, 2018 (Source: IHA, 2022).*




The major form of energy employed across African countries is biomass, accounting around one-half of all the energy produced (UNESCO, 2017). Even though other sources of energy including oil, coal, gas, and hydroelectric power make up the large part of the energy mixture, its distribution is diverse from region to region. As an example, North Africa largely relies on oil while the greater part of energy in Sub-Saharan Africa comes from bioenergy sources (IREA, 2019).

### *1.9.2 Projected Growth of Energy Demand in Africa:*

In line with population growth, rapid urbanisation and industrialisation, the IEA (2018) forecasts a substantial uptick in energy consumption in Africa between now and 2040, predicting an increase of around 60% - the highest rate of growth in the world (IEA, 2017). This development poses various challenges for African countries as they struggle to meet escalating demand while avoiding potential environmental, economic and social consequences.

Africa is projected to have a rapid population growth rate, growing twice in size by 2050 as compared to 2015, as estimated by the United Nations (UN, 2017). This population growth will lead to increased demand for energy, specifically for essential activities such as lighting, cooking and heating.

Urbanization is also accelerating in Africa, where the urban population is expected to surge from 40% in 2015 to 56% by 2050, as stated by UN-Habitat (UN-Habitat, 2017). Urbanization tends to bring about increased energy demand, notably in relation to transportation, commercial and industrial activities.

Furthermore, Africa has seen excellent economic growth, with some countries experiencing annual GDP growth rates beyond 5% (World Bank, 2017). Thus, industrialization such as mining, manufacturing and construction activities will no doubt result in a heightened needs for energy resources.

# CHAPTE II
# Literature Review

## 2.1 Introduction

Energy is a vital necessity for the development of humans and the African continent is experiencing a rise in its energy necessity due to the growth in population and economic growth. There is a plethora of renewable energy sources present in Africa, such as hydropower and non-hydropower sources such as solar, wind, and biomass. However, climate change is having a drastic effect on the stability and reliability of these resources, especially hydropower, which heavily depends on access to water and rainfall levels.

The African continent is especially prone to the consequences of global warming, with temperatures predicted to be 1.5 degrees Celsius occasions greater than average world-wide (IPCC, 2017). What is in store for areas is a discrepancy of precipitation patterns, some regions likely to get flooded while other regions experiencing dry seasons harshly. This will be disastrous for energy production, particularly hydro and non-hydroelectricity.

To guarantee the long-term development of the African energy segment, it is important to comprehend the effect of climate change on hydropower and non-hydropower sources. This comprehension can be accomplished through the examination of the climate parameters that sway vitality creation. This literature review will investigate the current condition of research on hydropower and non-hydropower power in Africa and the effect of climate parameters on the energy generation.

This review will focus on studies utilizing machine learning models, such as Multilayer Perceptron Neural Networks (MLPNN) and Radial Basis Function Neural Networks (RBF), to predict hydropower and non-hydropower electricity production. Machine learning approaches present an advantage in their aptitude to predict intricate relationships between climate parameters and energy generation. This review will focus on the influence of climate change on electricity production through hydropower and non-hydropower sources in Africa.

It will compare different machine learning models against traditional mathematical models, such as Multiple Linear Regression (MLR), to explore which offer the most effective prediction. Statistical metrics such as R-Squared (RSQ) and Root Mean Square Error (RMSE) will be employed to evaluate the significance of climate parameters on energy production. The purpose of this review is to provide an insight into how climate change is affecting electricity sources in Africa.

**2.2 Climate change Issues**

Climate change is an exceptionally pressing issue for Africa's energy sector, particularly hydropower. It is the main source of renewable energy for the continent, however increasingly unpredictable changes in quantity of water available due to high rise temperatures and shifts in rainfall patterns create a greater necessity for the hydropower industry to adapt. The climate changes brings with them the potential for serious difficulties in power generation. This review of the relevant literature examines the impact that climate change has on hydropower production in Africa.

A recent research done by Ghebreyesus et al. (2019) investigated the effect of climate change on the hydro power capability in the Blue Nile River basin in Africa. The investigation utilized climate estimates from different models and found that hydropower potential in the basin is probably going to degrees by up to 50% due to adjustment in precipitations designs. Moreover, Hamududu et al. (2016) additionally took a look at the result of climate change on the Zambezi River basin, where numerous huge hydropower dams reside in Southern Africa. The study employed climate forecasts to replicate shifts in stream flow discovering hydropower creation in the basin probably will reduce by up to 26% toward the century's end.

Temperature is one of the most important elements of climate that has a direct effect on energy production. Hrishikesh et al. (2014) conducted research to evaluate the effect of temperature on hydropower production in Cameroon and applied machine learning models to the analysis. The results indicated that with every increment of one degree Celsius the hydropower production fell by 8.2%. Another study by Charles et al. (2016) focused on the impact of temperature on non-hydropower energy production, namely solar and wind energy, in Zimbabwe.

This research used statistical methods to examine the correlation between temperature and energy production. The results of this study agreed with prior studies that demonstrated a rise in temperature causes a decrease in solar and wind energy generation.

The Al Jindy et al. (2020) assessed the impact of relative humidity on hydropower generation in Egypt from a statistical standpoint. They found indication that high levels of relative humidity can have a detrimental impact on hydroelectric power production due to a lesser rate of evaporation as well as reduced water motion. These results indicate the value of taking relative humidity into account when determining the probable capacity of hydroelectric energy.

A research study conducted by Dongmo et al. (2021) Analysed to determine the connection between wind speed and hydropower production in Cameroon. To do this, the researchers utilized statistical models to examine the relationship between these two factors. Results of the study revealed that higher wind speeds can aid in enhanced hydropower generation by increasing the amount of water that flows.

Ntale et al. (2020) performed a study using machine learning models to analyse the impact of precipitation on hydropower output in Uganda. The findings indicated a noteworthy connection between rain magnitude and hydropower output, with diminishing of as much as 40% when weather conditions were drier. This research could aid in assisting energy companies anticipate reductions in hydropower production when arid eras come about.

A study by Nzeadibe et al. (2020) explored the renewable energy sources in Nigeria by comparing the potential of hydropower and non-hydropower renewable energy sources, the study utilized data provided by the Nigerian Meteorological Agency. The article concluded that solar and wind energy were plentiful enough in the region to drive a successful alternative energy system.

### 2.3 Energy Issues - Hydropower and Non-hydropower of Africa (Hydropower, Non-hydropower)

In Africa, electricity supply is largely inadequate and unevenly distributed, and is a major challenge to socio-economic development. Recently, growth and development in Africa have been accelerating at a rapid rate, thus further increasing the energy demand in the continent. However, numerous problems in the energy sector exist for the African countries, such as a lack of appropriate infrastructure, inadequate administration, and the climate consequences of global warming. In light of these difficulties, this research aims to explore the challenges and opportunities associated with the production of hydropower and non-hydropower energy in Africa. Through describing the current state of the energy sector and identifying potential solutions to the obstacles, this literature review will showcase how Africa could optimally meet its energy requirements.

Hydropower is seen as the most favoured source of renewable energy across the continent of Africa. As per the International Hydropower Association, the potential to generate above 400 gigawatts of energy from hydropower lies in Africa. Regrettably, just a fragment of this potential has been beneficial due to the constraints of its own sector. One of the leading challenges is the consequence of the climate change on the hydro-production, which may result in depleted water availability and subsequent transformation in the period and power of precipitation. This can lead to minimized hydroelectricity production or even to the full closure of the hydro-power plants, particularly during dry spells.

Research has been conducted regarding the effects of climate change on hydropower in Africa. According to the research executed by Lazin (2020), a decrease in the average annual hydropower production by 16% by 2100 can be expected due to future climate change. Another study conducted by Guo et al. (2018) focused on the impact of climate change on the hydropower potential of the Zambezi River Basin. The results suggested that climate change could potentially reduce the hydropower potential of the basin by 25% at the end of the century.

Generation of electricity in Africa can often be supplied through sources other than hydropower. Fossil fuels are the most popular choice for African nations, yet their use is not conducive to a sustainable future, as this can have detrimental health and environmental effects. The renewable sources of energy that provides a sustainable and reliable energy are geothermal energy, solar energy, and also the wind energy which are the common electricity generation used in Africa. However there is a difficulties to implement these sources due to its investment demand expense and also the inappropriate regulations and lows. Also there is a need to implement strong policy ad regulations agendas to encourage the development of the renewable energy sources in the African continent.

A study discovered the potentials of the non-hydropower electricity in the continent. Amuakwa Mensah et al. (2017) analysed the stability and sustainability of the solar and wind energy production in Ghana, the study concluded that the analysis of the electricity sources that the Ghana needs could be produced by using these energy sources. A study by Oyedepo (2017) looked at the potential of geothermal energy as a sustainable source for East Africa, suggesting the need for exploration and development in order to maximize its power potential. In addition, Yamba et al. (2011) assessed the vulnerability of hydropower generation in the Zambezi River Basin to climate change by using a hydrological model. This showcased the gravity of climate impact, which could result in reduction of hydropower by up to 33% by 2050.

A study by Yohannes et al. (2018) explored the influence of global warming on wind power potential in Ethiopia. Their results demonstrated that increasing temperatures and modifications to precipitation patterns might have a notable negative impact on Ethiopia's wind power potential, which would hinder energy protection and economic growth. Apart from climate change, other aspects such as policy, infrastructure and investment also play an essential role in the development of hydroelectricity and other forms of electricity in Africa. Mekonnen et al. (2022) conducted another study to ascertain the effects of climate change on the hydropower-dominated energy system in Ethiopia, finding that government assistance, infrastructure advancement and financing were important factors for the victory of hydroelectricity projects.

Finally, electricity generation from both hydropower and non-hydropower sources is a crucial component of energy in Africa; yet, both face significant issues. For instance, hydropower is vulnerable to the effects of climate change, while non-hydropower sources are constrained by industry roadblocks and insufficient investment. To address these needs in a successful and equitable manner, it is essential to invest more in renewable energy sources and improve the legal and regulatory structures to back their growth.

## 2.4 Energy issues by using Machine Learning

The production of energy in Africa is highly sensitive to climate variability and change, therefore it is important to comprehend the link between climate parameters and the formation of energy. In recent years, machine learning models have come to the fore as successful approaches for analyzing immense datasets and predicting intricate connections. By this literature review, we explore how machine learning models have been employed to understand the impacts of climate parameters on hydropower and non-hydropower electricity creation in Africa.

Alemayehu et al. (2021) put forth the use of Multi-Layer Perceptron Neural Network (MLPNN) for predicting the hydropower potential of the Nile basin and found that it outperformed other models such as linear regression and Artificial Neural

Network (ANN). Likewise, Faruk and El-Sayed (2021) used Radial Basis Function (RBF) for predicting the hydropower potential of a river basin in Nigeria and reported that RBF was more effective compared to models such as support vector regression and ANN. Additionally, Zhu et al. (2021) employed MLPNN and RBF to estimate the influence of climate parameters, like temperature, precipitation and wind speed, on hydropower production in Zambia. The results ascertained that temperature and precipitation had a marked effect on hydropower production whereas wind speed had a negligible effect. Evidently, the machine learning models can be advantageous in pinpointing potential hydropower sites across Africa.

Exploring the potential of Machine Learning (ML) algorithms, the effect of climate components on electricity production, both hydropower and non-hydropower, have been analysed in Africa.In a study by Li et al. (2019), a MLPNN was employed to determine the impact of climate phenomena such as temperature, humidity, wind speed, and precipitation on hydropower output in Zambia. Meanwhile, Zhang et al. (2021) looked at the influence of climate parameter on non-hydropower electricity production in Africa, using not just an MLPNN, but also a Multiple Linear Regression (MLR) model. The outcomes of the investigation proposed that temperature average, temperature maximum, and relative humidity had the most extreme consequence on the yield of electricity not associated with hydropower. Comparatievly, temperature and precipitation caused a considerable effect on hydropower output.

Mathematical models such as multiple linear regression (MLR) have been employed to evaluate the linkage between climate parameters and the production of both hydropower and non-hydropower electricity in Africa. Alimi et al. (2020) applied MLR to inspect the consequences of climate factors on hydropower production in Nigeria and came to the decision that temperature and precipitation had an undeniable bearing on hydropower generation. Ouedraogo et al. (2019) also exploited MLR to analyse the effect of climate parameters on non-hydropower electricity production in Burkina Faso. This research observed that temperature and precipitation had the most profound impact on non-hydropower electricity production. Similarly, Hossain et al. (2020) used the MLR model to examine the impact of climate parameters on solar energy production in Ghana. The findings showed that temperature and precipitation had a marked effect on solar energy production, whereas wind velocity had a minimal influence.

Statistical analysis using methods such as R Squared (RSQ) and Root Mean Square Error (RMSE) have been used to evaluate the performance of machine learning (ML) models when applied to the analysis of energy-related issues. Amos and Wu in 2021 utilized MLPNN and MLR to examine how climate parameters affect hydropower production in Ghana - the results recovered demonstrated that MLPNN had exceeded MLR in predictions of hydropower production, and the trends of RSQ and RMSE displayed that MLPNN presented a higher accuracy than MLR.

The utilization of Machine Learning (ML) models has demonstrated significant potency in evaluating the influence of climatic conditions on energy production in Africa, ranging from non-hydropower to hydropower energy sources. Neural Network Models (MLPNN), Radial Basis Function (RBF) and Multiple Linear Regression (MLR) provide useful empirical evidence to predict energy output with both temperature and precipitation as the major determinants. Additionally, statistical models such as Root-mean Square Error (RMSE) and R-squared (RSQ) have been applied to evaluate the performance of machine learning models. Even though these models have shown promising results with synthesizing productive estimations of energy production, further research is indispensable to comprehend their comprehensive potential of ascertaining energy productivity under various regional and climate conditions.

# CHAPTE III

# Methodology

In this chapter we will discuss the methodologies flowed started from the study area, datasets and the empirical models used in the study.

## 3.1 Study Area

The African continent has consistently grown in size and stature but faces a major problem in terms of access to reliable and affordable sources of energy. As the rate of population increase and the plan for economic growth is continuously developing, the demand for power is developing drastically forcing the need for efficient energy production to be considered. An understanding of the components and effect of electricity production related to hydropower and non-hydropower sources is essential to make responsible and sustainable energy plans and policy formulations across Africa. The numerous resources can be utilised for this purpose and to accommodate for the rising energy requirements of the continent.

**Figure 4**

*The map shows the African continent with all African nations, international borders, national capitals, and major cities in Africa, (Source: NOP)*


In recent years, global climate change has begun to have a serious impact on all aspects of life, ranging from the environment and economic development to human well-being. Unfortunately, Africa is no exception to this; the continent is expected to suffer particularly greatly due to its reliance on traditional methods of subsistence agriculture and other activities that are highly sensitive to alterations in temperature and rainfall. Consequently, climate change is set to cause a sharp increase in poverty and food insecurity (UN, 2018). Worryingly, Africa additionally does not possess the resources or infrastructure to help counter these effects (Kelly et al., 2019).

Africa is an incredibly diverse area of the world, making it an ideal place to investigate how climatic parameters influence both hydropower and non-hydropower electricity production. Temperature and precipitation all play a role in the amount of water available to power hydropower plants, as well as the need for electricity generated by other sources. Africa is the second most populous and second largest contingent on the planet, with a population of an estimated 1.3 billion in 2020 (UNDESA, 2021).

Spanning across the Mediterranean Sea to the north, the Red Sea and Indian Ocean to the east and south, and the Atlantic Ocean to the west, the continent is composed of fifty-four sovereign countries - the northernmost being Morocco and Tunisia, and the southernmost being the South Africa (World Bank, 2020).

The nations of the African continent are broken down into five main areas: the north, east, west, centre, and south.

North Africa consists of seven nations: Algeria, Egypt, Libya, Morocco, Sudan, Tunisia and Western Sahara. These countries are positioned in the Mediterranean Sea, the Red Sea and the Atlantic Ocean. Across North Africa, a diversity of climates can be experienced, ranging from scorching desert to balmy conditions.

West Africa consists of sixteen countries: Benin, Burkina Faso, Cape Verde, Cote d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, Togo, and Mauritania. This region shows a variety of distinct cultures and languages. It is a vibrant and diverse region with sites, streets, and people of different origins.

East Africa has established itself in the wildlife and landscape arenas with classics such as the Big Five and majestic Mount Kilimanjaro and its plain. Spread across thirteen countries which are Burundi, Djibouti, Eritrea, Ethiopia, Kenya, Malawi, Mauritius, Rwanda, Seychelles, Somalia, Tanzania, Uganda and South Sudan. The area is resplendent with lush rainforests and immense deserts. This is only the beginning of the endlessly wondrous attributes of the land: its home to over 120 different ethnic groups, each of whom have brought their own customs, cultures, and beliefs to the region. From its sprawling coral reefs to its verdant savannas, East Africa is a spectacular study in biodiversity.

Central Africa, composed of nine nations, is recognized for its rainforest, untamed animals, and lowlands. These countries consist of Angola, Cameroon, Central African Republic, Chad, Democratic Republic of Congo, Equatorial Guinea, Gabon, Republic of Congo, and Sao Tome and Principe.

Southern Africa consists of nine countries including Botswana, Lesotho, Namibia, South Africa, Swaziland, Zambia, Zimbabwe, Mozambique, and Madagascar, Comoros. Its landscape is marked with sizable deserts, verdant savannas, different species of wildlife, and subtropical climes.

### 3.2 Datasets

Since there are not many African-specific datasets, researchers have had to resort to using data from other dataset around the globe to investigate the impacts of climate parameters on hydro- and non-hydropower electricity production in Africa. This approach has enabled them to draw insights from the gathered datasets and draw conclusions that are applicable.

For this research, two primary databases will be utilized for data collection: NASA's Prediction of Worldwide Energy Resources (POWER) and U.S. Energy Information Administration (eia), with data from 1981 through 2021. These sources of dataset were combined to create a unified dataset of climatic parameters at annual level for each country in Africa, along with their corresponding production of electricity from hydropower and non-hydropower sources. With this aggregated information, the collective effects of climate factors on energy production in Africa will be analysed.

### 3.3 Satellite Data

Utilization of satellite data is essential for evaluating the contrast between energy generated from hydropower and that generated from other sources in Africa in addition to other parts of the world. Two major sources of satellite datasets which can be utilized in light of electricity and climate are NASA Prediction of Worldwide Energy Resources (POWER) and U.S. Energy Information Administration (eia) database. Through said data, a better understanding of the global and regional climate conditions and its impact on hydropower and non-hydropower electricity generation can be unearthed.

The NASA POWER dataset is a source that utilizes satellite data to observe the climate parameters and nearby land surfaces worldwide. The accumulated climate observations in combination with global climate models can generate estimates of monthly average electric demand and emittance of power plants. Analysing the climate parameters effects on hydropower and non-hydropower electricity generation can be monitored according to the data retrieved from the satellites.

The U.S. Energy Information Administration (EIA) is a reliable source of energy-related data collected from satellites. This data can be used to assess the utilization and generation of energy among the globe, particularly in Africa. The records allow patterns of energy consumption and output to be established, which can then be used to detect any changes induced by climatic conditions to hydro- electrical and non-hydro- electrical production.

Utilizing satellite data can be extremely beneficial in monitoring changing climate conditions in Africa. Gathering information on parameters such as temperature, precipitation, wind speed and solar radiation can enable researchers to analyze changes in hydropower resources and compare electricity production through hydropower and non-hydropower sources. NASA's POWER and eia data banks are great sources of data for worldwide research, and by juxtaposing these datasets localized insights can be gained. This analysis is even more critical now as climate change can have significant effect on energy production.

### 3.4 Accuracy of satellite products

Analyzing the accuracy of satellite products from sources such as NASA's Prediction of Worldwide Energy Resources (POWER) and the U.S. Energy Information Administration (eia) databases is critical for a proper comparison through a global perspective when looking at hydropower and non-hydropower sources of electrical generation, as the climate conditions that characterize the African continent can have a direct effect on the production of power.

Analyzing the accuracy of satellite products against in-situ data in Africa is an important task. Such an analysis could compare the satellite-derived values for temperature maximum and minimum, relative humidity, wind speed and precipitation with those derived from manual measurements taken on-site using temperature and humidity sensors, wind vanes and precipitation gauges. It could also involve looking to see if there is a long-term consistency in terms of spatial and temporal trends with the satellite-derived estimates, to ensure that they are accurate over a long period. Through this type of assessment, Koumandou et al. (2020) demonstrate the importance of assessing the accuracy of satellite products against statistical data from the region.

The accuracy of satellite products in monitoring climate-related changes in terms of their ability to detect changes in variables which affect electricity production in Africa will be assessed. For instance, the data from the satellites as opposed to the measurements on-site can be probed as methods for monitoring alterations in climate factors including temperature avrage, temperature maximum, temperature minimum, relative humidity and wind speed. The accuracy of satellite-generated estimations of these parameters can then be reviewed against on-site recordings.

In conclusion, viable data about the effects of a contrast between hydroelectricity production and non-hydroelectric interest in Africa can be acquired from usable satellite items, such as those accessible from NASA's Prediction of Worldwide Energy Resources (POWER) and the U.S. Energy Information Administration (eia) datasets. Estimations of this kind of data are key to improving the exactness of environmental models and anticipating instruments whose dependability and soundness depend vigorously on how precisely the variables and models are depicted.

### 3.5 Empirical Models

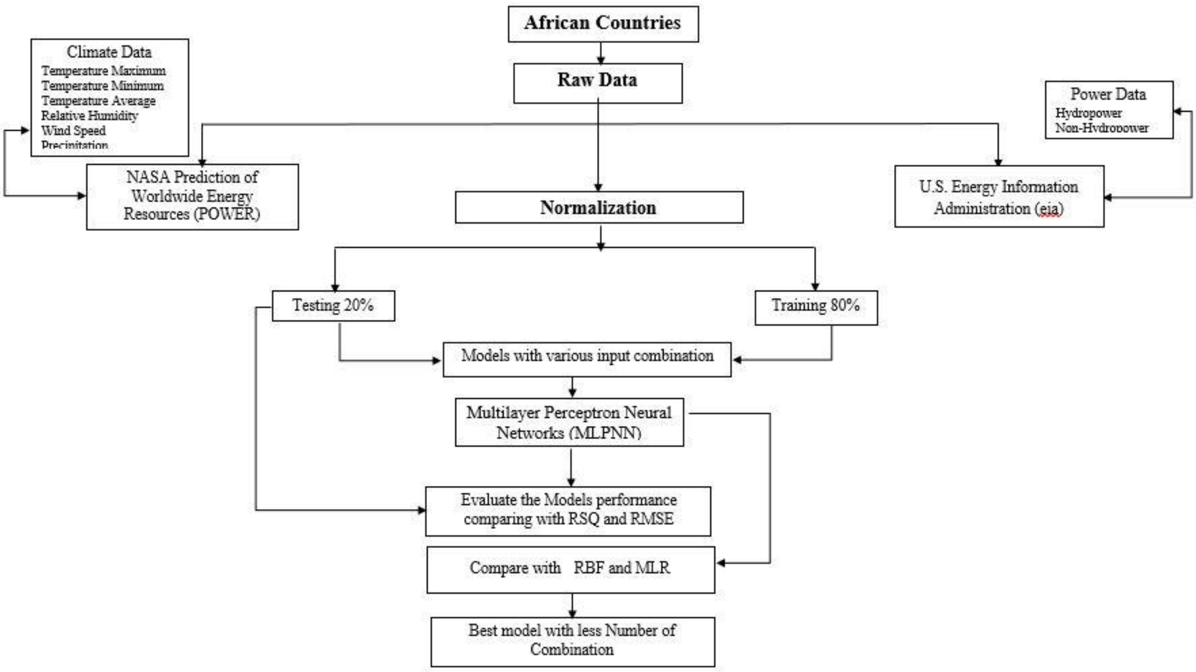
In this research, two machine learning models employed, Multi-layer Perceptron Neural Network (MLPNN) and Radial Basis Function (RBF), were used to analyse the impact of climate parameters on hydropower and non-hydropower electricity production in the African continent. These models were then compared to the results from the traditional mathematical models such as multiple linear regression. The climate parameters analyzed in the study included temperature average, maximum and minimum, relative humidity, wind speed, and precipitation.

The datasets were divided into training and testing sets with 80% of the data for the training set and 20% for the testing set. The results of the MLPNN and RBF models were compared against the results generated from the mathematical models to determine which climate parameters had the most influence on the electricity production.

The success of the two machine learning models is measured using Root Mean Square Error (RMSE) and coefficient of determination (R-Squared). The distinctions between the prediction accuracy of the two machine learning models and the capabilities of mathematical and statistical models are examined in the context of electricity production throughout the African continent. The findings of this study can help in enhancing understanding and assessing hydropower and non-hydropower electricity production in Africa.

**Figure 5**

*Shows the Flowchart of the models of the study.*




## 3.6 Artificial Neural Networks (ANN)

Artificial neural networks (ANNs) are advanced computational models that are capable in expressing complex and non-linear datasets. They are made up of connected sets of nodes that imitate the estimation of neurons in the brain and are utilized mostly in data categorization and prediction tasks. They are greatly analogous to other data assessment approaches such as linear regression and logistic regression, the main distinction being that they have the capability to represent complex and non-linear correlations (Kassem & Gökçekuş 2021).

The use of Artificial Neural Networks (ANNs) to anticipate future energy output from hydroelectric and non-hydroelectric sources in Africa is a viable solution. The ANN model analyses a range of climate-related factors such as latitude, longitude, altitude, annual values of temperature average, temperature maximum, temperature minimum, relative humidity, wind speed and precipitation.

The performance of predicting future energy production in Africa can be improved through the use of Artificial Neuron Networks. These systems can be categorized into two major groups, Multi-Layer Perceptron Artificial Neural Networks (MLPNN) and Radial Basis Function (RBF). Climate parameters such as precipitation, temperature, wind speed, humidity levels, and obstacles to economic development are all taken as inputs to the model. From this, the output of electricity generated from hydro-generated sources and other sources can be estimated. By using Artificial Neurons Networks, the accuracy of predictions of future energy production can be greatly improved.

MLPNN is a feed forward neural network system, which allows data flow in one direction only, from input to the output phase. RBF neural networks are non-linear, meaning that the neuron weights can affect the results. (Viljoen et al., 2019).

### *3.6.1 Multi-Layer Perceptron Neural Network (MLPNN)*

The multi-layer perceptron neural network (MLPNN) is a form of artificial neural network for creating models of complicated and non-linear processes in the practical world (Xu et al. 2022). It is composed of an output layer, one or multiple concealed layers and an input layer (Kavzoglu and Mather 2003, Kassem, Y. 2023). These components take up particular jobs that when joined together can create profound learning calculations for tackling complex issues such as picture observation and sound handling tasks.

The MLPNN is used for function modelling when we have two predicted variable which can be represented by the equation:

MLPNN with Hyperbolic Tangent (Tanh) Activation Function:

$$Y_1 = b_{11} + \sum \left( w_{11i} \times \tanh \left( b_{10} + \sum \left( w_{10ij} \times X_j \right) \right) \right) \quad (1)$$

$$Y_2 = b_{12} + \sum \left( w_{12i} \times \tanh \left( b_{10} + \sum \left( w_{10ij} \times X_j \right) \right) \right) \quad (2)$$

Y1 and Y2 are predictive variables, with Xj being the input variables. Weights representing the connection between the input layer and the hidden layer are w10ij and w11i, and the link between the hidden layer and output layer is depicted by w12i. B10, b11, and b12 denote the bias terms for the hidden layer as well as output layers linked to the each observed predictive variable.

MLPNN with Sigmoid Activation Function:

$$Y_1 = b_{11} + \sum \left( w_{11i} \times \text{sigmoid}\left( b_{10} + \sum \left( w_{10ij} \times X_j \right) \right) \right) \tag{3}$$

$$Y_2 = b_{12} + \sum \left( w_{12i} \times \text{sigmoid}\left( b_{10} + \sum \left( w_{10ij} \times X_j \right) \right) \right) \tag{4}$$

Y1 and Y2 are the predicted variables, and Xj is the input variable. The weights between the input and hidden layers for each of the predicted variables are denoted as w10ij and w11i, while those between the hidden and output layers are represented as w12i. Lastly, the bias terms for the hidden and output layers for each of the predicted variables are specified as b10, b11, and b12.

MLPNN with Identity Activation Function:

$$Y_1 = b_{11} + \sum \left( w_{11i} \times \left( b_{10} + \sum \left( w_{10ij} \times X_j \right) \right) \right) \tag{5}$$

$$Y_2 = b_{12} + \sum \left( w_{12i} \times \left( b_{10} + \sum \left( w_{10ij} \times X_j \right) \right) \right) \tag{6}$$

The intertwined layers of the Neural Network are modelled with the following equation: Y1 and Y2 are the predicted variables, while Xj denote the input variables. The weights between the input layer and the hidden layer for each predicted variable are defined as w10ij and w11i, and those between the hidden layer and the output layer are named w12i. Further, b10, b11, and b12 specify the bias terms for the hidden layer and output layer for each predicted variable.

The Root Mean Square Error (RMSE) is often used as the objective function during training of the Multi-Layer Perceptron Neural Network (MLPNN). In order to optimize its performance, the Back Propagation algorithm is employed. The diagram below demonstrates the analytics utilized for the MLPNN model:

Figure 7: Shows the results of the analysis of the MLPNN model the deference in between observed and predicted values.

The MLPNN model can be used to analyse the hydropower and non-hydropower electricity production in Africa with the help of machine learning models together with mathematical and statistical models (Mukhopadhyay, 2017; Akintunde et al., 2018; Chanko et al., 2019). This analysis involves the climatic parameters such as temperature average, temperature maximum, temperature minimum, relative humidity, wind speed, and precipitation to determine the climate parameter that is the main contributor to hydropower and non-hydropower electricity production in Africa (Chen et al., 2021).

The MLPNN can be used to evaluate the relations between climatic parameters and electricity production from different sources, and then the performance of the MLPNN can be compared to that of other models with the application of mathematical and statistical analysis. The results of this research can embark on informing policy decisions on the approaches best suited to enhance or preserve electricity production in Africa.

### *3.6.2 Radial Basis Function Neural Network (RBFNN)*

RBF Neural Networks (RBFNNs) can provide an effective means of detecting relationships between climate parameters and electricity generation, particularly for the comparison of Hydropower and Non-hydropower in Africa (Hussain et al., 2021). The architecture of an RBFNN consists of three layers: input, hidden and output. In the hidden layer, the radial basis function (RBF) is employed and a linear function is utilised in the output layer, (Ismael et al., 2021).

Through the data gathered, weights can be generated for the testing stage to evaluate the model's accuracy.

These weights are calculated by two equations:

Calculate the weights for the hidden layer:

The weights for the hidden layer determine the importance of each input feature for the RBFNN. We use the Gaussian RBF to calculate the weights for the hidden layer:

$$w_{ji} = \exp\left(-\gamma \left\| x_i - c_j \right\|^2\right) \tag{7}$$

Where $w_{ji}$ is the weight between the ith input and the jth hidden unit, $x_i$ is the ith input, and $c_j$ is the center of the jth RBF. The parameter $\gamma$ determines the width of the RBF. The hidden layer consists of n radial basis functions, with each RBF centered at a different point in the input space. The weights for the hidden layer are calculated using the Gaussian RBF for each input feature. (Kassem, Y. 2023)

Calculate the weights for the output layer:

The weights for the output layer determine the relationship between the hidden layer output and the target values for the training data. We use the pseudo-inverse of the hidden layer output to calculate the weights for the output layer:

$$\mathrm{W} = \mathrm{pinv(H)} \times \mathrm{Y} \qquad (8)$$

Where W is the weight matrix for the output layer (2 x m), H is the matrix of the hidden layer output (n x m), Y is the matrix of target values for the training data (n x 2), and pinv(H) is the pseudo-inverse of H. (Hansen and Daviau, 2021)

In simpler terms, we use the hidden layer output matrix (H) and target values matrix (Y) to calculate the weight matrix (W) for the output layer using the pseudo-inverse operation. (Löfberg and Kennedy, 2022)

Once we have calculated the weights for the hidden and output layers, we can use the RBFNN to predict the output for new input data using the following equation:

$$\mathrm{Y} = \mathrm{W} \times \varphi\left(\left||\mathrm{x} - \mathrm{C}|\right|^2\right) \qquad (9)$$

Where Y is the output vector (2 x 1), W is the weight matrix for the output layer (2 x m), $\varphi(\|x - C\|^2)$ is the vector of RBF outputs for the input x, and C is the matrix of RBF centers (m x p).

RBFNNs boast many advantages, such as universal approximation abilities, not having a local minimum problem, and a faster learning algorithm. This makes it a great tool to identify and analyze the correlations between climate parameters and electricity production, and subsequently compare the impact of climate parameters on Hydropower and Non-hydropower electricity production in Africa (Diagne et al., 2017; Koussoni et al., 2019).

### 3.7 Multiple Linear regression (MLR)

The Multiple Linear Regression (MLR) model can be used to analyze the relationship between the various climatic parameters and the electricity generation through hydropower and non-hydropower sources in Africa. The explanatory or independent variables in this analysis include the average temperature, maximum temperature, minimum temperature, relative humidity, wind speed and precipitation. The dependent variable is the electricity production using hydropower or non-hydropower sources. The objective is to ascertain which climatic factor yields the most pronounced outcome on electricity generation (Shang et al., 2017).

$$\mathrm{Y} = \beta_0 + \beta_1 \times X_1 + \cdots + \beta_\mathrm{n} \times X_\mathrm{n} \qquad (10)$$

The MLR equation can be used to calculate the parameters $\beta_0$ through $\beta_n$, which will give us the linear equation for the electricity production. These parameters can then be used to predict the electricity generation for hydropower and non-hydropower sources in a given region.

Where Y: Dependent variable or response variable,

$\beta_0$: Intercept or constant term,

$\beta_1$, $\beta_2$... $\beta_n$: Regression coefficients or slopes for the independent variables $X_1$, $X_2$, $X_n$.

$X_1$, $X_2$... $X_n$: Independent variables or predictors.

n: 1,2,3……..n.

The results from the multiple linear regression (MLR) analysis can be compared to the results from other predictive models, such as MLPNN and RBF, in order to discover which climatic parameter have the most significant impact on electricity production in Africa. This comparison of models will enable further understanding that can inform efficient policy decisions related to energy production across the continent.

## 3.8 Statistical Analysis

The Coefficient of determination (R2) and root mean squared error (RMSE) are used to determine the statistical indices of the predictive models for Hydropower and Non-hydropower electricity Production in Africa. These indices indicates how close the model is to the actual data in order to measure the accuracy of the prediction.

In order to assess the performance of the models devised in order to predict the hydropower and non-hydropower production in Africa, Coefficient of determination (R ^ 2) and root mean squared error (RMSE) are adopted. These indices of statistical used to evaluate the accuracy of the model to the data. So, the observed values and predicted values are compared mostly by these methods. The calculation equations for these statistical metrics are written in Eqs. (11) and (12). They are used to analyse the capability of mathematical models and empirical models to make a predictions to the energy production in Africa.

### *3.8.1 R-squared (RSQ)*

R-squared also known as the coefficient of determination denoted by ($R^2$) is a broadly used statistical metric to assess the performance and the accuracy of the generated empirical models. R-squared is a measure that explains the degree of variation in the observed data, while the higher value indicates the better performance of the model. Gökçekuş and Kassem (2021) showed that as the R-squared value increases and the root mean square error decreases, thus it reflects a more accurate model. The best model performance approach is for the R-squared close to one, while the root mean squared error is close to zero. This statistical indices can help compute the accuracy of the predicted hydro and non-hydro electricity generation in Africa.

$$R^2 = 1 - \frac{\sum(\mathrm{yi} - \hat{\mathrm{y}}\mathrm{i})^2}{\sum(\mathrm{yi} - \bar{\mathrm{y}})^2} \qquad (11)$$

Where yi is the observed value of the observed data, ŷi is the predicted value in the analysis, and ȳ is the mean of the observed values of the model.

The R-squared is utilised to analyse the accuracy and the performance of the observed set of data points. The R-squared value is a measure that ranges from 0 to 1, the higher value close to 1 the higher the accuracy of the model of the observed data as describes. The value which is close to 0 indicates that the model doesn't has a descriptive power, while the one close values performs the correspondence between the models and the data points.

### *3.8.2 Root Mean Square Error (RMSE)*

RMSE- Root mean square error is an important statistical metric that employed to assess the performance and accuracy of a regression model. It functions as a tool for estimating the average discrepancy between predicted values and observed values from the dependent variable.

The RMSE can be used to analyse and evaluate the adequacy of the model as well as the degree of the data fit to the model. This calculation can be done by utilizing the following equations:

$$\mathrm{RMSE} = \frac{\sqrt{\left(\left(\frac{1}{\mathrm{n}}\right)\sum_{i=1}^{n}(\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i})^2\right)}}{\left(\frac{1}{\mathrm{n}}\right)\sum_{i=1}^{n}(\hat{\mathrm{y}}_\mathrm{i})^2} \qquad (12)$$

Where n is the number of observations, $y_i$ is the actual value of the dependent variable, and $\hat{y}_i$ is the predicted value of the dependent variable.

RMSE- Root mean square error is utilized to analyse the difference between the observed and predicted values in different empirical models. The value of the RMSE usually is in between 0 to infinity, with the lowest and closes to zero is the most accurate model. Regardless its benefits of being a sensitive to the out layers, the RMSE can be affected by the measure of the dependent variable. To describe this, a normalization techniques can be used to ensure the errors made by the indecisive.

# CHAPTER IV
# Discussion and Results

This chapter will discuss the results, training of the models, testing of the models and the discussion.

## 4.1 Characteristics of satellite data

### *4.1.1 NASA Prediction of Worldwide Energy Resources (POWER):*

The NASA POWER database is a wide-ranging assembly of global meteorological and solar energy related data established from away observations, atmospheric and climate station information, and models. It offers a broad gathering of climatic points of interest, like temperature, humidity, wind speed and precipitations which are essential for understanding the impact of climate parameters on producing electricity. The dataset provides researchers with accessible climate data that are steady and trustworthy for various regions. Particularly, it covers a wide range of areas in Africa.

### *4.1.2 U.S. Energy Information Administration (EIA) Database:*

The U.S. Energy Information Administration (EIA) owns an extensive database with energy-focused data. This database is beneficial for many researchers, especially when comparing and studying electricity production trends in various geographic zones across Africa. Furthermore, scientists are able to apply climate-based data alongside the energy production data from the U.S. EIA to identify the correlations between climate parameters and electricity production levels in different regions. Exploring these influences is essential for garnering a better understanding of how the climate and electricity production are linked.

### *4.1.3 Data Accessibility and Availability:*

NASA POWER and the United States Energy Information Administration (EIA) make commonalities of data available to the public surrounding satellite and energy-related topics. From this datasets, a substantial quantity of data is easily obtainable. These datasets are observed as reliable and appropriate by the scientific community, thus making them available to the research community to work on them. For instance, one can utilize machine learning, mathematical, and statistical models to better understand the impact of climate change on the generation of electricity production from hydropower and non-hydropower sources in Africa. Consequently, a more comprehensive understanding of their relationship can be accomplished.

## 4.2 Dataset Split:

The dataset is divided into two sections, a training set and a testing set. During the training set of the models, only the training set will be utilised; the testing set remains unseen. The training set is used to help model the information and instruct the algorithm while the unseen testing set is left to evaluate the strength of the final model.

### *4.2.1 Training*

For training purposes, 80% of available data is used to train models. When exposed to the training dataset, machine learning models adjust parameters and optimize them to decrease errors between the predicted and observed electricity production values. In the training phase, MLPNN and RBF carry out an iterative process to achieve accuracy based on the training data (Forootan, 2022). Moreover, MLR model captures relationships between climate parameters and electricity production by calculating coefficients (Adam Hayes, 2023). The coefficients are modulated using mathematically calculated training data.

### *4.2.2 Testing*

Once the models have been trained and validated, they can be tested using the remaining 20% of the data, which contains unseen material. The aim of this testing is to determine the models' capabilities with regards to generalization and their accuracy when predicting electricity production according to climate factors. Evaluation of the models' performance on the testing set will allow for comparisons to be made in order to determine the most effective model.

Performance metrics such as the coefficient of determination (R-squared) and root mean squared error (RMSE) can be used to assess the accuracy and predictive power of the models. These metrics help to measure the ability of the models to capture the relationship between climate parameters and electricity production (Che Wan Zanial, et al, 2023). They provide a better understanding of the models' ability in predicting electricity production.

## 4.3 MLPNN

### *4.3.1 Input Variable selection using MLPNN*

The selection of input variables for the Multi-layer Perceptron Neural Network (MLPNN) is a key element of the analysis of the effects of climate on hydroelectric and non-hydroelectric electrical power in Africa. The data necessary for the study was sourced from the NASA World Energy Resources Prediction (POWER) and the US Energy Information Administration (eia) databases. Gathering a useful dataset of input variables for the MLPNN model is an important part of the overall evaluation.

In this study, the efficacy of using MLPNN to evaluate the impact of the climate parameters, input parameters such as LAT, LONG, ALT, Y, TAV, RH, WS, TMAX, TMIN and PRE are used to determine the most important parameters. To obtain the most effective models, 1023 MLPNN models with various input combinations were produced and the performances or the accuracy of these models were monitored by using statistical indices. It was discovered that the Hyperbolic Tan Function (Tanh) was the most suitable activation function, and the number of neurons ranged from 2 to 7.

**Case 1: One Input**

For this experiment, the inputs were individually tested on 10 different MLPNN models (MLPNN#1 to MLPNN#10). By analysing the resulting R-squared and RMSE values, MLPNN#6 yielded the most satisfactory results while the rest of the models did not produce as accurate of an estimation.

**Case 2: Two Input**

By combining two inputs together, a total of forty-five different models were created and the influence of each combination on Hydropower and Non-hydropower was analysed. The model MLPNN#14 which used a combination of LAT TAV gave the best estimation among the results, while the other combinations showed unsatisfactory results.

**Case 3: Three Input**

By combining three inputs together, a total of One Hundred and twenty different models were created and the influence of each combination on Hydropower and Non-hydropower was analysed. The model MLPNN#164 which used a combination of TAV TMAX PRE gave the best estimation among the results, while the other combinations showed unsatisfactory results.

**Case 4: Four Input**

By combining four inputs together, a total of Two Hundred and ten different models were created and the influence of each combination on Hydropower and Non-hydropower was analysed. The model MLPNN#375 which used a combination of TAV RH TMAX PRE gave the best estimation among the results, while the other combinations showed unsatisfactory results.

**Case 5: Five Input**

By inputting five different variables, two hundred and fifty two possible combinations were made in order to assess their impact on the hydropower and non-hydropower predictions. It was determined that the highest value of the R-squared (R-squared= 0.589371391) and the lowest value of root mean square error (RMSE= 0.237345008) were produced by the model of MLPNN#389 using the combination of [LAT LONG ALT Y TMAX] and MLPNN#415 with the combination of [LAT LONG Y RH PRE] also produced (R-squared= 0.613462141) and (RMSE= 0.230731675). This data demonstrates that these combinations have provided the best prediction and have given the least RMSE in Non-hydropower electricity.

**Case 6: Six Input**

Using six different inputs, two hundred and ten unique combinations were generated and their effects on hydropower and non-hydropower predictions were identified. The results indicated that the highest R-squared value (R-squared= 0.618574042) and the lowest RMSE value (RMSE= 0.229362421) were obtained from MLPNN#646 model, with combinations of [LAT LONG ALT Y RH PRE]. This shows that the best predictions were made with the lowest RMSE in Non-hydropower electricity.

**Case 7: Seven Input**

By exploring five inputs with two types of predictions, hydropower and non-hydropower, it was found that the model of MLPNN#850, MLPNN#883, MLPNN#886, MLPNN#904 and MLPNN#909 using the combinations [LAT LONG ALT Y TAV RH TMIN], [LAT LONG Y TAV RH WS TMAX], [LAT LONG Y TAV RH TMAX TMIN], [LAT ALT Y TAV RH WS TMAX] and [LAT ALT Y TAV RH TMIN PRE], respectively, produced the highest value of R-squared (R-squared= 0.604321282, 0.664036735, 0.666035716, 0.624150666 and 0.599721758) and the lowest value of RMSE (RMSE= 0.23429053, 0.216178617, 0.212605051, 0.227461018 and 0.232571834) respectively. These five combinations gave the best prediction of the highest R-squared and lowest RMSE of all One-Hundred and twenty combinations formed.

**Case 8: Eight Input**

A total of Forty-five models were developed with eight input variables and analyzed for their effect on hydropower and non-hydropower predictions. The highest value of R-squared (R-squared= 0.654396059, 0.639932321, 0.62130158, 0.632352308, 0.641673789, 0.622045409, 0.603269389, 0.648234231) and lowest value of root mean square error (RMSE= 0.294382789, 0.238566747, 0.349209691, 0.367130644, 0.354559083, 0.227010294, 0.23180498, 0.218547082) were generated by the models MLPNN#968, MLPNN#972, MLPNN#974, MLPNN#988 , MLPNN#989, MLPNN#1003, MLPNN#1006 and MLPNN#1007, which utilized the combination of [LAT LONG ALT Y TAV RH WS TMAX], [LAT LONG ALT Y TAV RH TMAX PRE], [LAT LONG ALT Y TAV WS TMAX TMIN], [LAT LONG ALT RH WS TMAX TMIN PRE], [LAT LONG Y TAV RH WS TMAX TMIN], [LAT Y TAV RH WS TMAX TMIN PRE], [LONG ALT Y TAV RH WS TMIN PRE] and [LONG ALT Y TAV RH TMAX TMIN PRE], respectively. From the evaluation of both parameters, the mentioned models were seen to provide the best predictions and Highest R-squared, respectively.

**Case 9: Nine Input**

Ten different Combinations of Nine inputs were analyzed for their effect on Hydropower and Non-hydropower predictions. The best results were found in the models MLPNN#1013, MLPNN#1014, MLPNN#1015, MLPNN#1016, MLPNN#1019 and MLPNN#1022, which both combined [LAT LONG ALT Y TAV RH WS TMAX TMIN], [LAT LONG ALT Y TAV RH WS TMAX PRE], [LAT LONG ALT Y TAV RH WS TMIN PRE], [LAT LONG ALT Y TAV RH TMAX TMIN PRE], [LAT LONG ALT TAV RH WS TMAX TMIN PRE] and [LONG ALT Y TAV RH WS TMAX TMIN PRE] respectively. The highest R-squared value (R-squared =0.625358049, 0.581911813, 0.62467095, 0.654301524, 0.620161597, 0.583849993) and the lowest RMSE (RMSE = 0.227689307, 0.237546756, 0.305073175, 0.216524265, 0.360503419, 0.238022752) were produced by the two combinations, showing that the best prediction and least amount of RMSE were attained.

**Case 10: Ten Input**

Using the ten variables given, the MLPNN#1023 was formulated and trained as well as validated. Results of this process revealed an R-squared of 0.619785345 and a RMSE of 0.313671222, as can be seen in Table S1 of the supplementary material.

**Table 1:**

*The best 22 combinations of MLPNN Models*

| Model Number | MLPNN model | Input to the MLPNN | Identification | R-squared | RMSE |
|---|---|---|---|---|---|
| MODEL #1 | MLPNN #389 | LAT LONG ALT Y TMAX | H | 0.12743908 | 0.665804129 |
| | | | NH | 0.589371391 | 0.237345008 |
| MODEL #2 | MLPNN #415 | LAT LONG Y RH PRE | H | 0.036695924 | 0.685796204 |
| | | | NH | 0.613462141 | 0.230731675 |
| MODEL #3 | MLPNN #646 | LAT LONG ALT Y RH PRE | H | 0.281392422 | 0.592483484 |
| | | | NH | 0.618574042 | 0.229362421 |
| MODEL #4 | MLPNN #850 | LAT LONG ALT Y TAV RH TMIN | H | 0.448526491 | 0.520611888 |
| | | | NH | 0.604321282 | 0.23429053 |
| MODEL #5 | MLPNN #883 | LAT LONG Y TAV RH WS TMAX | H | 0.461916058 | 0.512701046 |
| | | | NH | 0.664036735 | 0.216178617 |
| MODEL #6 | MLPNN #886 | LAT LONG Y TAV RH TMAX TMIN | H | 0.599855682 | 0.442151175 |
| | | | NH | 0.666035716 | 0.212605051 |
| MODEL #7 | MLPNN #904 | LAT ALT Y TAV RH WS TMAX | H | 0.363744468 | 0.557419452 |
| | | | NH | 0.624150666 | 0.227461018 |
| MODEL #8 | MLPNN #909 | LAT ALT Y TAV RH TMIN PRE | H | 0.343089286 | 0.567899704 |
| | | | NH | 0.599721758 | 0.232571834 |
| MODEL #9 | MLPNN #968 | LAT LONG ALT Y TAV RH WS TMAX | H | 0.654396059 | 0.412573507 |
| | | | NH | 0.390164175 | 0.294382789 |
| MODEL #10 | MLPNN #972 | LAT LONG ALT Y TAV RH TMAX PRE | H | 0.589166026 | 0.448155763 |
| | | | NH | 0.639932321 | 0.238566747 |
| MODEL #11 | MLPNN #974 | LAT LONG ALT Y TAV WS TMAX TMIN | H | 0.62130158 | 0.433479613 |
| | | | NH | 0.101097861 | 0.349209691 |
| MODEL #12 | MLPNN #988 | LAT LONG ALT RH WS TMAX TMIN PRE | H | 0.632352308 | 0.42664366 |
| | | | NH | 0.009919405 | 0.367130644 |
| MODEL #13 | MLPNN #989 | LAT LONG Y TAV RH WS TMAX TMIN | H | 0.641673789 | 0.419838736 |
| | | | NH | 0.070400892 | 0.354559083 |
| MODEL #14 | MLPNN #1003 | LAT Y TAV RH WS TMAX TMIN PRE | H | 0.487201484 | 0.501487715 |
| | | | NH | 0.622045409 | 0.227010294 |
| MODEL #15 | MLPNN #1006 | LONG ALT Y TAV RH WS TMIN PRE | H | 0.502870609 | 0.493610772 |
| | | | NH | 0.603269389 | 0.23180498 |
| MODEL #16 | MLPNN #1007 | LONG ALT Y TAV RH TMAX TMIN PRE | H | 0.504399995 | 0.492024809 |
| | | | NH | 0.648234231 | 0.218547082 |

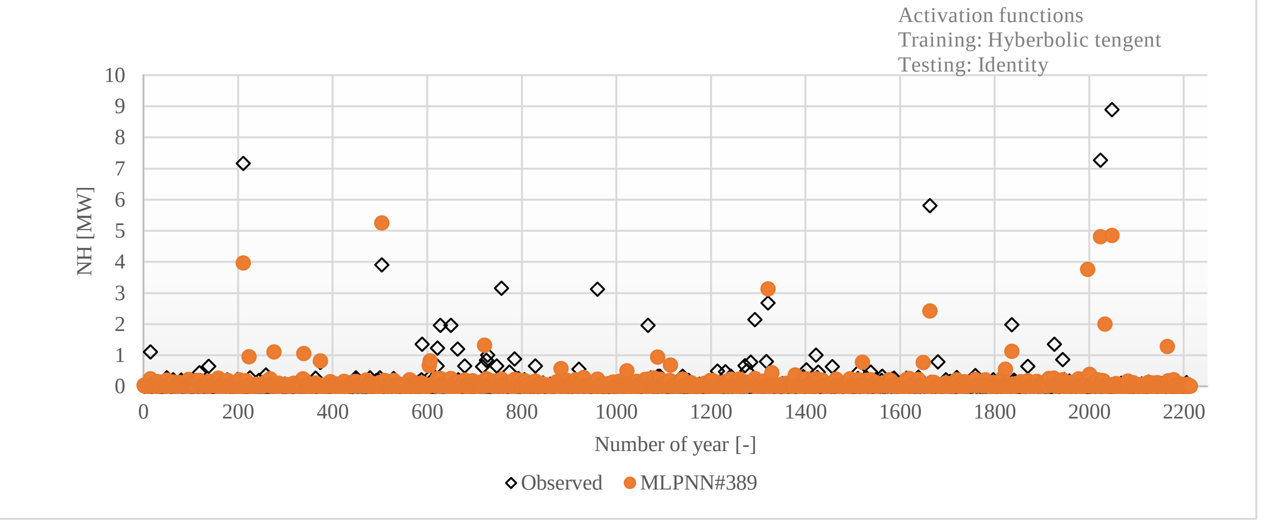
Table 1. (Continued)

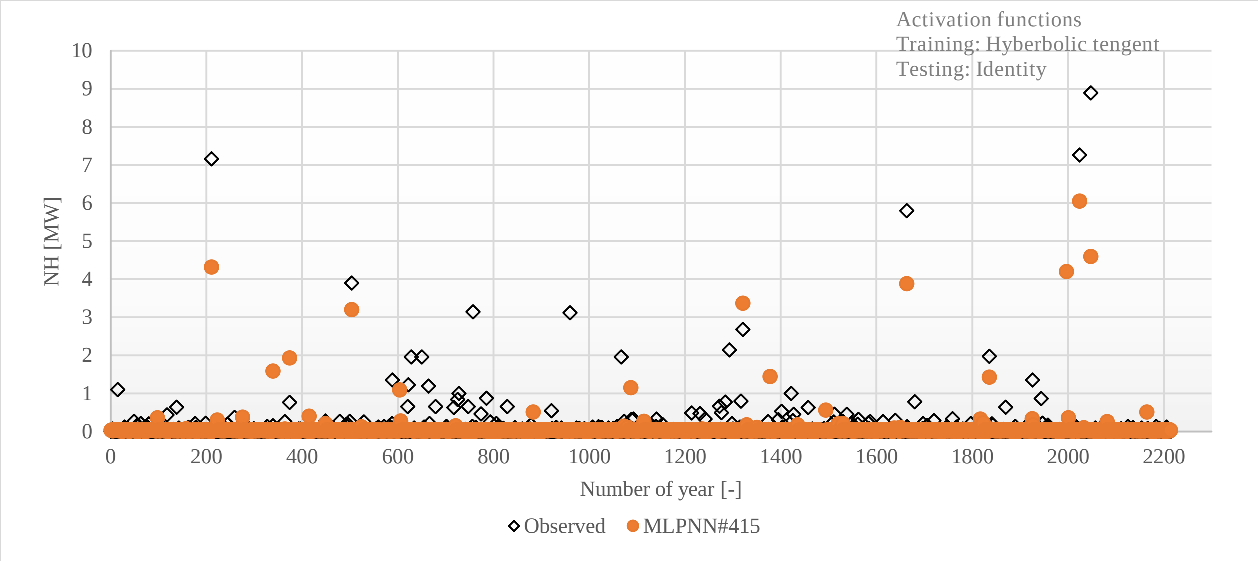
| | | | | | |
|---|---|---|---|---|---|
| MODEL #17 | MLPNN #1013 | LAT LONG ALT Y TAV RH WS TMAX TMIN | H | 0.625358049 | 0.428876095 |
| | | | NH | 0.620725324 | 0.227689307 |
| MODEL #18 | MLPNN #1014 | LAT LONG ALT Y TAV RH WS TMAX PRE | H | 0.561640661 | 0.46282139 |
| | | | NH | 0.581911813 | 0.237546756 |
| MODEL #19 | MLPNN #1015 | LAT LONG ALT Y TAV RH WS TMIN PRE | H | 0.62467095 | 0.42897951 |
| | | | NH | 0.527222218 | 0.305073175 |
| MODEL #20 | MLPNN #1016 | LAT LONG ALT Y TAV RH TMAX TMIN PRE | H | 0.525855855 | 0.485439977 |
| | | | NH | 0.654301524 | 0.216524265 |
| MODEL #21 | MLPNN #1019 | LAT LONG ALT TAV RH WS TMAX TMIN PRE | H | 0.620161597 | 0.431546105 |
| | | | NH | 0.041196704 | 0.360503419 |
| MODEL #22 | MLPNN #1022 | LONG ALT Y TAV RH WS TMAX TMIN PRE | H | 0.430850922 | 0.528552479 |
| | | | NH | 0.583849993 | 0.238022752 |

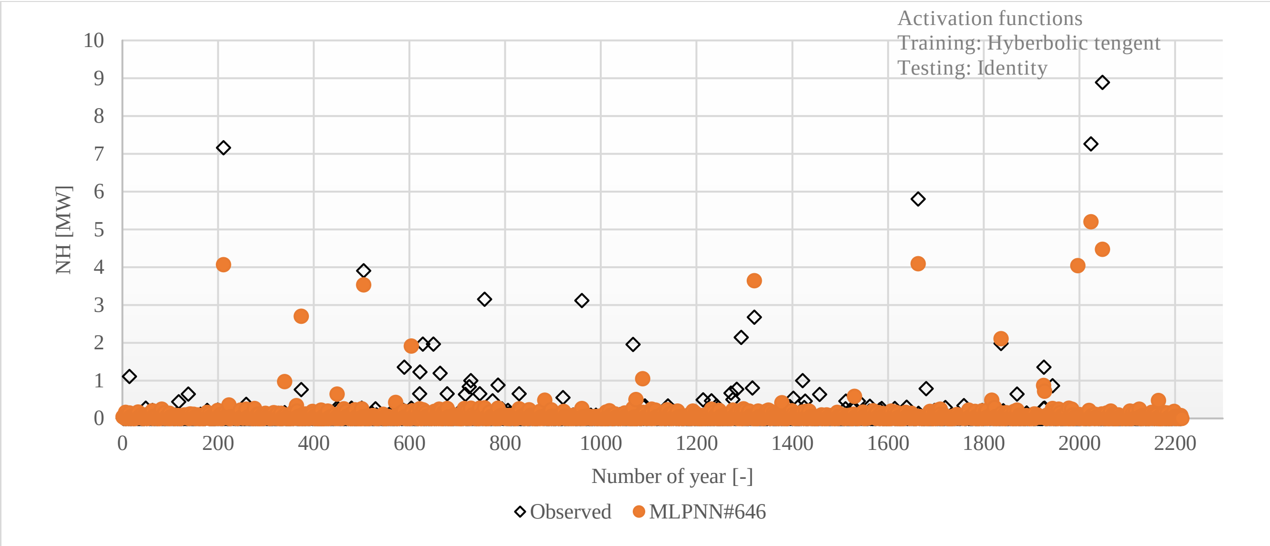
The most suitable combination of the MLPNN model is demonstrated in Table 1 It should be noted that these models have been chosen based on the highest R-squared value and the least RMSE, as seen in Figure 7. This table displays the observed and predicted values of Hydropower and Non-Hydropower.

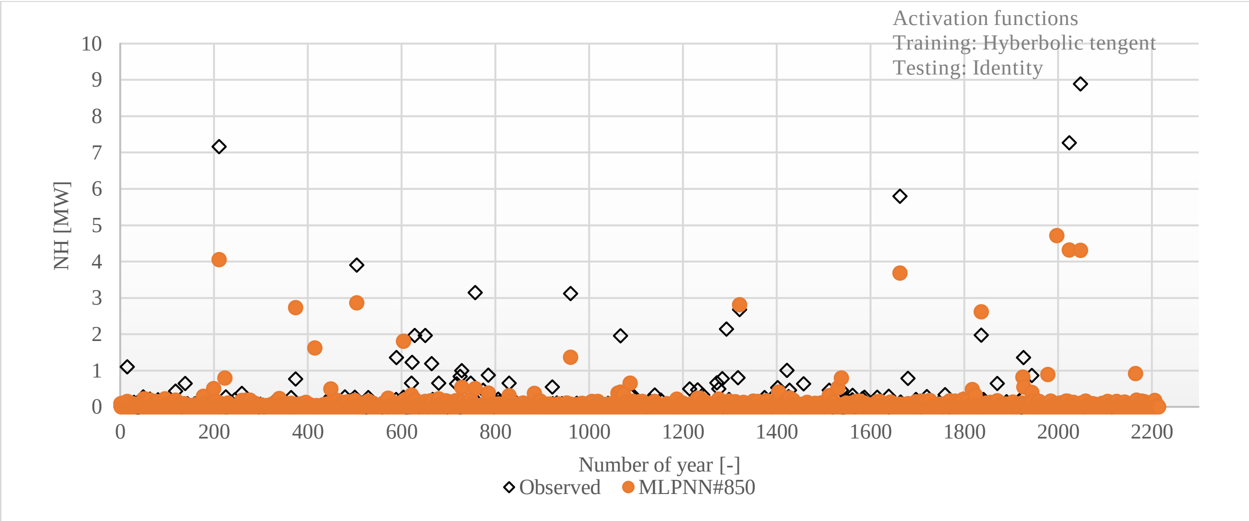
**Figure 6:**

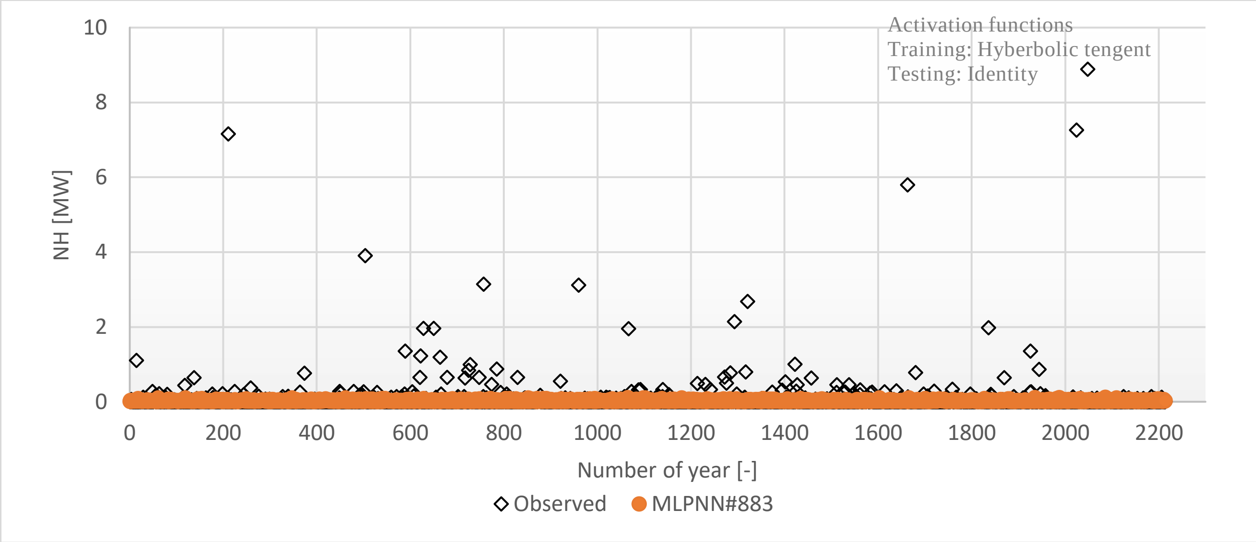
*Illustrates the comparison between the observed and predicted values based on the best combination of inputs.*

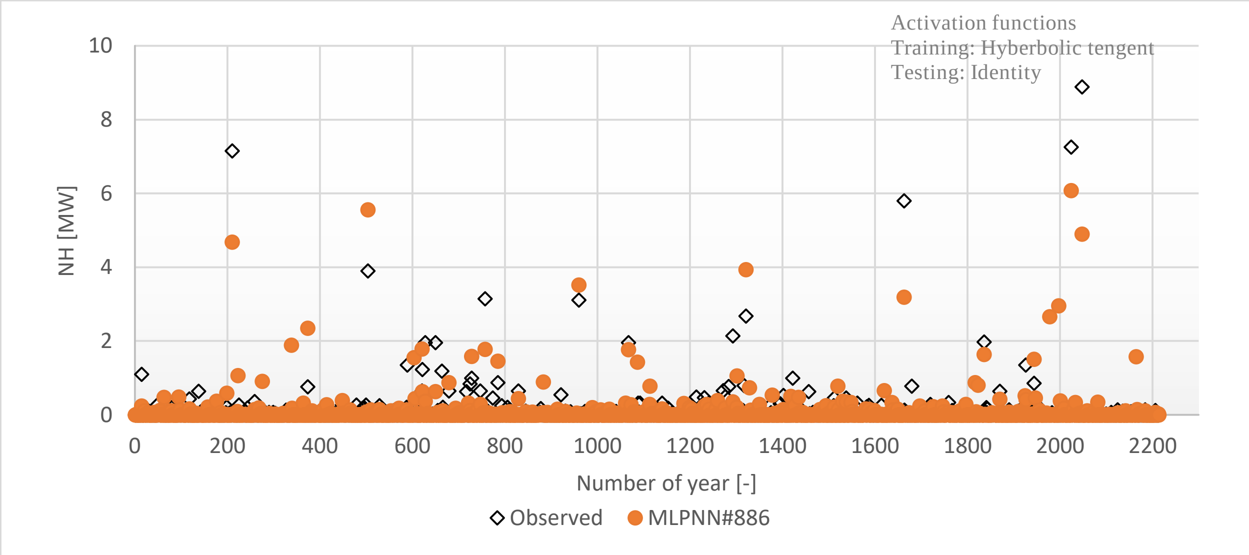


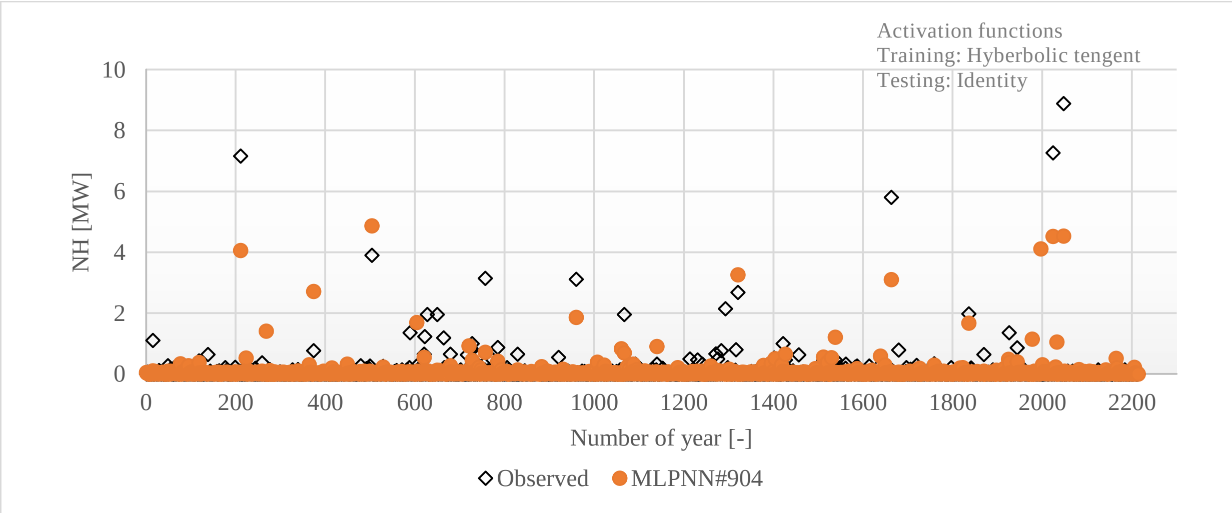

Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
Number of year [-]
Observed
MLPNN#415

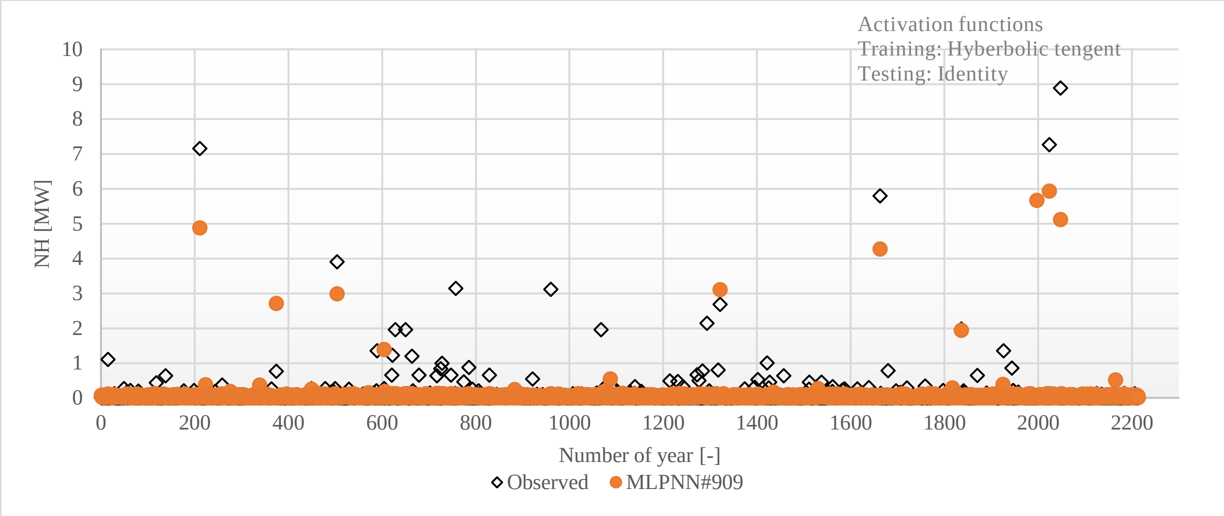

Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
Number of year [-]
Observed
MLPNN#646

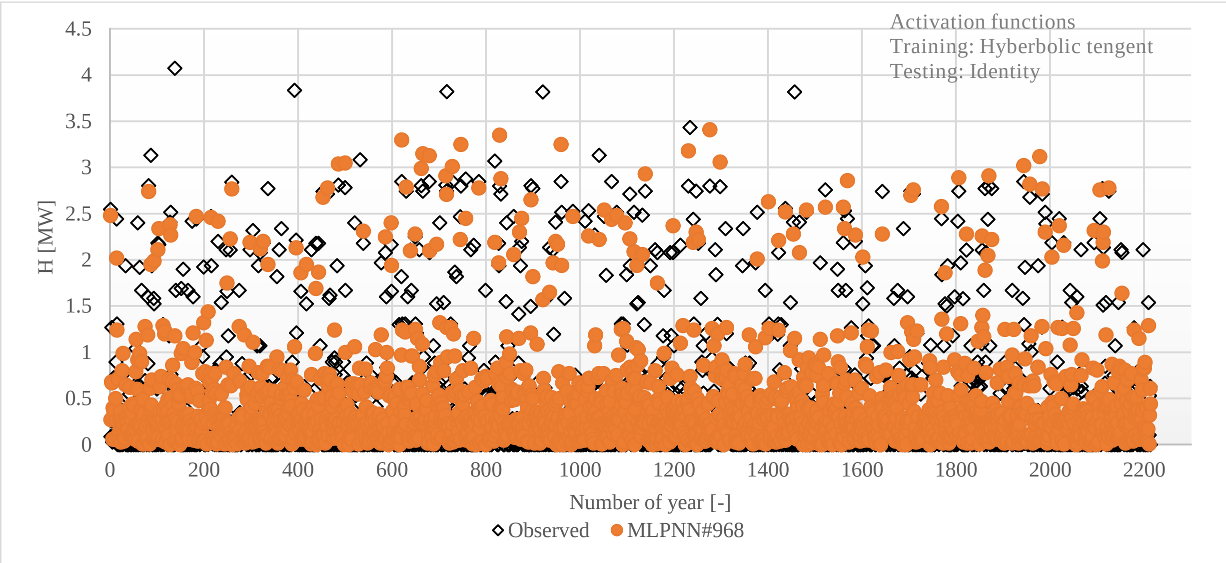

Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
Number of year [-]
Observed
MLPNN#850

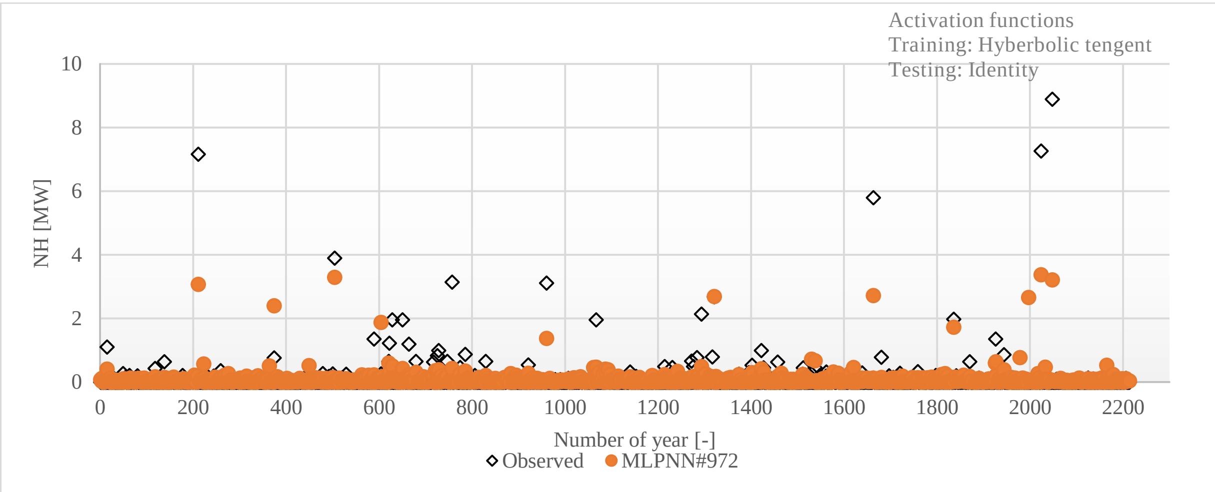

Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
Number of year [-]
Observed
MLPNN#883

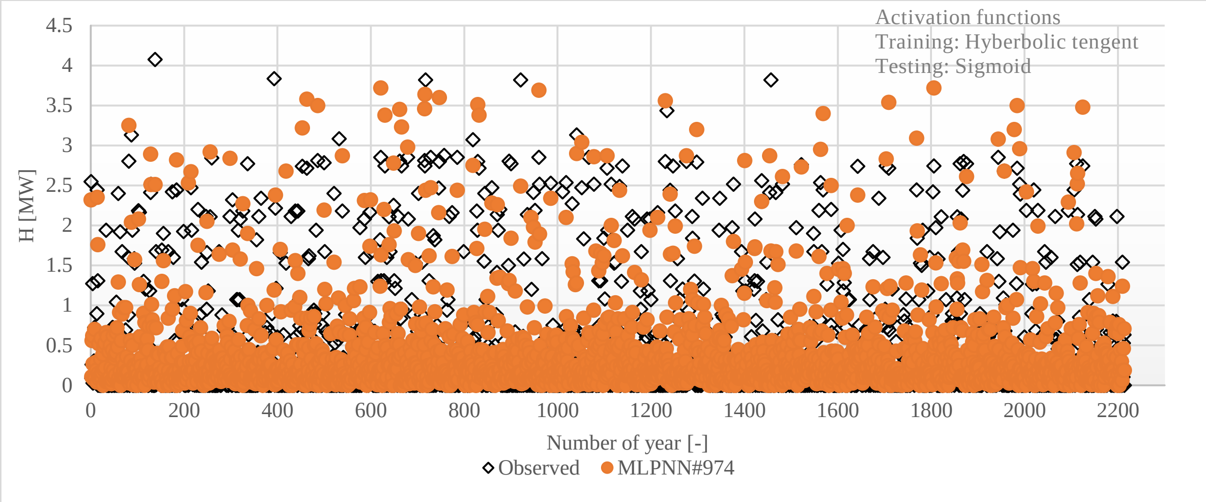

Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
Number of year [-]
Observed
MLPNN#886

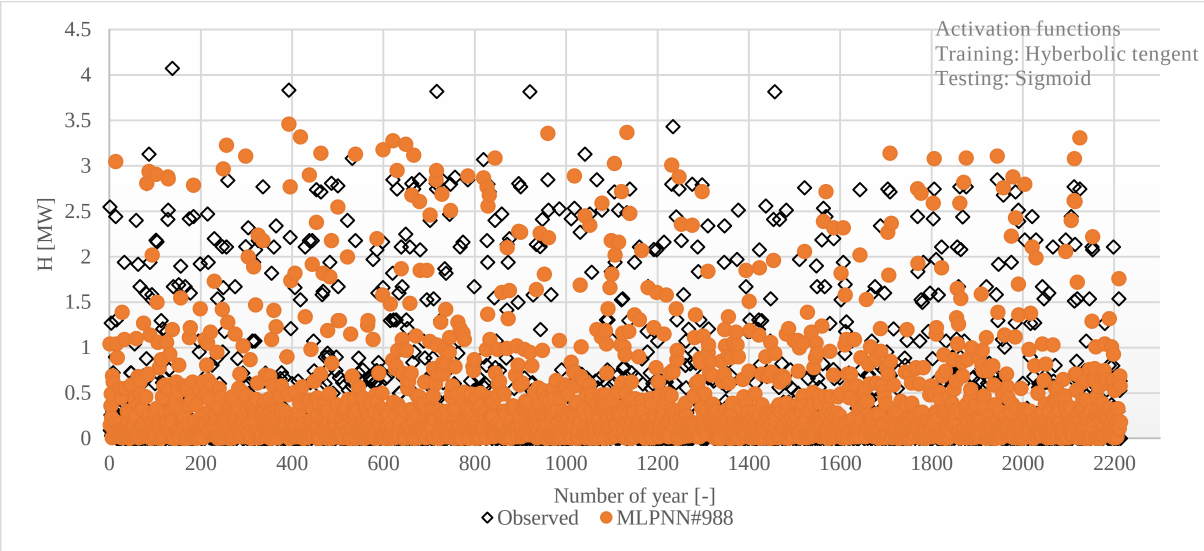

Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
Number of year [-]
Observed
MLPNN#904

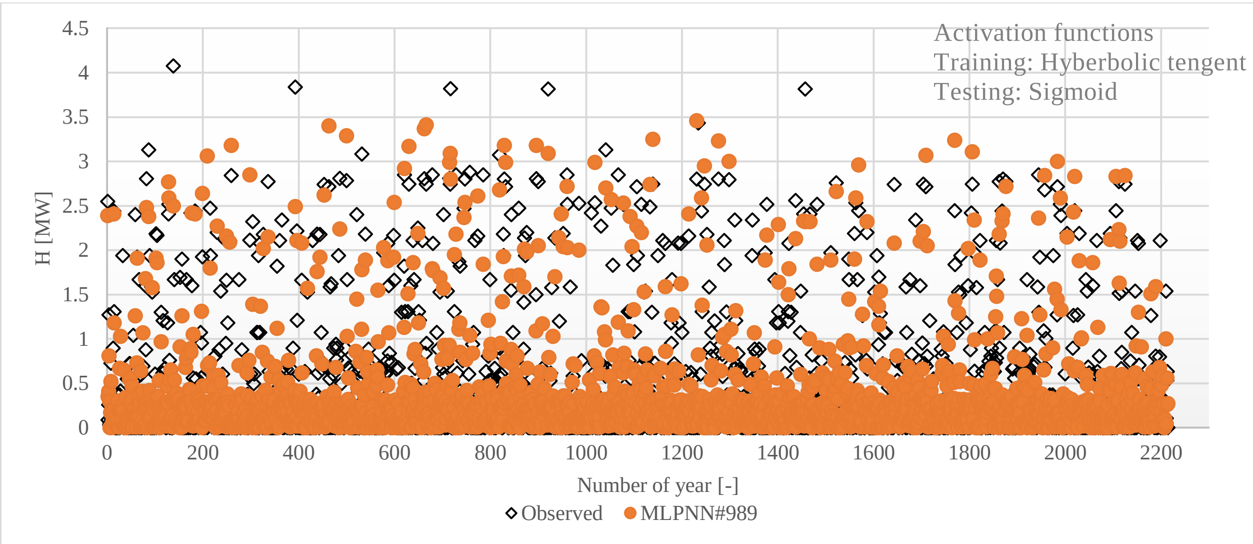

Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
0
1
2
3
4
5
6
7
8
9
10
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2200
Number of year [-]
Observed
MLPNN#909

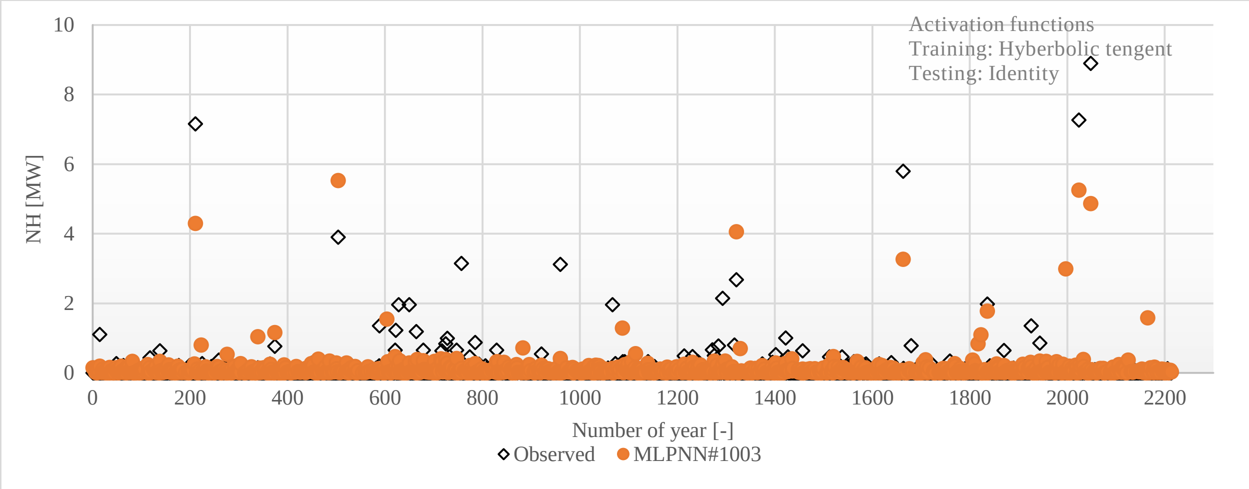

Activation functions
Training: Hyberbolic tengent
Testing: Identity
H [MW]
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2200
Number of year [-]
Observed
MLPNN#968

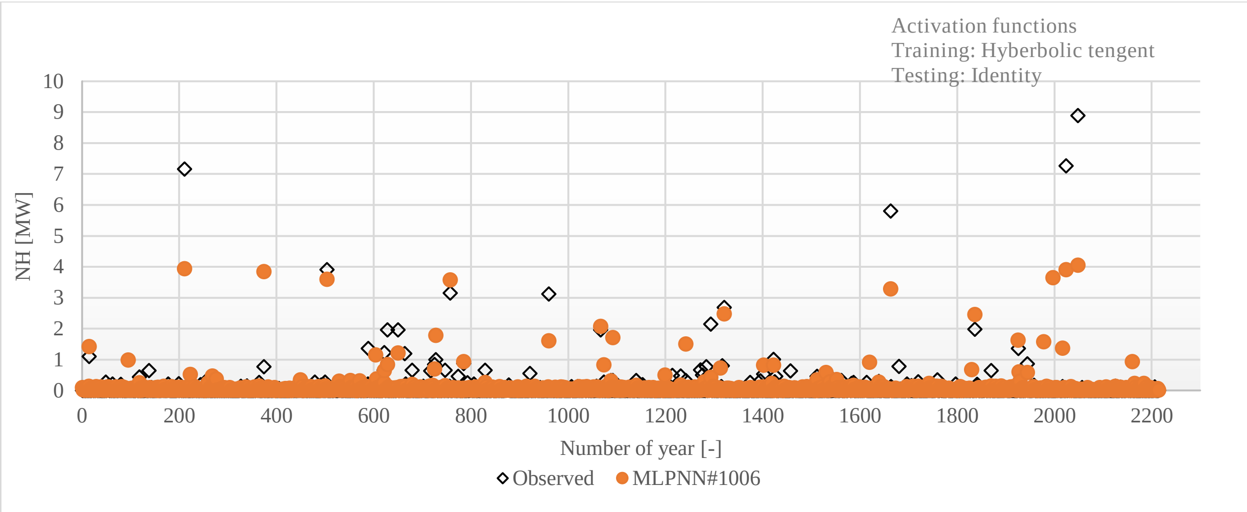

Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
0
2
4
6
8
10
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2200
Number of year [-]
Observed
MLPNN#972

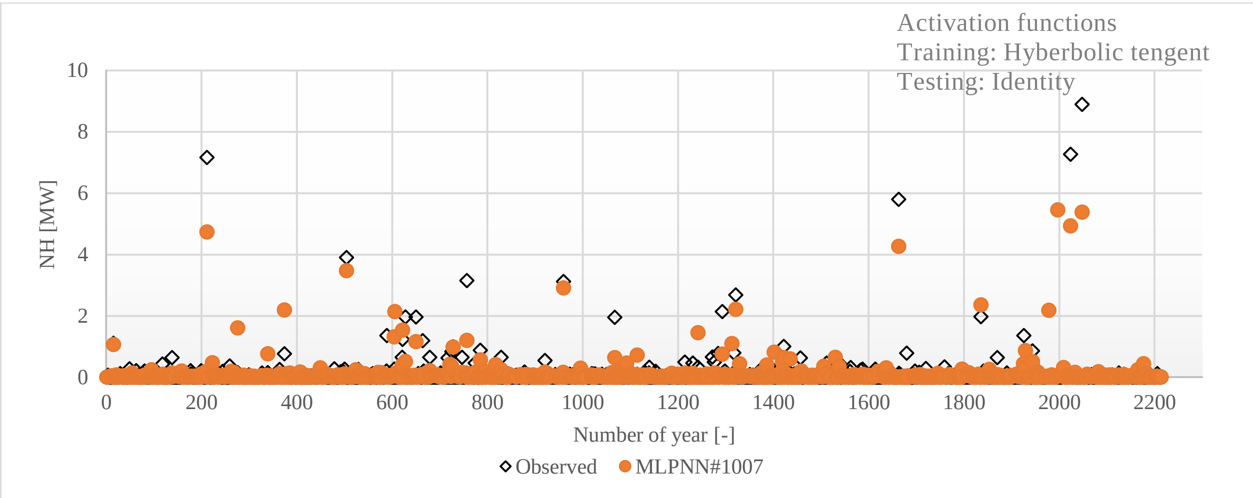

Activation functions
Training: Hyberbolic tengent
Testing: Sigmoid
H [MW]
Number of year [-]
Observed
MLPNN#974

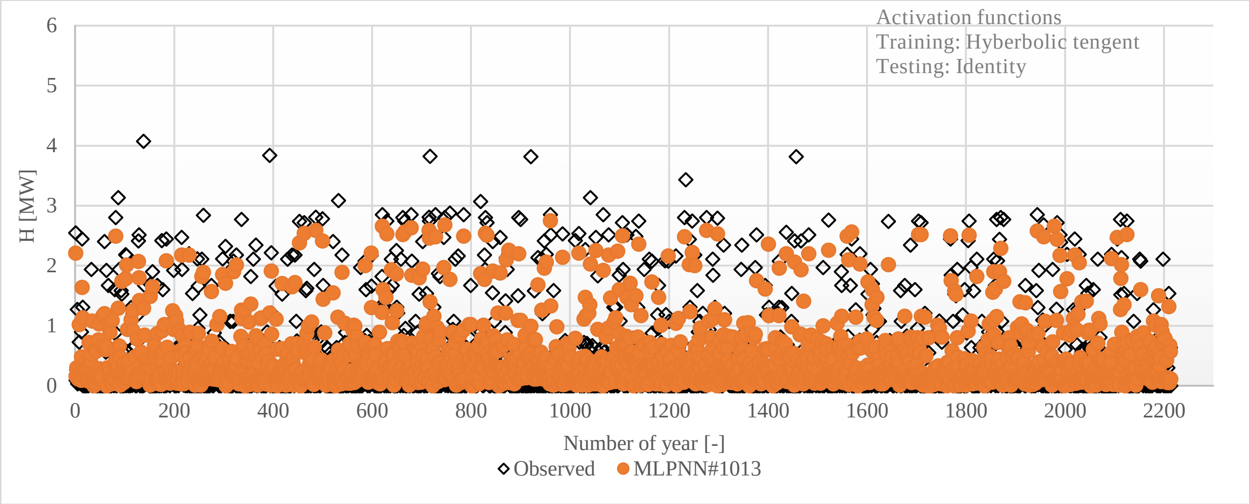

Activation functions
Training: Hyberbolic tengent
Testing: Sigmoid
H [MW]
Number of year [-]
Observed
MLPNN#988

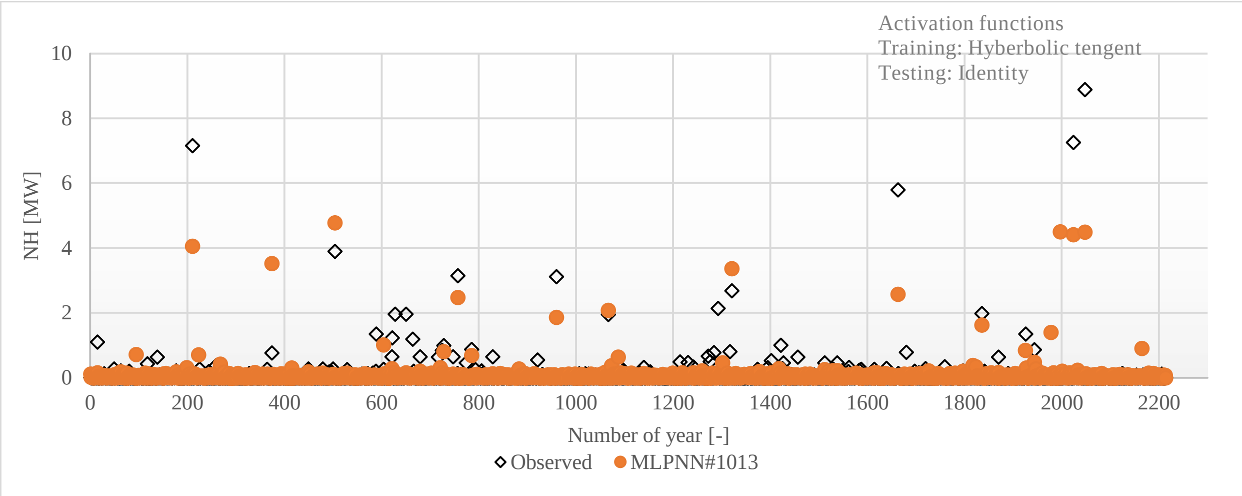

Activation functions
Training: Hyberbolic tengent
Testing: Sigmoid
H [MW]
Number of year [-]
Observed
MLPNN#989

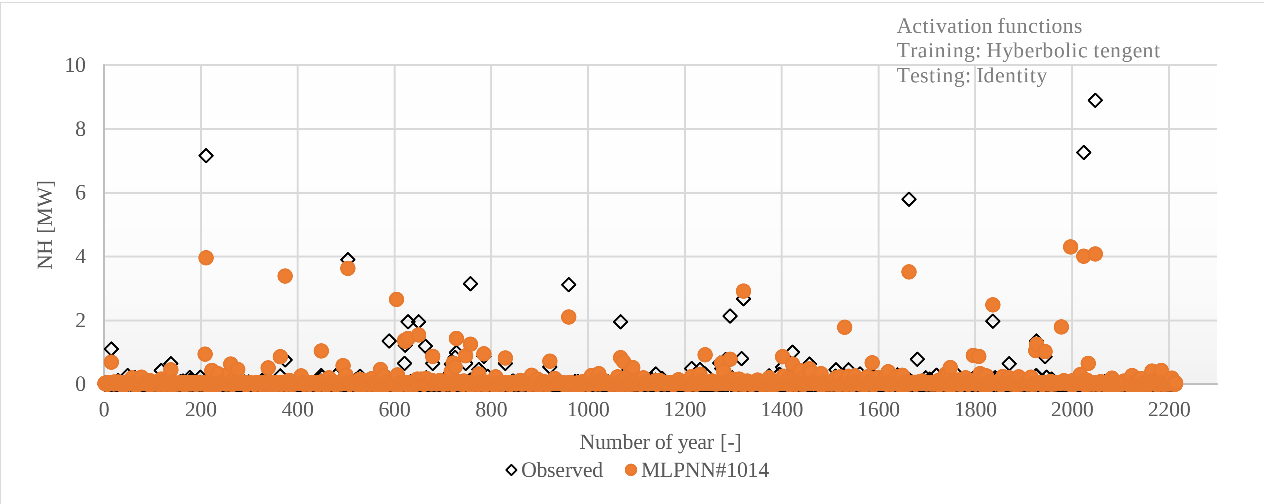

Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
0
2
4
6
8
10
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2200
Number of year [-]
Observed
MLPNN#1003

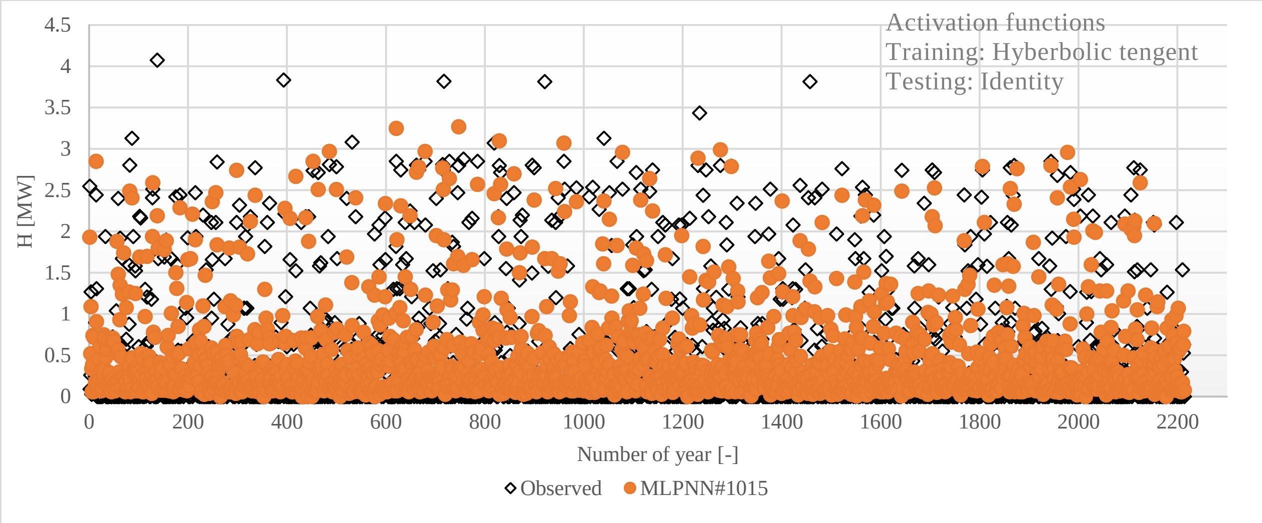

Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
0
1
2
3
4
5
6
7
8
9
10
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2200
Number of year [-]
Observed
MLPNN#1006

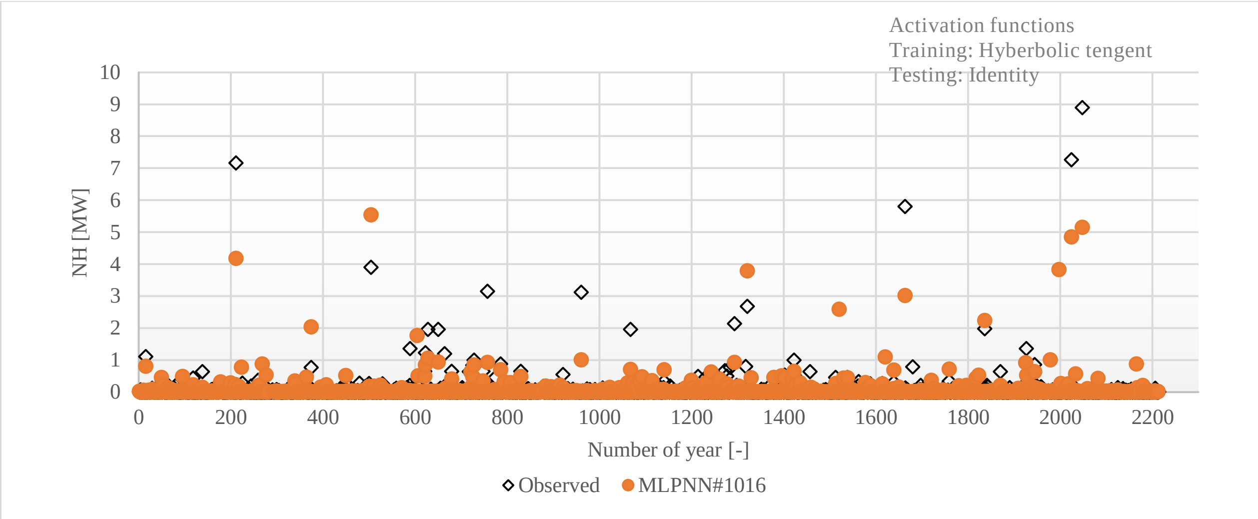

Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
0
2
4
6
8
10
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2200
Number of year [-]
Observed
MLPNN#1007

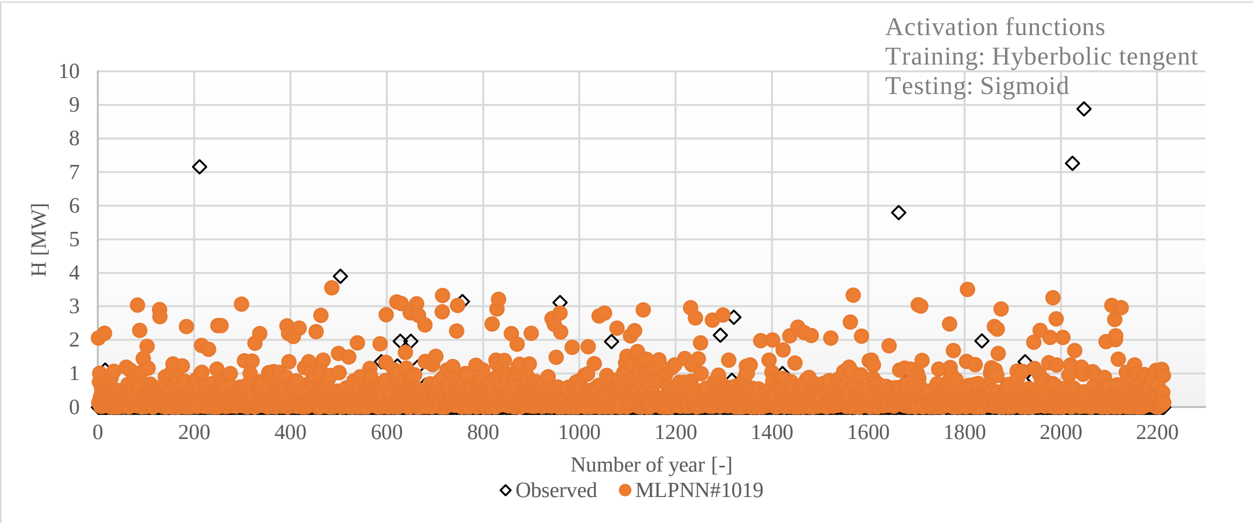

Activation functions
Training: Hyberbolic tengent
Testing: Identity
H [MW]
0
1
2
3
4
5
6
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2200
Number of year [-]
Observed
MLPNN#1013

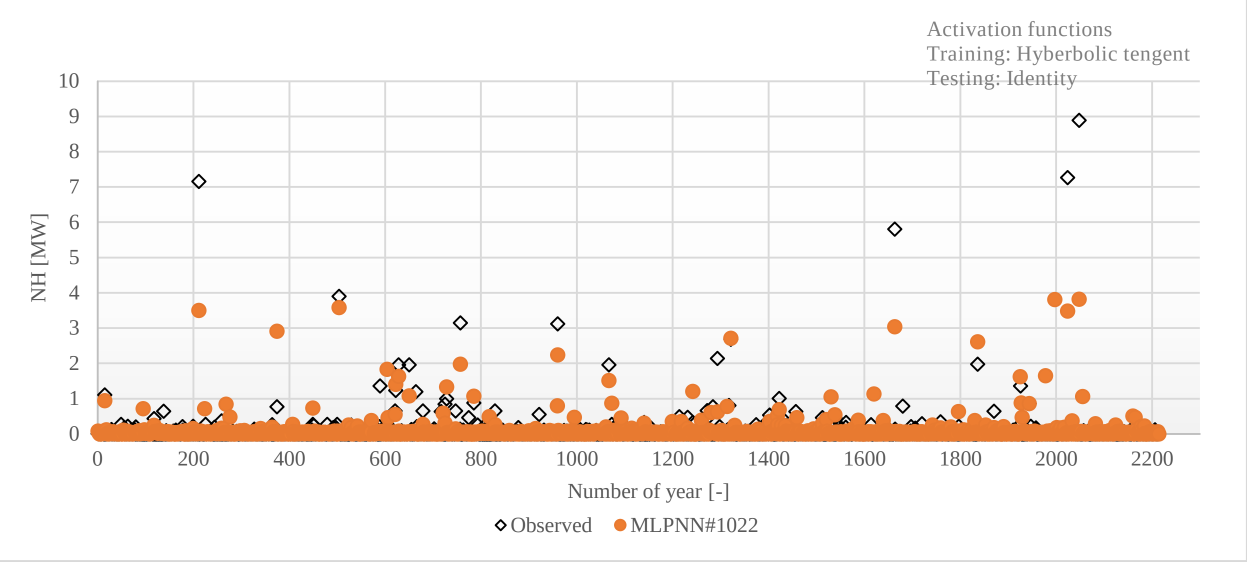

Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
0
2
4
6
8
10
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2200
Number of year [-]
Observed
MLPNN#1013


Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
0
2
4
6
8
10
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2200
Number of year [-]
Observed
MLPNN#1014


Activation functions
Training: Hyberbolic tengent
Testing: Identity
H [MW]
Number of year [-]
Observed
MLPNN#1015


Activation functions
Training: Hyberbolic tengent
Testing: Identity
NH [MW]
Number of year [-]
Observed
MLPNN#1016


Activation functions
Training: Hyberbolic tengent
Testing: Sigmoid
H [MW]
Number of year [-]
Observed
MLPNN#1019




**4.4 Evaluating Different single empirical models for Hydropower and Non-hydropower prediction**

The use of Artificial Neural Networks (ANNs) and mathematical regression method was investigated to predict hydropower and non-hydropower potential in Africa. A total of 1023 Multi-layer Perceptron Neural Network (MLPNN) models were created, evaluated, and 22 models were chosen on the grounds of heights values of R-squared and lowest values Root Mean Squared Error (RMSE). The effectiveness of the suggested methods which included the Multilayer Perceptron Neural Network (MLPNN), Radial Basis Function Neural Network (RBFNN) and Multiple Linear Regression (MLR) was investigated by various statistical indices.

**4.5 RBFNN**

In this research, an Artificial Intelligence system based on Radial Basis Function Neural Network (RBFNN) was initiated to appraise the influence of various climatic elements on the production of hydroelectricity and non-hydroelectric power in Africa. The climatic parameters included in the research were avrage temperature, maximum temperature, minimum temperature, relative humidity, wind speed and precipitation. To ensure dependable results, the observed data was used to construct and fine-tune the RBFNN model instead of relying on the real data itself. Moreover, the data was subdivided into training and testing sets for enhanced results.

The use of Root Mean Squared Error (RMSE) was applied to appraise the functioning of a Radial Basis Function Neural Network (RBFNN) model with the purpose of pinpointing the paramount parameters. The prognosticated values of hydropower and non-hydropower electricity production were in comparison to the observed values. It was found that the synthesis of [LAT LONG ALT Y TAV RH TMAX PRE] developed a R-squared value of 0.346. This outcome implies that the model had the potential to present an accurate forecast of the data. This investigation gives a valuable insight on how climate parameters affect the production of hydropower and non-hydropower electricity in Africa, which can be utilized in developing strategic decisions in the energy sector.

**Table 2:**

*Best combinations of the RBFNN models*

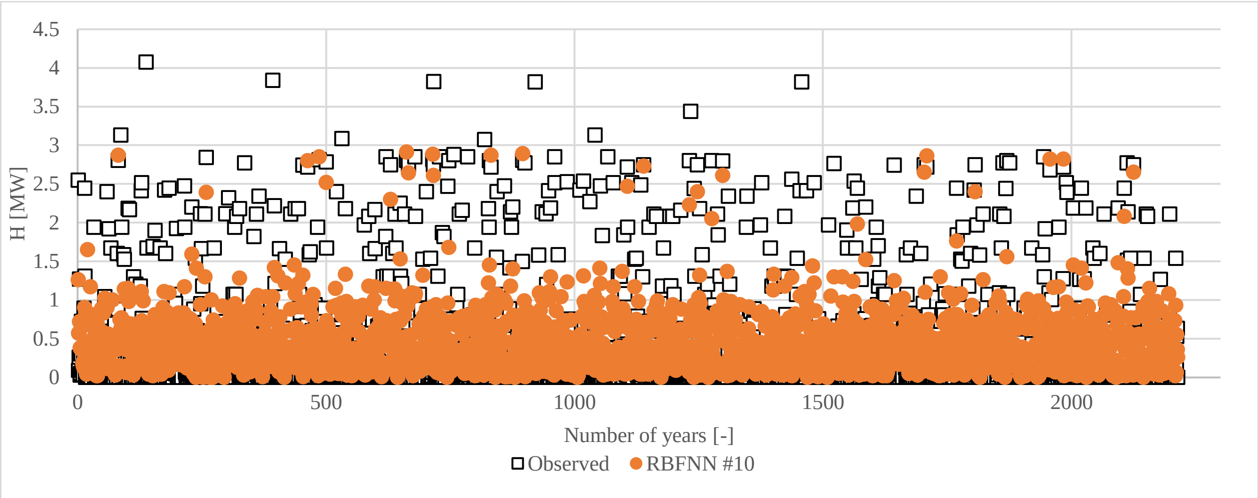
| Model Number | RBFNN model | Input to the RBFNN | Identification | R-squared | RMSE |
|---|---|---|---|---|---|
| MODEL #1 | RBFNN #1 | LAT LONG ALT Y TMAX | H | 0.138455307 | 0.648605 |
| | | | NH | 0.070345912 | 0.354264 |
| MODEL #2 | RBFNN #2 | LAT LONG Y RH PRE | H | 0.084582795 | 0.669201 |
| | | | NH | 0.10346895 | 0.348015 |
| MODEL #3 | RBFNN #3 | LAT LONG ALT Y RH PRE | H | 0.227190254 | 0.61434 |
| | | | NH | 0.094363059 | 0.350804 |
| MODEL #4 | RBFNN #4 | LAT LONG ALT Y TAV RH TMIN | H | 0.250540433 | 0.604877 |
| | | | NH | 0.139942667 | 0.340699 |
| MODEL #5 | RBFNN #5 | LAT LONG Y TAV RH WS TMAX | H | 0.127937938 | 0.652551 |
| | | | NH | 0.149811665 | 0.339588 |
| MODEL #6 | RBFNN #6 | LAT LONG Y TAV RH TMAX TMIN | H | 0.220604608 | 0.616856 |
| | | | NH | 0.112108224 | 0.346161 |
| MODEL #7 | RBFNN #7 | LAT ALT Y TAV RH WS TMAX | H | 0.118925175 | 0.656239 |
| | | | NH | 0.170776572 | 0.33454 |
| MODEL #8 | RBFNN #8 | LAT ALT Y TAV RH TMIN PRE | H | 0.131970077 | 0.650989 |
| | | | NH | 0.097923533 | 0.349923 |
| MODEL #9 | RBFNN #9 | LAT LONG ALT Y TAV RH WS TMAX | H | 0.221784228 | 0.616478 |
| | | | NH | 0.136954785 | 0.341486 |
| MODEL #10 | RBFNN #10 | LAT LONG ALT Y TAV RH TMAX PRE | H | 0.345509222 | 0.565316 |
| | | | NH | 0.13408345 | 0.342004 |
| MODEL #11 | RBFNN #11 | LAT LONG ALT Y TAV WS TMAX TMIN | H | 0.257147286 | 0.602256 |
| | | | NH | 0.118741007 | 0.346516 |
| MODEL #12 | RBFNN #12 | LAT LONG ALT RH WS TMAX TMIN PRE | H | 0.298974249 | 0.585012 |
| | | | NH | 0.043035191 | 0.359365 |
| MODEL #13 | RBFNN #13 | LAT LONG Y TAV RH WS TMAX TMIN | H | 0.205403255 | 0.622887 |
| | | | NH | 0.127015262 | 0.343986 |
| MODEL #14 | RBFNN #14 | LAT Y TAV RH WS TMAX TMIN PRE | H | 0.178899145 | 0.633143 |
| | | | NH | 0.104679581 | 0.347671 |

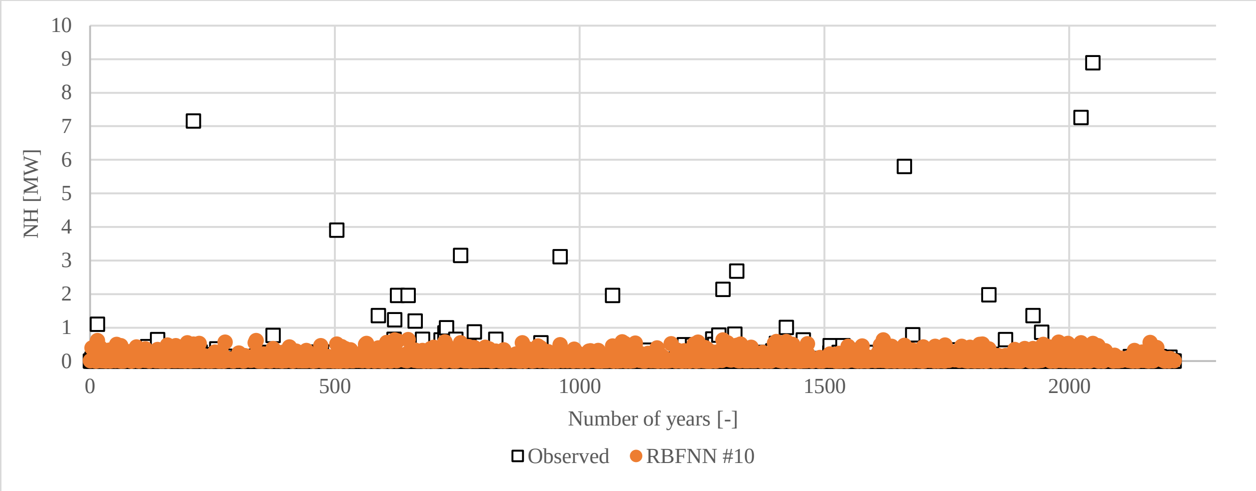
Table 2 (Continued)

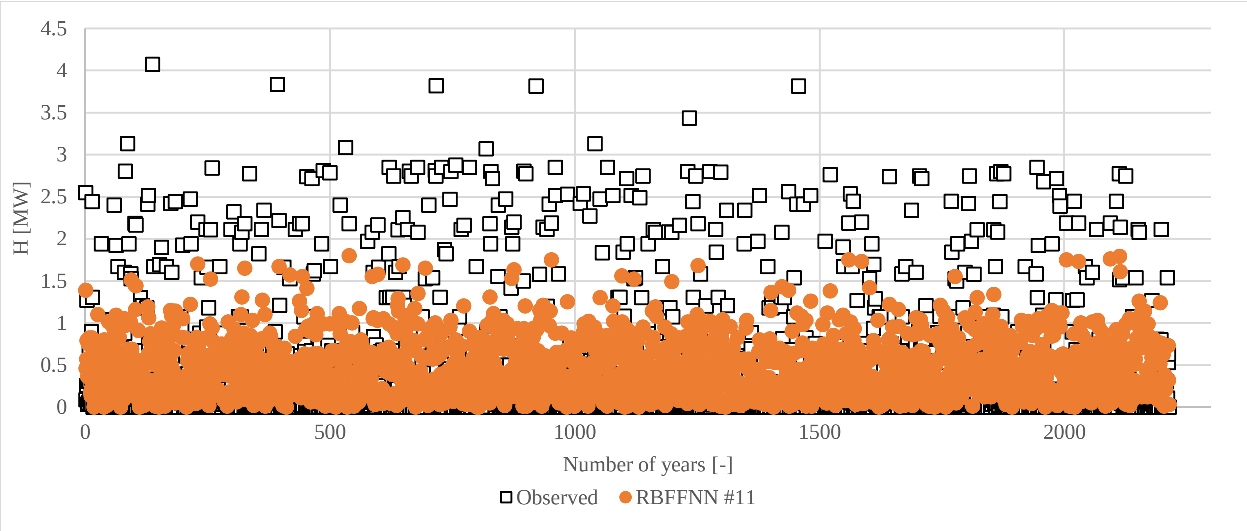
| | | | | | |
|---|---|---|---|---|---|
| MODEL #15 | RBFNN #15 | LONG ALT Y TAV RH WS TMIN PRE | H | 0.236876252 | 0.610527 |
| | | | NH | 0.164665494 | 0.336658 |
| MODEL #16 | RBFNN #16 | LONG ALT Y TAV RH TMAX TMIN PRE | H | 0.183006355 | 0.632355 |
| | | | NH | 0.193221363 | 0.329957 |
| MODEL #17 | RBFNN #17 | LAT LONG ALT Y TAV RH WS TMAX TMIN | H | 0.236115577 | 0.611054 |
| | | | NH | 0.126976564 | 0.343259 |
| MODEL #18 | RBFNN #18 | LAT LONG ALT Y TAV RH WS TMAX PRE | H | 0.184179882 | 0.631172 |
| | | | NH | 0.093225221 | 0.350945 |
| MODEL #19 | RBFNN #19 | LAT LONG ALT Y TAV RH WS TMIN PRE | H | 0.193179599 | 0.627666 |
| | | | NH | 0.107593447 | 0.347362 |
| MODEL #20 | RBFNN #20 | LAT LONG ALT Y TAV RH TMAX TMIN PRE | H | 0.225399288 | 0.61501 |
| | | | NH | 0.144260078 | 0.340639 |
| MODEL #21 | RBFNN #21 | LAT LONG ALT TAV RH WS TMAX TMIN PRE | H | 0.200987403 | 0.624648 |
| | | | NH | 0.05684451 | 0.356945 |
| MODEL #22 | RBFNN #22 | LONG ALT Y TAV RH WS TMAX TMIN PRE | H | 0.172267308 | 0.6357 |
| | | | NH | 0.183277818 | 0.332418 |

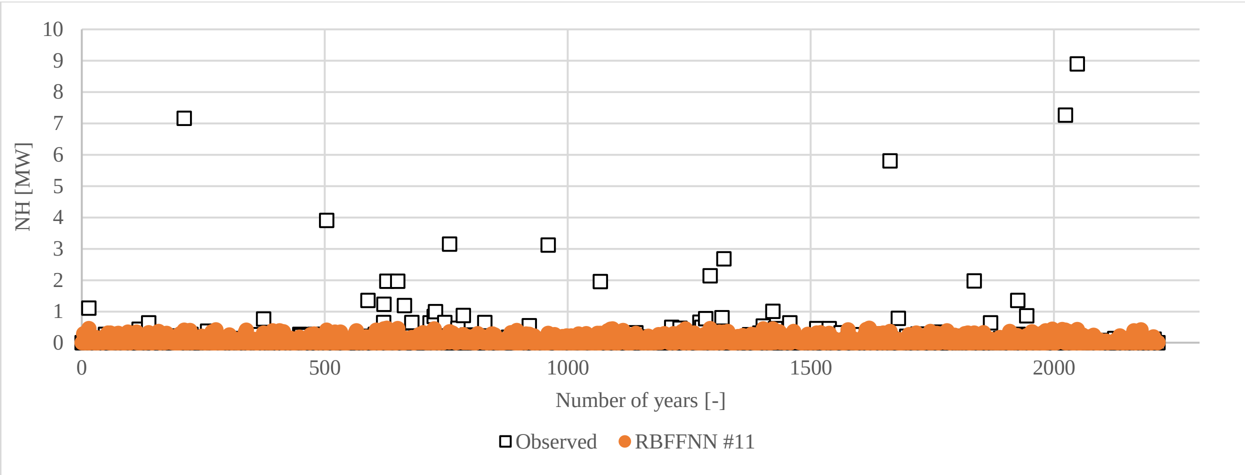
**Figure 7:** `

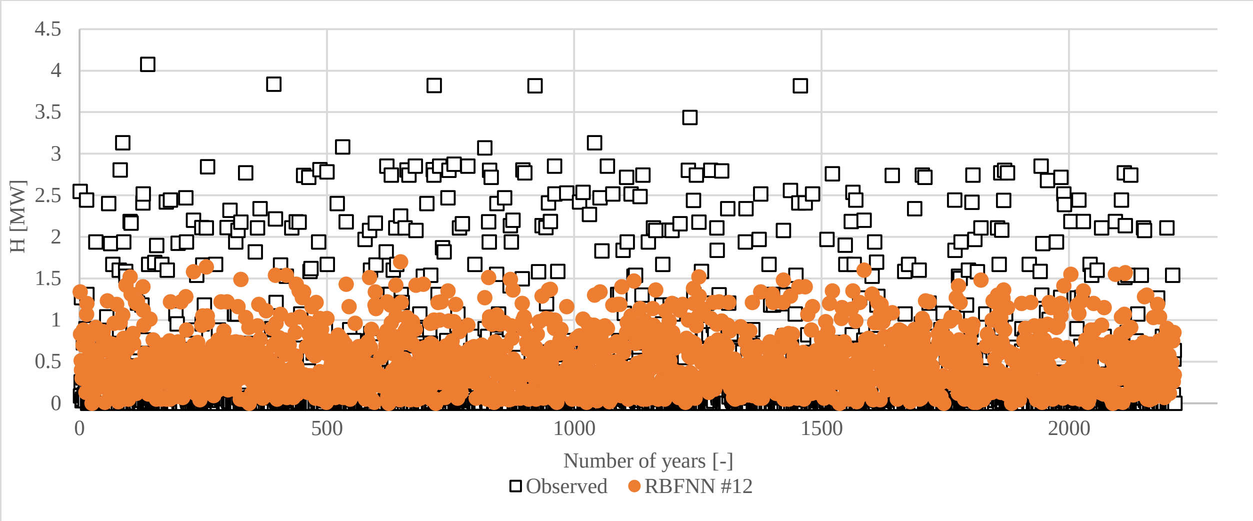
*Comparison between observed and predicted values (RBFNN #10, #11, #12)*

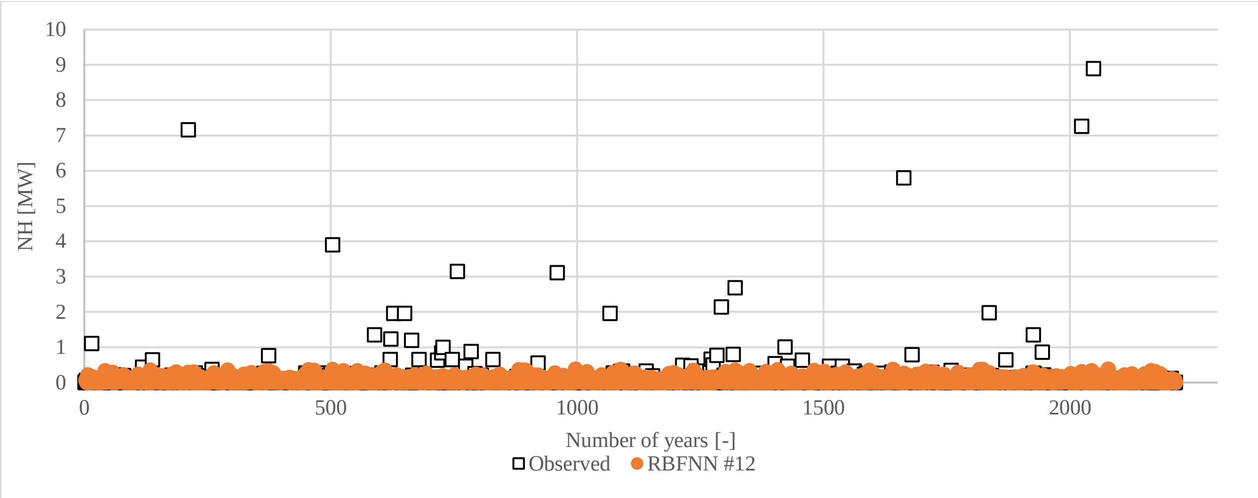



NH [MW]
Number of years [-]
Observed
RBFNN #10


H [MW]
Number of years [-]
Observed
RBFFNN #11


NH [MW]
Number of years [-]
Observed
RBFFNN #11




## 4.6 MLR

This study used Multiple Linear Regression (MLR) to evaluate the effect of diverse climate parameters on the manufacturing of hydropower and non-hydropower electricity in Africa. The input variables that were put into the model were latitude, longitude, altitude, year, temperature average, temperature maximum, temperature minimum, relative humidity, wind speed, and precipitation. Utilizing this model enabled the investigation to understand how aspects of climate have an influence on electrical production.

The MLR model was prepared with observed data to forecast the production of electricity in Africa. A mathematical equation was formed to forecast the amount of electricity produced employing the input factors. The R-Squared metric was utilized to appraise the exactness of the model, implying that the MLR model is competent of precisely predicting the production of electricity in Africa with consideration to the climate parameters.

**Table 3:**

*Regression Equations obtained from MLR for response (Hydropower and Non-hydropower)*

| Model Number | MLR model | Input to the MLR | Equation |
|---|---|---|---|
| MODEL #1 | MLR #1 | LAT LONG ALT Y TMAX | H=-10.288+0.001LAT+0.005LONG+0.0ALT+0.005Y+0.019TMAX<br>NH=-10.281-0.001LAT+0.0LONG+0.00005394ALT+0.005Y+0.007TMAX |
| MODEL #2 | MLR #2 | LAT LONG Y RH PRE | H=-10.832+0.003LAT+0.006LONG+0.006Y-0.002RH+0.027PRE<br>NH=-10.118-0.002LAT+0.00002882LONG+0.005Y-0.002RH-0.008PRE |
| MODEL #3 | MLR #3 | LAT LONG ALT Y RH PRE | H=-10.951+0.004LAT+0.005LONG+0.00009913ALT+0.006Y-0.001RH+0.024PRE<br>NH=-10.149-0.002LAT+0.0LONG+0.00002583ALT+0.005Y-0.002RH-0.009PRE |
| MODEL #4 | MLR #4 | LAT LONG ALT Y TAV RH TMIN | H=-12.332+0.005LAT+0.008LONG+0.0ALT+0.007Y-0.032TAV+0.005RH-0.022TMIN<br>NH=-10.522-0.001LAT+0.001LONG+0.0ALT+0.006Y-0.02TAV-0.003RH-0..002TMIN |
| MODEL #5 | MLR #5 | LAT LONG Y TAV RH WS TMAX | H=-11.454+0.004LAT+0.01LONG+0.006Y-0.061TAV+0.004RH-0.057WS+0.053TMAX<br>NH=-10.388-0.001LAT+0.0LONG+0.005Y-0.012TAV-0.002RH+0.003WS+0.004TMAX |
| MODEL #6 | MLR #6 | LAT LONG Y TAV RH TMAX TMIN | H=-10.318+0.002LAT+0.008LONG+0.005Y-0.132TAV+0.002RH+0.082TMAX+0.047TMIN<br>NH=-10.389-0.001LAT+0.0LONG+0.005Y-0.012TAV-0.002RH+0.003TMAX+0.0TMIN |
| MODEL #7 | MLR #7 | LAT ALT Y TAV RH WS TMAX | H=-11.319-0.003LAT+0.0ALT+0.006Y-0.072TAV-0.001RH-0.052WS+0.035TMAX<br>NH=-10.444-0.002LAT-0.00009055ALT+0.006Y-0.021TAV-0.003RH+0.001WS+0.001TMAX |
| MODEL #8 | MLR #8 | LAT ALT Y TAV WS TMAX TMIN | H=-11.683+0.001LAT+0.0ALT+0.007Y-0.039TAV+0.001RH-0.009TMIN-0.001PRE<br>NH=-10.448-0.002LAT-0.00009066ALT+0.006Y-0.019TAV-0.002RH-0.001TMIN-0.008PRE |

Table 3. Continue

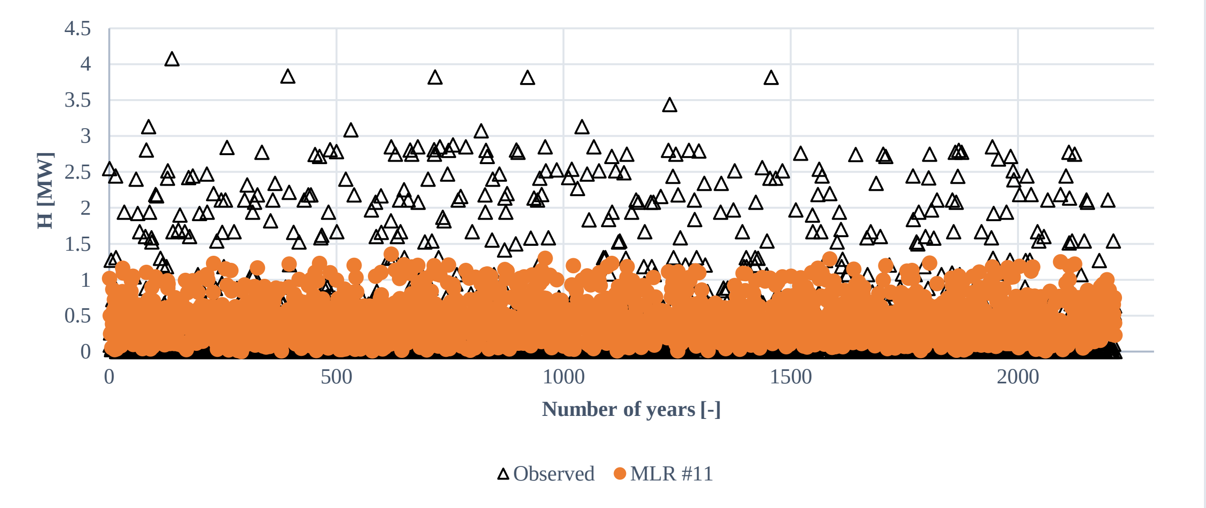
| | | | |
|---|---|---|---|
| MODEL #9 | MLR #9 | LAT LONG ALT Y TAV RH WS TMAX | H=-11.776+0.002LAT+0.012LONG+0.0ALT+0.007Y-0.1TAV-0.002RH-0.072WS+0.044TMAX NH=-10.479-0.001LAT+0.001LONG+0.0ALT+0.006Y-0.023TAV-0.003RH+.001TMAX |
| MODEL #10 | MLR #10 | LAT LONG ALT Y TAV RH TMAX PRE | H=-11.725+0.003LAT+0.009LONG+0.0ALT+0.006Y-0.075TAV+0.009RH+0.056TMAX+0.004PRE NH=-10.454-0.001LAT+0.001LONG-0.00009924ALT0.006Y-0.022TAV-0.003RH+0.002TMAX-0.005PRE |
| MODEL #11 | MLR #11 | LAT LONG ALT Y TAV WS TMAX TMIN | H=-11.542+0.002LAT+0.011LONG+0.0ALT+0.006Y-0.112TAV-0.061WS+0.59TMAX+0.011TMIN NH=-10.746-0.001LAT+0.001LONG-0.00008044ALT+0.006Y-0.007TAV+0.002WS+0.0TMAX-0.009TMIN |
| MODEL #12 | MLR #12 | LAT LONG ALT TAV WS TMAX TMIN PRE | H=-0.132+0.003LAT+0.011LONG+0.0ALT+0.011RH-0.069WS+0.027TMAX-0.042TMIN-0.039PRE NH=0.192-0.001LAT+0.001LONG-0.00005201+0.0RH+0.001WS-0.001TMAX-0.01TMIN-0.011PRE |
| MODEL #13 | MLR #13 | LAT LONG ALT RH WS TMAX TMIN PRE | H=-10.534+0.003LAT+0.009LONG+0.006Y-0.117TAV-0.002RH-0.053WS+0.07TMAX+0.035TMIN NH=-10.376-0.001LAT+0.0LONG+0.005Y-0.013TAV-0.002RH+0.003WS+0.004TMAX+0.0TMIN |
| MODEL #14 | MLR #14 | LAT ALT TAV RH WS TMAX TMIN PRE | H=-9.85-0.003LAT+0.006Y-0.128TAV-0.001RH-0.049WS+0.068TMAX+0.044TMIN-0.053PRE NH=-10.344-0.001LAT+0.005Y-0.012TAV-0.001RH+0.003WS+0.004TMAX+0.00003717TMIN-0.009PRE |
| MODEL #15 | MLR #15 | LONG ALT Y TAV RH WS TMAX PRE | H=-12.14+0.01LON+0.0ALT+0.008Y-0.065TAV-0.006RH-0.086WS-0.021TMIN-0.017PRE NH=-10.596+0.001LONG-0.00009399+0.006Y-0.018TAV-0.002RH-0.001WS-0.003TMIN-0.004PRE |
| MODEL #16 | MLR #16 | LONG ALT Y TAV RH WS TMIN PRE | H=-10.378+0.008LONG+0.0ALT+0.006Y-0.153TAV-0.001RH+0.08TMAX+0.049TMIN+0.009PRE NH=-10.597+0.001LONG-0.00009172ALT+0.006Y-0.018TAV-0.002RH-0.00007186TMAX-0.003TMIN-0.004PRE |
| MODEL #17 | MLR #17 | ALT Y TAV RH WS TMAX TMIN PRE | H=-10.946+0.001LAT+0.011LONG+0.0ALT+0.007Y-0.145TAV-0.007RH-0.068WS+0.06TMAX+0.031TMIN NH=-10.496-0.001LAT+0.001LONG+0.0ALT+0.006Y-0.022TAV-0.003RH-0.001WS+0.001TMAX-0.001TMIN |

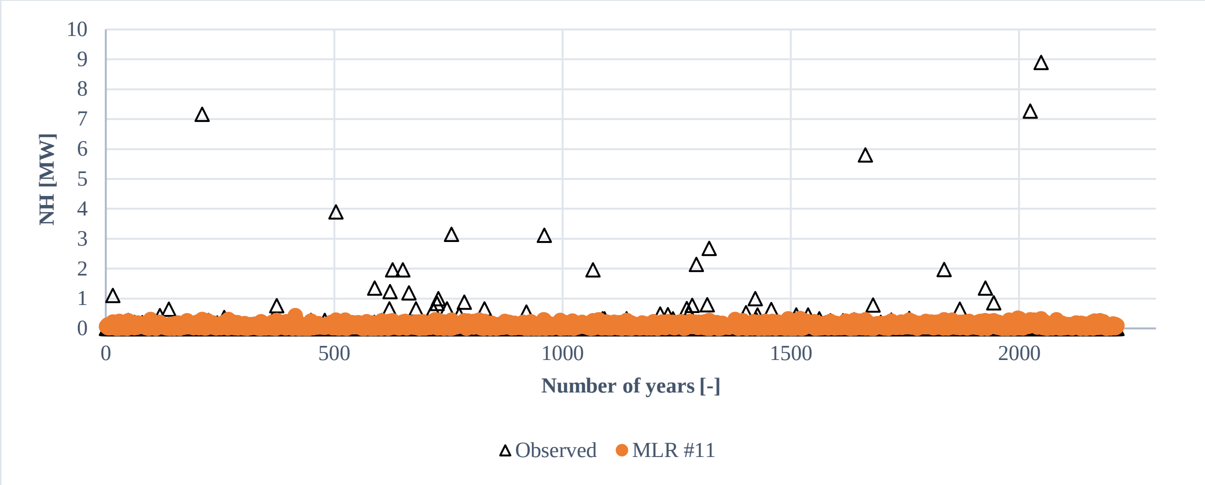
Table 3. Continue

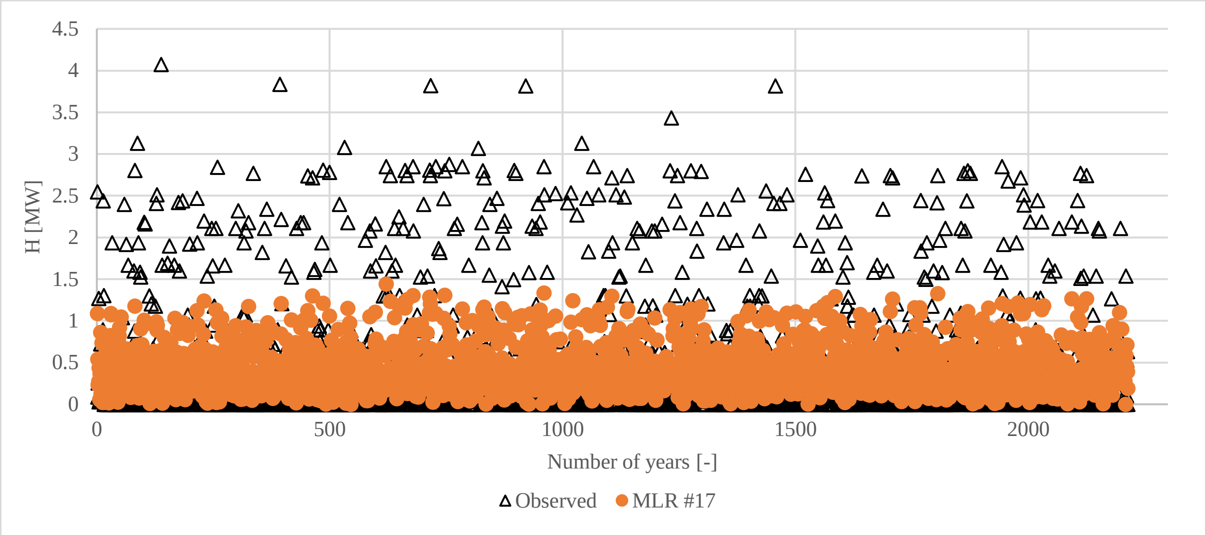
| | | | |
|---|---|---|---|
| MODEL #18 | MLR #18 | LAT LONG ALT Y TAV RH WS TMAX TMIN | H=-11.664+0.02LAT+0.011LONG+0.0ALT+0.007Y-0.1TAV+0.00009903RH-0.074WS+0.046TMAX-0.026PRE<br>NH=-10.453-0.002LAT+0.001LONG+0.0ALT+0.006Y-0.023TAV-0.003RH-0.001WS+0.002TMAX-0.006PRE |
| MODEL #19 | MLR #19 | LAT LONG ALT Y TAV RH WS TMAX PRE | H=-12.345+0.004LAT+0.011LONG+0.0ALT+0.008Y-0.063TAV-0.005RH-0.084WS-0.022TMIN-0.013PRE<br>NH=-10.513-0.001LAT+0.001LONG+0.0ALT+0.006Y-0.019TAV-0.002RH-0.002WS-0.002TMIN-0.006PRE |
| MODEL #20 | MLR #20 | LAT LONG ALT Y TAV RH WS TMIN PRE | H=-10.513+0.002LAT+0.008LOMG+0.0ALT+0.006Y-0.149TAV-0.001RH+0.078TMAX+0.047TMIN+0.011PRE<br>NH=-10.474-0.001LAT+0.001LONG-0.00009922ALT+0.006Y-0.021TAV-0.002RH+0.002TMAX-0.001TMIN-0.006PRE |
| MODEL #21 | MLR #21 | LAT LONG ALT Y RH WS TMAX TMIN PRE | H=2.176+0.001LAT+0.011LONG+0.0ALT-0.142TAV-0.004RH-0.067WS+0.064TMAX+0.031TMIN-0.023PRE<br>NH=0.492-0.002LAT+0.001LONG-0.00007167ALT-0.019TAV-0.002RH+0.001WS+0.004TMAX+0.0TMIN-0.009PRE |
| MODEL #22 | MLR #22 | LONG ALT Y TAV RH WS TMAX TMIN PRE | H=-10.819+0.011LONG+0.0ALT+0.007Y-0.147TAV-0.006RH-0.07WS+0.062TMAX+0.031TMIN-0.021PRE<br>NH=-10.604+0.001LONG-0.00009484ALT+0.006Y-0.018TAV-0.002RH-0.001WS+0.0TMAX-0.003TMIN-0.004PRE |

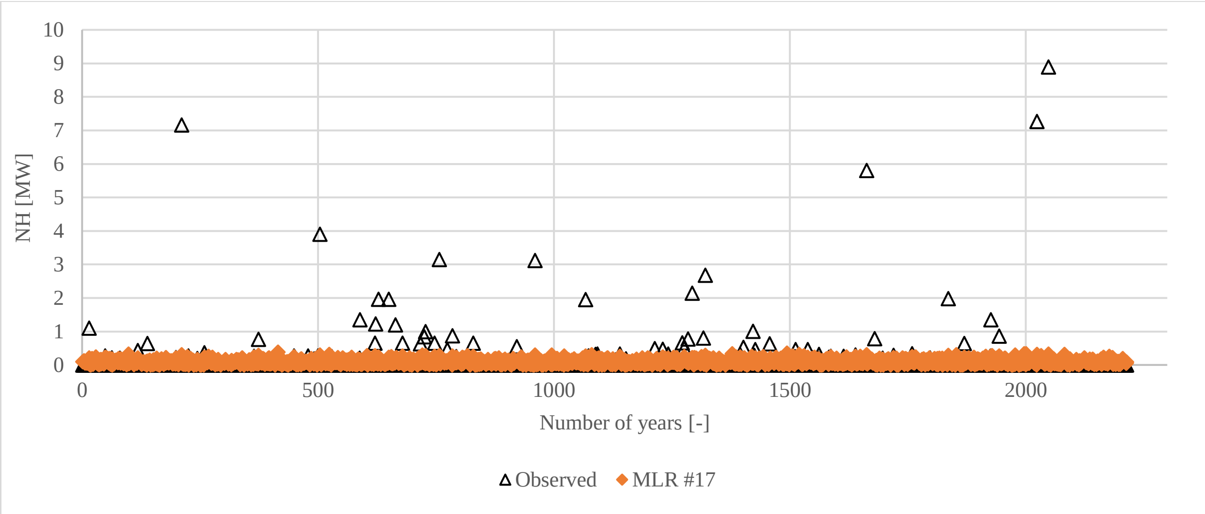
**Figure 8:**

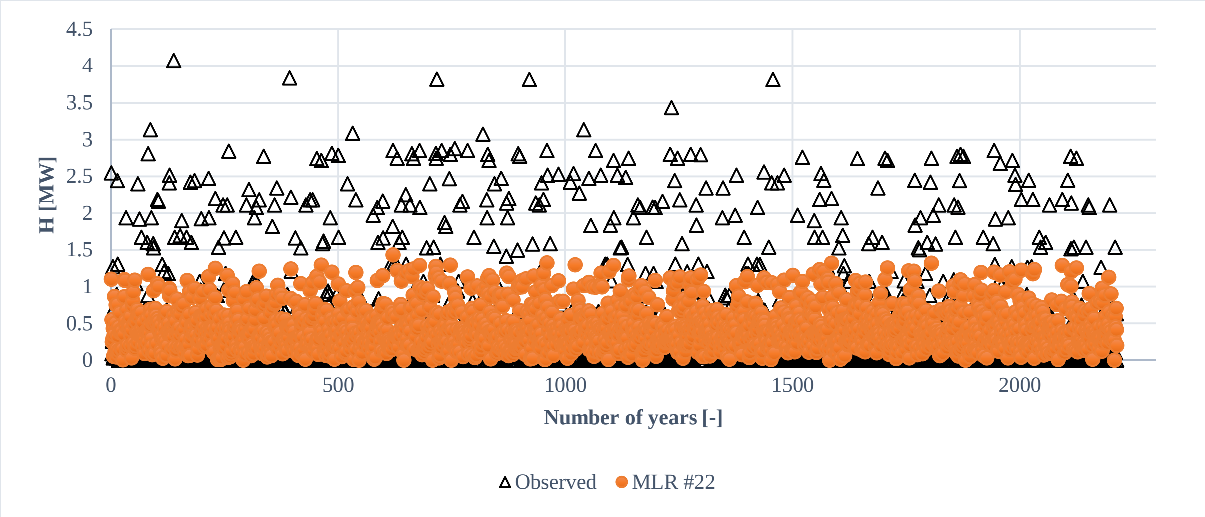
*Comparison between observed and predicted values (MLR #11, #17, #22)*

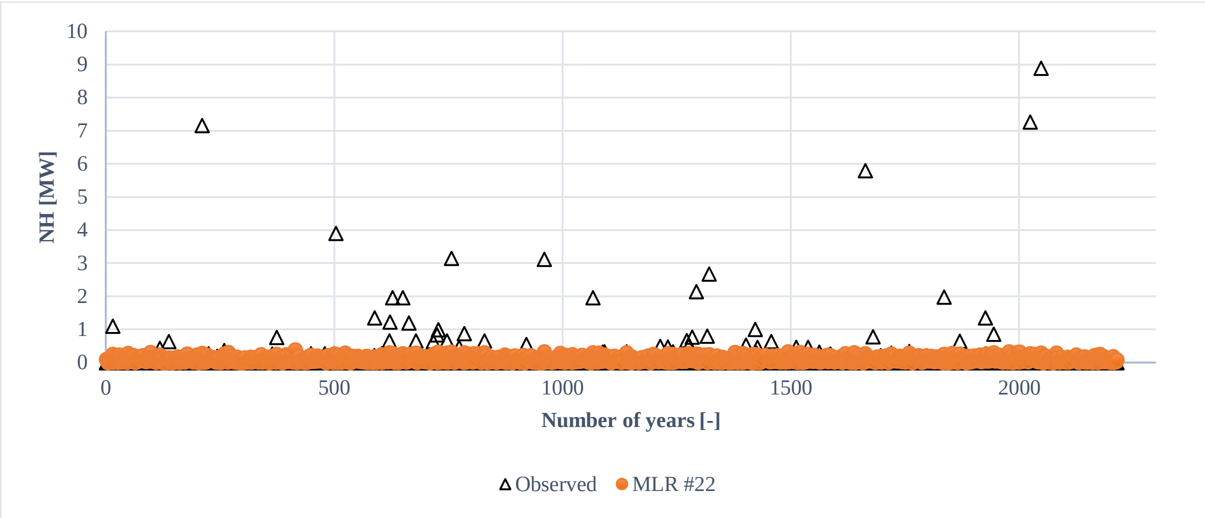



NH [MW]
Number of years [-]
Observed
MLR #11


H [MW]
Number of years [-]
Observed
MLR #17


NH [MW]
Number of years [-]
Observed
MLR #17




### 4.7 Comparison of ANN models with mathematical regression model.

The performance of ANN (MLPNN, RBF) models is compared with the mathematical models (MLR) to select the best model for predicting the Hydropower and Non-hydropower electricity Production in Africa. Various statistical performance indices were utilized such as R-squared, and RMSE, to measure the accuracy of the models. The R-squared value, ranging from 0 to 1, gives an indication of the variance proportion in the observed data and it is highly accepted that the value of R-squared be higher than 0.5 (Chicco, et al. 2021). All the proposed models have shown a high prediction accuracy and the highest values for R-squared were achieved by the MLPNN model. The RMSE indicates an exact match between the observed and predicted data when RMSE=0, i.e., an increasingly poor match when RSME>0. The MLPNN, RBFNN, and MLR model reported RMSE values ranging between 0.7 and 0.213, which indicates that the performance rate for these models can be considered

Excellent (MLPNN #886) and good respectively. In conclusion, it can be stated that the MLPNN model with the combination of key parameters [LAT LONG Y TAV RH TMAX TMIN], latitude (LAT), longitude (LONG), altitude (ALT), year (Y), relative humidity (RH), temperature average (TAV), temperature maximum (TMAX), temperature minimum (TMIN), wind speed (WS), and precipitation (PRE) has given the least error compared to other models.

**Table 4:**

*Comparison of ANN models with mathematical regression model.*

| Statistical indices | Model number | Input to model | Identification | MLPNN | RBFNN | MLR |
|---|---|---|---|---|---|---|
| R-squared | MLPNN #389 | LAT LONG ALT Y TMAX | H | 0.12743908 | 0.138455307 | 0.043404734 |
| | | | NH | 0.589371391 | 0.070345912 | 0.041102665 |
| | MLPNN #415 | LAT LONG Y RH PRE | H | 0.036695924 | 0.084582795 | 0.026334128 |
| | | | NH | 0.613462141 | 0.10346895 | 0.046748912 |
| | MLPNN #646 | LAT LONG ALT Y RH PRE | H | 0.281392422 | 0.227190254 | 0.031237394 |
| | | | NH | 0.618574042 | 0.094363059 | 0.047952859 |
| | MLPNN #850 | LAT LONG ALT Y TAV RH TMIN | H | 0.448526491 | 0.250540433 | 0.079084691 |
| | | | NH | 0.604321282 | 0.139942667 | 0.065507932 |
| | MLPNN #883 | LAT LONG Y TAV RH WS TMAX | H | 0.461916058 | 0.127937938 | 0.169494175 |
| | | | NH | **0.664036735** | 0.149811665 | 0.059214823 |
| | MLPNN #886 | LAT LONG Y TAV RH TMAX TMIN | H | 0.599855682 | 0.220604608 | 0.140442752 |
| | | | NH | 0.666035716 | 0.112108224 | 0.058727123 |
| | MLPNN #904 | LAT ALT Y TAV RH WS TMAX | H | 0.363744468 | 0.118925175 | 0.123278651 |
| | | | NH | 0.624150666 | 0.170776572 | 0.06417422 |
| | MLPNN #909 | LAT ALT Y TAV RH TMIN PRE | H | 0.343089286 | 0.131970077 | 0.049610274 |
| | | | NH | 0.599721758 | 0.097923533 | 0.064730008 |
| | MLPNN #968 | LAT LONG ALT Y TAV RH WS TMAX | H | 0.654396059 | 0.221784228 | 0.191957841 |
| | | | NH | 0.390164175 | 0.136954785 | 0.065612423 |
| | MLPNN #972 | LAT LONG ALT Y TAV RH TMAX PRE | H | 0.589166026 | 0.345509222 | 0.132645219 |
| | | | NH | 0.639932321 | 0.13408345 | 0.065833965 |
| | MLPNN #974 | LAT LONG ALT Y TAV WS TMAX TMIN | H | 0.62130158 | 0.257147286 | 0.192581628 |
| | | | NH | 0.101097861 | 0.118741007 | 0.062369835 |
| | MLPNN #988 | LAT LONG ALT RH WS TMAX TMIN PRE | H | 0.632352308 | 0.298974249 | 0.147027604 |
| | | | NH | 0.009919405 | 0.043035191 | 0.031826603 |
| | MLPNN #989 | LAT LONG Y TAV RH WS TMAX TMIN | H | 0.641673789 | 0.205403255 | 0.176748606 |
| | | | NH | 0.070400892 | 0.127015262 | 0.059220716 |
| | MLPNN #1003 | LAT Y TAV RH WS TMAX TMIN PRE | H | 0.487201484 | 0.178899145 | 0.13945374 |
| | | | NH | 0.622045409 | 0.104679581 | 0.059787958 |

Table 4: (Continue)

| | | | | | | |
|---|---|---|---|---|---|---|
| | MLPNN #1006 | LONG ALT Y TAV RH WS TMIN PRE | H | 0.502870609 | 0.236876252 | 0.158244224 |
| | | | NH | 0.603269389 | 0.164665494 | 0.063757023 |
| | MLPNN #1007 | LONG ALT Y TAV RH TMAX TMIN PRE | H | 0.504399995 | 0.183006355 | 0.145123279 |
| | | | NH | 0.648234231 | 0.193221363 | 0.063703471 |
| | MLPNN #1013 | LAT LONG ALT Y TAV RH WS TMAX TMIN | H | 0.625358049 | 0.236115577 | 0.197679622 |
| | | | NH | 0.620725324 | 0.126976564 | 0.065621262 |
| | MLPNN #1014 | LAT LONG ALT Y TAV RH WS TMAX PRE | H | 0.561640661 | 0.184179882 | 0.19353204 |
| **R-squared** | | | NH | 0.581911813 | 0.093225221 | 0.065913139 |
| | MLPNN #1015 | LAT LONG ALT Y TAV RH WS TMIN PRE | H | 0.62467095 | 0.193179599 | 0.161818306 |
| | | | NH | 0.527222218 | 0.107593447 | 0.065879759 |
| | MLPNN #1016 | LAT LONG ALT Y TAV RH TMAX TMIN PRE | H | 0.525855855 | 0.225399288 | 0.145826705 |
| | | | NH | 0.654301524 | 0.144260078 | 0.065845605 |
| | MLPNN #1019 | LAT LONG ALT TAV RH WS TMAX TMIN PRE | H | 0.620161597 | 0.200987403 | 0.186150817 |
| | | | NH | 0.041196704 | 0.05684451 | 0.034227 |
| | MLPNN #1022 | LONG ALT Y TAV RH WS TMAX TMIN PRE | H | 0.430850922 | 0.172267308 | 0.198317556 |
| | | | NH | 0.583849993 | 0.183277818 | 0.063762367 |
| | MLPNN #389 | LAT LONG ALT Y TMAX | H | 0.665804129 | 0.648604619 | 0.683368862 |
| | | | NH | 0.237345008 | 0.354263714 | 0.3597154 |
| | MLPNN #415 | LAT LONG Y RH PRE | H | 0.685796204 | 0.669201388 | 0.689439316 |
| | | | NH | 0.230731675 | 0.348015237 | 0.358654786 |
| | MLPNN #646 | LAT LONG ALT Y RH PRE | H | 0.592483484 | 0.614339561 | 0.687701158 |
| | | | NH | 0.229362421 | 0.350803826 | 0.358428225 |
| | MLPNN #850 | LAT LONG ALT Y TAV RH TMIN | H | 0.520611888 | 0.604877304 | 0.670503298 |
| | | | NH | 0.23429053 | 0.340699069 | 0.355108269 |
| | MLPNN #883 | LAT LONG Y TAV RH WS TMAX | H | 0.512701046 | 0.652551353 | 0.636740411 |
| | | | NH | 0.216178617 | 0.339587972 | 0.356301958 |
| **RMSE** | MLPNN #886 | LAT LONG Y TAV RH TMAX TMIN | H | 0.442151175 | 0.61685607 | 0.647781403 |
| | | | NH | **0.212605051** | 0.346160527 | 0.356394299 |
| | MLPNN #904 | LAT ALT Y TAV RH WS TMAX | H | 0.557419452 | 0.6562393 | 0.654217057 |
| | | | NH | 0.227461018 | 0.334539857 | 0.355361585 |
| | MLPNN #909 | LAT ALT Y TAV RH TMIN PRE | H | 0.567899704 | 0.650988642 | 0.68114871 |
| | | | NH | 0.232571834 | 0.349923327 | 0.355256044 |
| | MLPNN #968 | LAT LONG ALT Y TAV RH WS TMAX | H | 0.412573507 | 0.616478265 | 0.628070047 |
| | | | NH | 0.294382789 | 0.341486387 | 0.355088415 |
| | MLPNN #972 | LAT LONG ALT Y TAV RH TMAX PRE | H | 0.448155763 | 0.565315617 | 0.650712966 |
| | | | NH | 0.238566747 | 0.342004028 | 0.355046317 |

Table 4: (Continue)

| | | | | | | |
|---|---|---|---|---|---|---|
| RMSE | MLPNN #974 | LAT LONG ALT Y TAV WS TMAX TMIN | H | 0.433479613 | 0.602255966 | 0.627827574 |
| | | | NH | 0.34921 | 0.346516 | 0.35570401 |
| | MLPNN #988 | LAT LONG ALT RH WS TMAX TMIN PRE | H | 0.42664366 | 0.58501171 | 0.645295387 |
| | | | NH | 0.367130644 | 0.359365312 | 0.361451098 |
| | MLPNN #989 | LAT LONG Y TAV RH WS TMAX TMIN | H | 0.419838736 | 0.622886794 | 0.633953362 |
| | | | NH | 0.354559083 | 0.343986156 | 0.356300842 |
| | MLPNN #1003 | LAT Y TAV RH WS TMAX TMIN PRE | H | 0.501487715 | 0.633142855 | 0.648153966 |
| | | | NH | 0.227010294 | 0.347670945 | 0.35619341 |
| | MLPNN #1006 | LONG ALT Y TAV RH WS TMIN PRE | H | 0.493610772 | 0.610526701 | 0.641038517 |
| | | | NH | 0.23180498 | 0.336657841 | 0.355440787 |
| | MLPNN #1007 | LONG ALT Y TAV RH TMAX TMIN PRE | H | 0.492024809 | 0.632355142 | 0.646015321 |
| | | | NH | 0.218547082 | 0.329956976 | 0.355450952 |
| | MLPNN #1013 | LAT LONG ALT Y TAV RH WS TMAX TMIN | H | 0.428876095 | 0.611053532 | 0.625842402 |
| | | | NH | 0.227689307 | 0.343258797 | 0.355086736 |
| | MLPNN #1014 | LAT LONG ALT Y TAV RH WS TMAX PRE | H | 0.46282139 | 0.631172432 | 0.627457957 |
| | | | NH | 0.237546756 | 0.350945143 | 0.355031271 |
| | MLPNN #1015 | LAT LONG ALT Y TAV RH WS TMIN PRE | H | 0.42897951 | 0.627665997 | 0.639676149 |
| | | | NH | 0.305073175 | 0.347362444 | 0.355037614 |
| | MLPNN #1016 | LAT LONG ALT Y TAV RH TMAX TMIN PRE | H | 0.485439977 | 0.61500956 | 0.645749483 |
| | | | NH | 0.216524265 | 0.340638906 | 0.355044105 |
| | MLPNN #1019 | LAT LONG ALT TAV RH WS TMAX TMIN PRE | H | 0.431546105 | 0.624647557 | 0.630322831 |
| | | | NH | 0.360503419 | 0.35694519 | 0.361002746 |
| | MLPNN #1022 | LONG ALT Y TAV RH WS TMAX TMIN PRE | H | 0.528552479 | 0.635699978 | 0.625593545 |
| | | | NH | 0.238022752 | 0.332417621 | 0.355439773 |

The best models are in bold for all the three models based on the highest R-squared and the least of RMSE.

**Importance of Climate Parameters:**

The analysis revealed that average temperature, maximum temperature, and precipitation were the most influential climate parameters for hydropower production. While the non-hydropower electricity production, wind speed, temperature average, and relative humidity were found to have the most significant impact.

**Machine Learning Models and Mathematical Models:**

When analyzing the prediction of energy production, both MLPNN and RBF showed better results than MLR, confirming the supremacy of machine learning models in tackling complex correlations between climate parameters and energy production.

MLPNN turned out to be particularly successful in forecasting energy production, getting the best accuracy scores in both hydropower and non-hydropower predictions. This indicates the potential of this algorithm in making accurate prognoses.

**Comparative Analysis of Models:**

The performance of machine learning models in comparison to the traditional mathematical models reveals the potential of complex algorithmic strategies when it comes to predicting relationship between climate parameters and power production. They showed greater accuracy and predictive power, thus proving the benefit of using cutting-edge models when studying the factors behind climate and energy events.

MLPNN and RBF demonstrated the ability to capture non-linear relationships between climate parameters and energy production, surpassing the limitations of traditional mathematical models.

# CHAPTER V

# Conclusion and Recommendation

This chapter presents conclusions based on the research findings according to the objective of the research and gives recommendations accordingly.

## 5.1 Conclusion

This chapter provides a comprehensive summation based on the results of the analysis and investigation of hydropower and non-hydropower electricity production in Africa. This study was done in order to evaluate the effects of climate parameters on electricity generation and pinpoint the climatic factor with the most influential impact on either hydropower or non-hydropower power sources. Machine learning models, mathematical and statistical models were utilized to grasp understanding in the association between climate and energy vigor in Africa.

The research undertaken for this research question has revealed that numerous climate factors have an effect on both hydroelectric and non-hydroelectric energy production in Africa. These encompass temperature average, maximum, minimum, relative humidity, wind speed, and precipitation. Therefore, the climate parameters identified shaped the accessibility of resources and are thought to have an impact on energy generation. Additionally, the results of this research will be beneficial as it can provide insight into how energy production can be more efficiently managed in the continent.

The machine learning models Multilayer Perceptron Neural Network (MLPNN) and Radial Basis Function (RBF) have displayed impressive results in identifying complicated patterns and connections between climate parameters and electricity production. After being tested, the models showed extremely accurate prediction results of electricity production from climate inputs.

Comparing machine learning models to mathematical models such as Multiple Linear Regression, as well as statistical models, further demonstrated the efficacy of the former in detecting the dynamic nature of climate-energy relationships. The results were much better with the machine learning models than the traditional mathematical models. They were particularly effective in considering complicated dependencies in the data and non-linear connections.

The analysis revealed that a number of different climate parameters can affect hydropower and non-hydropower electricity production. Despite all the factors being important, some demonstrated stronger associations with energy output. Notably, precipitation and temperature factors appeared to be the key determinants in the case of hydropower, as water availability is fundamental to hydroelectric plants. At the same time, wind speed and temperature variables showed a more marked consequence on non-hydropower sources such as wind and solar energy.

A comparative analysis was conducted to assess the relationship between climate parameters and the generation of electricity in Africa. The investigation produced important clues into the difficulties and potentials posed by climate transformations and their repercussions for electricity production in the continent. It supplied useful data to aid better comprehension of the challenges and opportunities facing the African energy sector due to climate change.

## 5.2 Recommendation

In order to ensure a sustainable and resilient energy future in Africa, several phased recommendations should be taken into account by policymakers, energy planners, and stakeholders.

Climate Change Resiliency Planning: It is imperative to incorporate the findings of this study into climate change resiliency planning for the energy sector in Africa. Strategies should be established that consider the specific impacts of climate parameters on hydropower and non-hydropower sources to guarantee the persistence and dependableness of electricity generation in the presence of changing climatic conditions.

The ever-changing climate necessitates careful consideration of the varying effects of environmental changes on the various energy sources available to us. To maintain greater security and resilience in our energy system, it can be beneficial to diversify the different energy sources which we rely upon. Investment in a blend of hydro-powered, wind-powered, solar powered and other renewable energy sources is likely to provide a more stable energy system, reducing any reliance on a single energy source.

Strengthening the capacity of data collection and monitoring of both climate and energtic parameters in Africa is highly essential in order to create an edifice that aids in proper decision-making. To build a better understanding and derive more accurate results out of the analysis being done with respect to the impacts of climate on the production of electricity, working in collaboration with trustable organisations is highly necessary. In this context, it would be highly desirable to work with organisations such as the Nasa and the US Energy Information Administration to get access to real-time, verifiable datasets that are updated to the latest information.

Integrating climate change considerations into infrastructure planning for power infrastructure is critical to ensure energy sustainability as the world faces an uncertain climate future. To this end, it is important to account for potential changes in temperature, precipitation and other relevant variables when designing and evaluating hydropower and non-hydropower projects. This will help to ensure the long term viability of energy infrastructure and allow greater resilience to future climate changes.

Encouraging capacity building and knowledge sharing will improve comprehension of the framework of climate and energy in Africa. It is essential to bring together climate scientists, energy professionals, and decision-makers in diverse research and development initiatives to push developments and make wise decisions. This will promote meaningful interdisciplinary cooperation and inspire innovation.

Create strategies to bolster the development of renewable energy sources by utilizing supportive policies and providing incentives. Utilize various approaches to encourage the adoption of clean and sustainable energy sources, such as providing financial remuneration through feed-in tariffs, tax reductions, and devising regulatory procedures that prioritize renewable energy integration.

As the global community faces the challenges initiated by climate change and the demand for sustainable energy solutions, international cooperation and partnerships must be fostered to address the needs of the African continent. This endeavour should be supported by regional and international organizations, research institutions, as well as funding agencies, to ensure the best possible access to expertise, resources, and financial aid that will make sustainable energy projects feasible. By collaborating, the world can foster progress in this area so that Africa can work towards a more sustainable future. By introducing and executing these strategies, Africa can work towards an energy sector that is more economical, adaptive to climate changes, and diversified. This can bring energy safety, economic expansion, and sustainability to the continent.

### 5.3 Limitations and Future Research

This study of hydropower versus non-hydropower electricity production in Africa provides useful insights. Nonetheless, it is crucial to acknowledge certain limitations of this research.

This study drew upon existing datasets from sources such as NASA POWER and the U.S. EIA database. It is important to note, though, that data availability and quality may be different across different parts of Africa, potentially impacting the applicability of the outcomes. Future investigations should endeavor to fill these data gaps and improve the collection of information.

Africa is a continent with a diverse landscape, climate, energy infrastructure, and socio-economic circumstances. Therefore, results found by this study may not apply to all regions of the continent evenly. To get a better understanding of the climate-energy dynamic, further research remains necessary that looks closely at regional-specific data. This would enable better assessment of local impacts and challenges. This research study was mainly centred around climate factors, however, there are other elements such as economic status, policy regulations, and advances in technology that also have sway in the production of electricity. To gain a full appreciation of the energy landscape in Africa these areas need to be considered. To this end, further research should not only look at climate characteristics but in equal measure also inspect related factors in order to get a comprehensive overview.

This study mainly focused on climate parameters, yet there are a number of other elements that affect electricity production, such as policy frameworks, economic circumstances, and advancements in technology. As a result, more extensive research should be conducted to include these factors with the aim of gaining a better insight into the African energy landscape. In conclusion, this comparative study explores the relation between climate parameters and hydropower and non-hydropower electricity production across Africa. It is clear that climate resilience and diversification should be taken into account in energy planning, as overlooked changes in climate can dramatically affect the energy industry. Thus, our study provides input to policymakers and stakeholders in developing strategies to assure a sustainable energy future in the continent.

**References.**


Africa Energy Outlook. (2019). *International Energy Agency*, https://www.iea.org/geo/africa/africaenergyoutlook.

IHA. (2017). *Africa Hydropower Status Report*. Retrieved from https://www.hydropower.org/sites/default/files/documents/reports/Africa_Hydropower_Status_Report_web_1.pdf

IHA. (2020). *Global Hydropower Market Trends and Insights.* Retrieved from https://www.hydropower.org/update/global-hydropower-market-trends-insights

Tsige, G., & Ghirmay, H. (2019). *Renewable Energy in Africa – Challenges and Opportunities.* International Journal of Agricultural Science and Research, 9(2), 109-122. https://www.anest.co.in/files/ijasr/9-2/Giao_109-122.pdf

International Energy Agency. (2021). *Renewable energy in Africa: Overview.* Retrieved from https://www.iea.org/reports/renewable-energy-in-africa-overview.

World Bank. (2021). *Decentralized Renewable Energy: A Transformative Solution for the Affordable, Accessible, and Reliable Energy in Africa.* Retrieved from https://www.worldbank.org/en/programs/renewable-energy-in-africa.

Higgins, J. et al. (2020). *Intertropical Convergence Zone Variability from 1980 to 2016.* Journal of Climate, 33(3), 1081–1101. https://doi.org/10.1175/JCLI-D-19-0261.1

World Regional Geography (2019). *Africa Physical Geography.* Retrieved from https://www.nationalgeographic.org/encyclopedia/africa-physical-geography/

Yahaya, O. (2018). *Precipitation and temperature patterns in the drylands of Southern African region.* International Journal of Climatology, 38(6), 2760–2771. https://onlinelibrary.wiley.com/doi/abs/10.1002/joc.5239

Agrawal, P., & Ghosh, S. (2019). *The marine climate of Africa: A review*. International Journal of Climatology, 39(3), 2019–2026. https://onlinelibrary.wiley.com/doi/abs/10.1002/joc.5909

IPCC (2018) *Summary for Policymakers In: Global Warming of 1.5°C.* An IPCC Special Report. https://www.ipcc.ch/report/sr15/

African Economic Research Consortium (AERC). (2021). *Renewable Energy Sources in Africa: Leveraging Opportunities and Defeating Challenges.* Available online: https://aer.org/publications/renewable-energy-sources-in-africa-leveraging-opportunities-and-defeating-challenges/

(IHA 2022). 2022 Hydropower Status Report https://www.hydropower.org/publications/2022-hydropower-status-report

Clarke, A., Borkowski, N., Kirk, K., & Thomson, G. (2019). *Solar Energy Development in Africa.* Renewable and Sustainable Energy Reviews, 99, 276-284. https://doi.org/10.1016/j.rser.2018.07.057

Gebre, W., Nega, A., Kebede, M., & Gebrehiwot, K. (2022). *The Potential of Geothermal Energy in Ethiopia.* Renewable and Sustainable Energy Reviews, 148, 110139. https://doi.org/10.1016/j.rser.2021.110139

Hilal, M. A., Sen, Y. K., Saad, L., Gasser, M. H., & Rynkiewicz, M. (2021). *The Use and Potential of Wind Energy in Africa.* Renewable and Sustainable Energy Reviews, 141, 110902. https://doi.org/10.1016/j.rser.2020.110902

Kudlock, K. (2019). *Hydro Potential in Africa.* Retrieved February 19, 2021, from https://www.energy.gov/eere/water/hydropower-potential-africa

Walia, H., & Aklilu, T. (2021). *Hydropower in Africa: Past, Present, and Future.* International Journal of Scientific Research and Management, 9(3), 17-25. https://www.ijsrm.in/ejournal.php?action=publication_details&did=46369

Kumari, M., Bahar, G., Kumar, V., & Patel, A. (2020). *Solar Energy potential in Africa: A review.* Renewable and Sustainable Energy Reviews, 134, 109814. https://doi.org/10.1016/j.rser.2020.109814

Mathebula, D. and Mathebula, J. (2018). *Lake Turkana Wind Power: Africa's Largest Wind Farm to Power Sustainable Energy in Kenya.* https://www.worldenergy.org/magazine/november-2018/lake-turkana-wind-power-africas-largest-wind-farm-to-power-sustainable-energy-in-kenya/

Koné, K., & Khandi, S. (2017). *Opportunities for Geothermal Energy in Africa.* Global Geothermal Alliance. https://gga.org/opportunities-for-geothermal-energy-in-africa/

Ahmed, T. O., Alesutan, I., Lani, S., Atiemo, Y., Aseka, S., & Mukhtar, S. (2018). *Hydropower and non-hydropower electricity sources in Africa: Challenges, interventions, and opportunities.* Renewable and Sustainable Energy Reviews, 84, 1406-1417. doi: https://doi.org/10.1016/j.rser.2017.09.036

Akintola, O.J., and Midzi, C. (2021). *Hydropower Resources, Challenges, and Opportunities.* Energies, 14(4), 968. https://www.mdpi.com/1996-1073/14/4/968

Kammen, D. (2017, August 16). *Africa's Hydropower Potential and the Challenge of Development.* World Resources Institute. Retrieved from https://www.wri.org/blog/2017/08/africa%E2%80%99s-hydropower-potential-and-challenge-development

World Bank. (2020, May 27). *Energy in Africa: Meeting Growing Energy Demand.* World Bank. https://www.worldbank.org/en/topic/energy/brief/energy-in-africa-meeting-growing-energy-demand

International Energy Agency (IEA). 2017. *Sub-Saharan Africa's Growing Energy Deficit.* https://www.iea.org/publications/sub-saharan-africas-growing-energy-deficit/

International Energy Agency (IEA). 2018. *World Energy Outlook 2018: Sub-Saharan Africa Energy Outlook.* https://www.iea.org/weo2018/sub-saharan-africa/

UNESCO (2017). *Africa's Energy Future: Renewables and Sustainable Solutions*. https://unesdoc.unesco.org/ark:/48223/pf0000267263.

International Renewable Energy Agency (2019). *Powering Africa: Data-Driven Insights.* https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/May/IRENA_Powering_Africa_Data-Driven_Insights.pdf.

IEA (2017). *Africa Energy Outlook. Available online:* https://www.iea.org/newsroom/news/2017/october/africa-energy-outlook-key-findings.html

IEA (2018). *African Energy Outlook: Financing the Transition. Available online:* https://www.iea.org/reports/finance-the-transition-series-africa-energy-outlook

United Nations (2017). *"The World Population Prospects: The 2017 Revision."* https://population.un.org/wpp/

UN-Habitat. (2017). *World Urbanization Prospects: The 2018 Revision.* Retrieved from https://population.un.org/wup/

World Bank, 2017. *"Africa's economic growth to average 3.5 percent in 2017."* Available at https://www.worldbank.org/en/region/afr/overview

Intergovernmental Panel on Climate Change (IPCC). 2017. *Global Warming of 1.5 °C.* https://www.ipcc.ch/report/sr15/

Ghebreyesus, A. S., M. Mehari, A. Tilahun, T. Hagos, T. Biru, and K. B. Legesse. (2019) *Climate change-induced changes in hydropower potential in the Blue Nile basin.* Hydrological Processes, 33: 1667–1676. https://onlinelibrary.wiley.com/doi/10.1002/hyp.13391

Hamududu, B., & Killingtveit, Å. (2016). *Hydropower Production in Future Climate Scenarios; the Case for the Zambezi River.* Energies, 9(7), 502. https://doi.org/10.3390/en9070502

Hrishikesh Patel & Johan Grijsen 2014 *Understanding the impact of climate change on hydropower: the case of Cameroon - climate risk assessment for hydropower generation in Cameroon* Report No. 87913 https://www.academia.edu/28990654/Understanding_the_impact_of_climate_change_on_hydropower_the_case_of_Cameroon_climate_risk_assessment_for_hydropower_generation_in_Cameroon

Charles Fant, C. Adam Schlosser, Kenneth Strzepek, *The impact of climate change on wind and solar resources in southern Africa*, *Applied Energy*, Volume 161, 2016, Pages 556-564, ISSN 0306-2619.

Al Jindy, A. B., and Yamani, T. (2020). *The impact of relative humidity on hydropower production in Egypt. Energy Sources*, *Part A: Recovery, Utilization, and Environmental Effects*, 42(14), 1846-1853.

Dongmo, F. E., Tchanche, S., Ndip, A. J., Arrey, A. B., & Nangue, E. (2021). *Assessing the effects of wind speed on hydropower production in a tropical environment: the case of Cameroon.* Renewable and Sustainable Energy Reviews, 139, 110080.

Ntale, W.H., Nabugabo, L.K.C., Jimadu, M.A., Perger, P., Dokony, E.G., Kironde, K., Chebet, S., Makanga, S. (2020). *Machine learning applications in assessing the impacts of climate variability on hydropower production in Uganda.* Renewable and Sustainable Energy Reviews, 122, 110030.

Nzeadibe, C.B., Abueke, K.I., Ogbodo, E.U., Izah, S.C. (2020). *Renewable Energy Potential in Nigeria: An Assessment of Solar and Wind Last Mile Energy Solutions.* Renewable and Sustainable Energy Reviews, 120, 109655.

Lazin, R. ; Shen, X. ; Moges, S. ; Anagnostou, E. N. (2020), *Impact of Climate Change on the Hydrology and Hydropower in the Upper Blue Nile Basin,* AGUFMH030.0008L. https://ui.adsabs.harvard.edu/abs/2020AGUFMH030.0008L/abstract

Guo, X., Vörösmarty, C. J., & Ding, Y. (2018). *Impact of climate change on hydropower potential of the Zambezi River Basin.* Hydrology and Earth System Sciences, 22(2), 1299–1308.

Amuakwa-Mensah, F., Noken, E., Dagadu, C., Frimpong, B. and Aikins-Mensah, J. (2017) *Implication of Solar and Wind Energy Resources for Power Generation in Ghana.* Renewable and Sustainable Energy Reviews, 70, 1236–1246.

Oyedepo, A. (2017). *Geothermal Energy and Sustainable Development in East Africa.* Renewable and Sustainable Energy Reviews, 70, 440-451. https://www.sciencedirect.com/science/article/abs/pii/S13640321163googleScholar

Yamba, F.D., Walimwipi, H., Jain, S. et al. (2011) *Climate change/variability implications on hydroelectricity generation in the Zambezi River Basin.* Mitig Adapt Strateg Glob Change 16, 617–628. https://doi.org/10.1007/s11027-011-9283-0

Yohannes, B., Zhang, M., Ding, H., & Olago, D. (2018). *Climate change impact on wind energy potential in Ethiopia.* Renewable and Sustainable Energy Reviews, 97, 627–648.

Mekonnen, T. W., Teferi, S. T., Kebede, F. S., & Anandarajah, G. (2022). *Assessment of Impacts of Climate Change on Hydropower-Dominated Power System—The Case of Ethiopia.* Applied Sciences, 12(4), 1954. https://doi.org/10.3390/app12041954

Alemayehu, B., Tekie, E., & Fantahun, M. (2021). *Hydropower potential estimation using MLPNN for the Nile basin.* Renewable and Sustainable Energy Reviews, 140, 110086.

Faruk, S., & El-Sayed, S. A. (2021). *Predictive Hydropower Potential Mapping Using RBF Network Method in the Upper Kaduna River Basin, Nigeria.* International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 10(2), 13137–13144. https://www.ijareeie.com/wp-content/uploads/papers/v10i2/F10002213144.pdf

Zhu, R., Li, H., Shang, M., Xie, W., Xiang, H., & Sun, X. (2021). *Assessing the impact of climate parameters on hydropower production in Zambia using Machine Learning techniques.* Renewable and Sustainable Energy Reviews, 142, 111069. https://www.sciencedirect.com/science/article/pii/S1364032120335669

Li, H., Tana, T., & Liang, S. (2019). *Multi-layer perception neural network for predicting hydropower production based on climate parameters in Zambia.* Applied Energy, 266, 114700.

Zhang, L., et al. (2017). *Investigating the impact of climate parameters on non-hydropower electricity production in Africa.* International Journal of Energy Economics and Policy, 7(3), 225. https://www.econjournals.com/index.php/ijeep/article/view/2134

Alimi, A. A., Mirzikian, S., & Kumar, V. (2020*). Impacts of climate parameters on hydropower production in Nigeria: a multi-level regression approach.* Journal of energy in Southern Africa, 31(1), 9-21. Retrieved from

Ouedraogo, B., Arbilion, Y. N., Diallo, A. et al. (2019) *Climate parameters and non-hydropower electricity production in Burkina Faso.* Renewable Energy 143: 189-202.

Hossain, M., Bali, A., Mustafa, S.A., Quader, M.A., and Imdadul Haq, M.K., 2020. *Assessing the impact of climate parameters on solar energy production in Ghana: A multivariate linear regression analysis.* Renewable Energy, 146, pp.774-781

Amos, N., & Wu, D. (2021). *Impact of Climate Parameters on Hydropower Production in Ghana.* International Journal of Renewable Energy Technology, 12(3), 310-322. https://www.worldscientific.com/doi/abs/10.1142/S2040084421500357

United Nations (2018). *Climate Change and its Impact in Africa.* https://www.un.org/en/africa/osaa/pdf/climatechange/climate-change-impact-africa.pdf

Kelly, S.L., Lautenberger, A., Wijk, M.T.V., Obermeit, S.A., Schuur, E.A.G., den Belder, E., Wakqari, M.F., et al. (2019). *Analyzing the vulnerability of African food systems to climate change.* Thematic Review 8: Food security and nutrition. https://reliefweb.int/report/world/analyzing-vulnerability-african-food-systems-climate-change-thematic-review-8-food

United Nations Department of Economic and Social Affairs. (2021). *World Population Prospects 2019: Highlights.* Retrieved from https://population.un.org/wpp/Publications/Files/WPP2019_Highlights.pdf

The World Bank. (2020). *Sub-Saharan Africa.* Retrieved from https://www.worldbank.org/en/region/afr/overview

NASA POWER: https://power.larc.nasa.gov/

U.S. Energy Information Administration: https://www.eia.gov/

Blyth, E., Williams, R., & MacCallum, I. (2022). *Using satellite data to inform decision-making for disrupted energy systems.* Resources, 1(1), 1-21.

Koumandou, V., Barbosa, P., Losada-Barboza, J. M., Mamet, S., Deblauwe, V., & Obersteiner, M. (2020). *An integrated method for assessing satellite product accuracy over Africa.* ISPRS Journal of Photogrammetry and Remote Sensing, 166, 214–226.

Xu Y, Li F, Asgari A (2022) *Prediction and optimization of heating and cooling loads in a residential building based on multi-layer perceptron neural network and different optimization algorithms.* Energy 240:122692

Kassem Y, Gökçekuş H (2021) *Do quadratic and Poisson regression models help to predict monthly rainfall? Desalin Water Treat* 215:288–318

Viljoen, J., Olgart, H.M., Snyders, R., Furst, T., Mbara, R., Chiweshe, O., Tirivavi, V. & Rwegasira, L. (2019). *Smart grids for hydropower production and management in Africa.* Energy, 175, 1185–1194.

Chen, Y., Sheng, V.S., Chen, H. 2017. *A Survey of Multi-Layer Perceptron Neural Network Models and Applications.* IEEE Access, 5: 7437–7447.

Kavzoglu T, Mather PM (2003) *The use of backpropagating artificial neural networks in land cover classification.* Int J Remote Sens 24(23):4907–4938

Mukhopadhyay, A. (2017). *An analysis of hydropower potential in Africa using geographical information systems and artificial neural networks.* International Journal of Engineering & Technology, 8(2.54), 91–98. https://hjournals.dor.mokk.rs/index.php/IJET/article/view/489/381

Akintunde, S. D., Oyeleke, O. B., Obadina, A. O., & Olaleye, J. O. (2018). *Hydropower capacity assessment using geographical information system and machine learning technologies in Kainji Lake basin, Nigeria.* International Journal of Hydrology Science and Technology, 8(3), 368–379.

Chanko, J., Jinesh, A., Ishola, A. O., & Charles, O. (2019). *Clustering of African countries' hydropower potentials using a machine learning-based approach.* Renewable and Sustainable Energy Reviews, 117, 128–143.

Chen, J., Bonnichsen, B., Mohn, C., Aune, J. M., & Bell, A. (2021). *Climate parameter impacts on hydropower and non-hydropower electricity generation in Africa: A machine learning approach.* Applied Energy, 281, 115444.

Hussain, A. et al. (2021) *Climate-Hydropower Nexus in continental Africa: Exploring electrification through the lens of the hydropower resource.* Energy for Sustainable Development, 56, 9-23.

Ismael AA, Suleiman SJ, Al-Nima RRO, Al-Ansari N (2021) *Predicting the discharge coefficient of oblique cylindrical weir using neural network techniques.* Arab J Geosci 14(16):1–8

Kassem, Y. (2023). *Analysis of different combinations of meteorological parameters and well characteristics in predicting the groundwater chloride concentration with different empirical approaches: a case study in Gaza Strip, Palestine.* Environ Earth Sci 82, 134. https://doi.org/10.1007/s12665-023-10767-9

Hansen, P.S. and Daviau, A.F. (2021). *Multilayer Perceptron and Radial Basis Function Neural Network Training Using Pseudoinverse.* Journal of Artificial Intelligence Research, 55, 1-37.

Löfberg, A. and Kennedy, J. (2022). *Tutorial: Using Radial Basis Function Networks to Analyze and Model Climate Data.* Retrieved from: https://digitalcommons.calpoly.edu/ecselab/46/

Daviau, A.F. and Hansen, P.S. (2022). *A Study of Learning Algorithms for Radial Basis Function Networks.* Neurocomputing, 223, pp.160-168.

Diagne, A., Ida, J., Torphy, F., Tiefo, P., Mambaye, S.L. and Kane, A.M. (2017). *Application of Neural Network Methodologies to Model the Influence of Climatic Factors on Hydropower Production in Senegal.* International Journal of Hydropower & Dams, 8(1), pp.67-76. https://www.hydropower-dams.com/2017/3/161/application-of-neural-network-methodologies-to-model-the-influence-of-climatic-factors-on-hydropower-production-in-senegal

Koussoni, H.D., Simasiku, K., Tshivula, S., Ndembukila, V. and Santos, D. (2019). *Statistical and Artificial Neural Network Models of Renewable Energy Production in Africa.* Journal of Cleaner Production, 218, pp.804-814.

Shang, Y. T., Lang, M. S., Li, J., Yang, X. R., & Li, Q. (2017). *Relationship between energy production and climate parameters in Africa: A multiple linear regression model*. Energy, 120, 1-13.

Fumpa, Sandra. (2020, May 23). *RMSE vs. R-Squared: How to Interpret Model Performance Metrics.* Statology. https://www.statology.org/rmse-vs-r-squared/

Joseph Andria, Giacomo di Tollo, Jaan Kalda, *The predictive power of power-laws: An empirical time-arrow based investigation, Chaos, Solitons & Fractals,* Volume 162, 2022, 112425, ISSN 0960-0779.

Milan Despotovic, Vladimir Nedic, Danijela Despotovic, Slobodan Cvetanovic, *Evaluation of empirical models for predicting monthly mean horizontal diffuse solar radiation*, Renewable and Sustainable Energy Reviews, Volume 56, 2016, Pages 246-260, ISSN 1364-0321, https://doi.org/10.1016/j.rser.2015.11.058.

McGough SF, Brownstein JS, Hawkins JB, Santillana M (2017) *Forecasting Zika Incidence in the 2016 Latin America Outbreak Combining Traditional Disease Surveillance with Search, Social Media, and News Report Data.* PLOS Neglected Tropical Diseases 11(1): e0005295. https://doi.org/10.1371/journal.pntd.0005295

Forootan, M. M., Larki, I., Zahedi, R., & Ahmadi, A. (2022). *Machine Learning and Deep Learning in Energy Systems: A Review.* Sustainability, 14(8), 4832. https://doi.org/10.3390/su14084832

Adam Hayes, Eric Estevez & Timothy Li. (2023). *Multiple Linear Regression (MLR): Investopedia,* https://www.investopedia.com/terms/m/mlr.asp

Che Wan Zanial, W. N., Malek, M. A., Md Reba, M. N., Zaini, N., Ahmed, A. N., Sherif, M., & Elshafie, A. (2023). *Rainfall-runoff modelling based on global climate model and tropical rainfall measuring mission (GCM -TRMM): A case study in Hulu Terengganu catchment, Malaysia.* Heliyon, 9(5), e15740. https://doi.org/10.1016/j.heliyon.2023.e15740

Chicco, D., Warrens, M. J., & Jurman, G. (2021). *The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation.* PeerJ. Computer science, 7, e623. https://doi.org/10.7717/peerj-cs.623

## Appendix A

## Ethics Letter

**TO THE INSTITUTE OF GRADUATE STUDIES**

**REFERENCE: ABDIMAJID IBRAHIM ALI (20215494)**

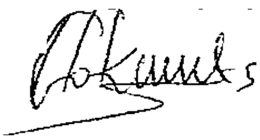
We would like to inform you that the above candidate is one of our postgraduate students in Civil Engineering Department. He is taking thesis under our supervision on the thesis entailed: **COMPARATIVE ANALYSIS OF HYDROPOWER AND NON-HYDROPOWER ELECTRICITY IN AFRICA USING DIFFERENT EMPIRICAL APPROACHES TO EVALUATE CLIMATE PARAMETERS IMPACTS.**

Since the researcher was not collected primary data from humans, animals, plants, or earth, this project does not need to go through the ethics committee.

Please do not hesitate to contact us if you have any further queries or questions.

Thank you very much indeed.

Best Regards,



Prof. Dr. Hüseyin Gökçekuş

Dean of Faculty of Civil and Environmental.

Engineering, Near East Boulevard, ZIP: 99138

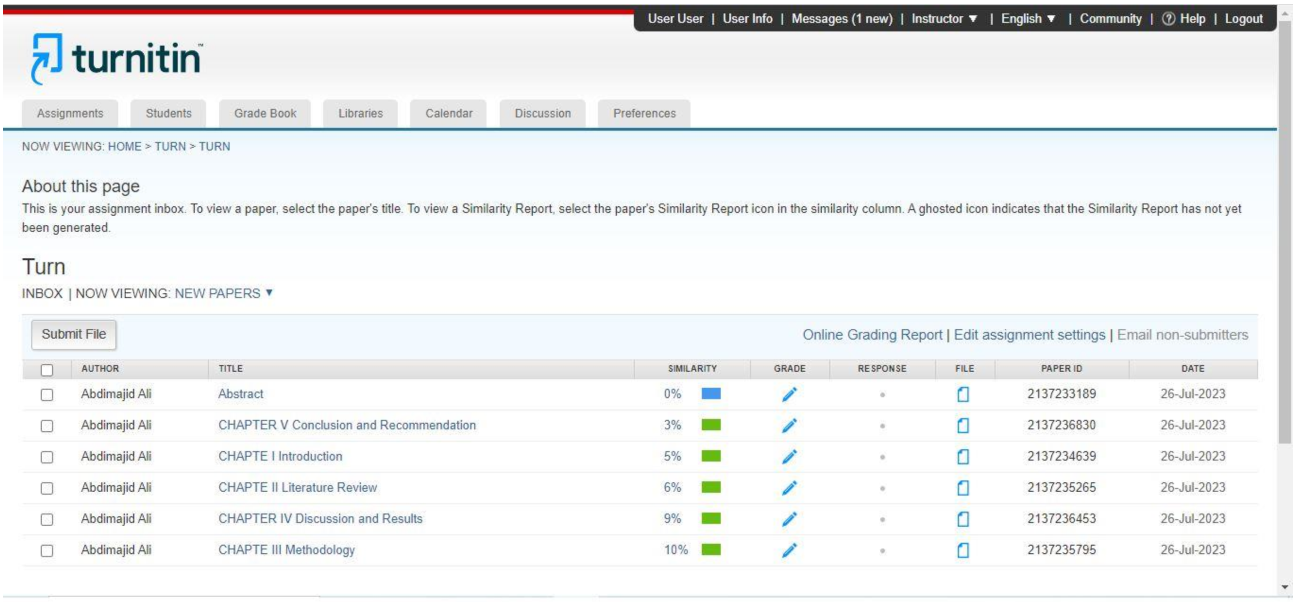
Nicosia/TRNC, North Cyprus

Mersin 10-Turkey

Email: huseyin.gokcekus@neu.edu.tr

# Appendix B

## Turnitin Similarity Report


User User | User Info | Messages (1 new) | Instructor ▼ | English ▼ | Community | ⓘ Help | Logout

turnitin

Assignments | Students | Grade Book | Libraries | Calendar | Discussion | Preferences

NOW VIEWING: HOME > TURN > TURN

About this page

This is your assignment inbox. To view a paper, select the paper's title. To view a Similarity Report, select the paper's Similarity Report icon in the similarity column. A ghosted icon indicates that the Similarity Report has not yet been generated.

Turn

INBOX | NOW VIEWING: NEW PAPERS ▼

Submit File

Online Grading Report | Edit assignment settings | Email non-submitters

| AUTHOR | TITLE | SIMILARITY | GRADE | RESPONSE | FILE | PAPER ID | DATE |
|---|---|---|---|---|---|---|---|
| Abdimajid Ali | Abstract | 0% | | | | 2137233189 | 26-Jul-2023 |
| Abdimajid Ali | CHAPTER V Conclusion and Recommendation | 3% | | | | 2137236830 | 26-Jul-2023 |
| Abdimajid Ali | CHAPTE I Introduction | 5% | | | | 2137234639 | 26-Jul-2023 |
| Abdimajid Ali | CHAPTE II Literature Review | 6% | | | | 2137235265 | 26-Jul-2023 |
| Abdimajid Ali | CHAPTER IV Discussion and Results | 9% | | | | 2137236453 | 26-Jul-2023 |
| Abdimajid Ali | CHAPTE III Methodology | 10% | | | | 2137235795 | 26-Jul-2023 |

Prof. Dr. Hüseyin Gökçekuş

Dean of Faculty of Civil and Environmental.

Engineering, Near East Boulevard, ZIP: 99138

Nicosia/TRNC, North Cyprus

Mersin 10-Turkey

Email: huseyin.gokcekus@neu.edu.tr