TAKUDZWA CHIKOWERO

PPREDICTING SOLAR RADIATION USIING MACHINE LEARNING MODELS IN GLOBAL HORIZONTAL IRRADIANCE(GHI)

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DEPARTMENT OF MECHANICAL ENGINEERING

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TAKUDZWA CHIKOWERO
20215146

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TAKUDZWA CHIKOWERO
20165146

Supervisor

Assoc. Prof . Dr. Youssef Kassem

Nicosia

June 2023

Approval

We certify that we have read the thesis submitted by TAKUDZWA CHIKOWERO titled **"PREDICTING SOLAR RADIATION USING MACHINE LEARNING MODELS IN GLOBAL HORIZONTAL IRRADIANCE (GHI)"** and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the Degree of Master of Mechanical Engineering.

Examining Committee	Name-Surname	Signature
Head of the Committee:	Prof . Dr. Hüseyin Gökçekus	....
Committee Member*:	Assoc. Prof. Dr. Hüseyin Çamur	....
Supervisor:	Assoc . Prof . Dr .Youssef Kassem	....

Approved by the Head of the Department

23/06/2023

Assoc. Prof. Dr. Hüseyin Çamur
Head of Department

Approved by the Institute of Graduate Studies

..../..../2023

Prof. Dr. Kemal Hüsnü Can Başer
Head of the Institute

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.

Takudzwa Chikowero
18/06/2023

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TAKUDZWA CHIKOWERO

Abstract

Predicting Solar Radiation using Machine Learning Models in Global Horizontal Irradiance (GHI)

Takudzwa Chikowero
M.Sc., Department of Mechanical Engineering
Supervisor's Name: Assoc . Prof . Dr. Youssef Kassem

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When it comes to the setup of photovoltaics (PV), the prediction of solar radiation in the global horizontal irradiance (GHI) using machine learning is very important. Furthermore, the meteorological variables that can affect solar production of photovoltaic panels and results derived from machine learning models exist. For this reason, it is necessary to identify the effects of certain parameters which may have an impact on model accuracy in order to achieve accurate predictions. With this main objective, three artificial intelligence techniques [Cascade Feed-forward Neural Network (CFNN), NARX regression neural network (NARX), and Layer Recurrent Neural Networks (LRNN)] were used to predict the effects of geographical parameters. To run the models, the annual data of (GHI), Latitude, longitude, altitude Surface Pressure, average, maximum, and minimum temperature, Relative Humidity, Wind Speed at 2m height, average, maximum, and minimum wind speed at 10m height, Wind Direction at 10m height, Dew/Frost Point, Wet Bulb Temperature, cloud amount, and precipitation were collected for all selected cities in Africa. These parameters were used as potential inputs to solar radiation prediction models. Annual data from 2000 to 2021 are covered by the NASA Data Set. Longitude, latitude, and altitude with other combinations of inputs were proposed and used to run the models to find the effects of geographical inputs to determine the effects of input parameters on the accuracy of the selected models. The reliability of utilized models was examined by correlation coefficient (R^2), mean absolute error (MAE), and root mean square error (RMSE).

Keywords: *Renewable Energy, Africa, GHI, Prediction, Machine Learning*

Özet

Küresel Yatay Işınımda Makine Öğrenimi Modellerini Kullanarak Güneş Radyasyonunu Tahmin

Takudzwa Chikowero
Yüksek Lisans, Makine Mühendisliği Bölümü
Danışmanın Adı: Assoc . Prof . Dr . Youssef Kassem
20/ Haziran/2023 80 sayfa

Fotovoltaik (PV) kurulumu söz konusu olduğunda, makine öğrenimi kullanılarak küresel yatay ışınımda (GHI) güneş ışınımının tahmini çok önemlidir. Ayrıca, fotovoltaik panellerin güneş üretimini etkileyebilecek meteorolojik değişkenler ve makine öğrenimi modellerinden elde edilen sonuçlar mevcuttur. Bu nedenle doğru tahminler yapabilmek için model doğruluğuna etki edebilecek bazı parametrelerin etkilerinin belirlenmesi gerekmektedir. Bu temel amaç doğrultusunda, coğrafi parametrelerin etkilerini tahmin etmek için üç yapay zeka tekniği [İleri Beslemeli Sinir Ağı (CFNN), NARX regresyon sinir ağı (NARX) ve Katmanlı Tekrarlayan Sinir Ağları (LRNN)] kullanılmıştır. Modelleri çalıştırmak için yıllık (GHI), Enlem, boylam, rakım Yüzey Basıncı, ortalama, maksimum ve minimum sıcaklık, Bağıl Nem, 2m yükseklikte Rüzgar Hızı, 10m yükseklikte ortalama, maksimum ve minimum rüzgar hızı verileri, Afrika'da seçilen tüm şehirler için 10m yükseklikte Rüzgar Yönü, Çiy/Don Noktası, Islak Termometre Sıcaklığı, bulut miktarı ve yağış toplandı. Bu parametreler, güneş radyasyonu tahmin modellerine potansiyel girdiler olarak kullanılmıştır. 2000'den 2021'e kadar olan yıllık veriler NASA Veri Kümesi kapsamındadır. Boylam, enlem ve rakım ile diğer girdi kombinasyonları önerildi ve girdi parametrelerinin seçilen modellerin doğruluğu üzerindeki etkilerini belirlemek için coğrafi girdilerin etkilerini bulmak üzere modelleri çalıştırmak için kullanıldı. Kullanılan modellerin güvenilirliği korelasyon katsayısı (R2), ortalama mutlak hata (MAE) ve ortalama karesel hatanın kökü (RMSE) ile incelenmiştir.

.

Anahtar Kelimeler: *Yenilenebilir Enerji, Afrika, GHI, Tahmin, Makine Öğrenimi*

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List of Abbreviations

MFFNN	Multilayer Feed-Forward Neural Network
CFNN	Cascade Feed-Forward Neural Network
RBFNN	Radial Basis Function Neural Network
WANN	Wavelet-Ann
WELM	Wavelet- Elm
WRBF	Wavelet-Rbf
ARIMA	Autoregressive Integrated Moving Average
DNN	Deep Neural Networks
FFNN	Feedforward Neural Network
KNN	K-Nearest Neighbors
MLM	Minimal Learning Machine
RF	Random Forests
GPR	Gaussian Process Regression
KNN	K-Nearest Neighbors.
ELM	Extreme Learning Machines
RBF	Radial Basis Function
BMA	Bayesian Model Averaging
GMDH	Group Method Of Data Handling
LSSVM	Least Squares Support Vector Machine
ENN	Emo- Tional Neural Network
RBFNN	Radial Basis Function Neural Network
BPNN	Backpropagation Neural Network
RNN	Recurrent Neural Network
MLP	Multi-Layer Perception

SVM	Support Vector Machine
GWO	Grey Wolf Optimization
MLR	Multiple Linear Regression
SVR	Support Vector Regression
DTR	Decision Tree Regression
RFR	Random Forest Regression
GBR	Gradient Boosting Regression
LSTM	Long-Short-Term Memory

CHAPTER I

Introduction

Energy is a component of our life since it is necessary for man's household and industrial activities and depends heavily on its accessibility(Phoumin & Kimura, 2019). The primary goal of all energy systems is to deliver energy services that are necessary for man, from residential tasks like heating, cooling, and cooking to commercial operations like manufacturing and building(Amir & Khan, 2022). For the sake of sustainability and progress, energy is a necessity for any society, and for many decades the majority of the energy used by humans came from the burning of fossil fuels. Oil, gas, coal, and low-carbon sources will make up about four equal portions of the energy supply mix by 2040 as the world's energy consumption is projected to increase by 37% (Abdullahi, 2015).

Energy may be derived from a variety of sources that are generally categorized as renewable and non-renewable sources. The non-renewable sources include resources that are located in the earth's crust. The rate at which these energy supplies replenish is not the same as the rate at which they are utilized. It takes millions of years for them to regenerate. Coal, oil, and natural gas are the key non-renewable resource examples. High world reliance on these conventional sources of energy has brought many negative effects which include air pollution, climate change, and rising fuel prices. This change in climate is a major concern as it causes problems such as shortage of water, damage from storms and floods, the evolution of illness, the annihilation of some species, etc. Another problem with relying only on traditional energy sources is that fossil fuels are finite and, at the current rate of usage, might run out within a few years. The release of greenhouse gases (such as carbon dioxide and methane) from the burning of fossil fuels by vehicles, factories, electricity generation, etc. has been proven to be the cause of the climatic change linked to global warming(Ramsami & Oree, 2015). The global community is adopting various measures to speed up the process to decrease the impact of these environmental and social challenges. To overcome these problems, the need for another source of energy is paramount.

Renewable energy sources are numerous and sustainable in nature(Mufutau Opeyemi, 2021). These energy sources are environmentally friendly and can be renewed organically. The following renewable energy sources are a few examples: solar, wind, hydro, geothermal, biomass, and tidal energy.

Renewable energy is generated from natural resources that recuperate more quickly than they are depleted. Sunlight, often known as solar energy, and wind, which may be used sparingly, make up renewable energy sources. Compared to burning fossil fuels, producing renewable energy produces less emissions(Razmjoo et al., 2021) Without running out, renewable energy can be utilized repeatedly. Renewable energy is considered as a clean energy source. The most prevalent sort of renewable energy that was available was solar energy(Qazi et al., 2019).

Solar energy is defined as the sun's rays that are capable of igniting chemical processes, producing heat, or creating electricity(Mekhilef et al., 2011). A feasible and inexpensive energy option for addressing long-term difficulties with the current energy crisis is solar energy, in addition to other renewable energy sources. (Kannan & Vakeesan, 2016). Due to the high demand for energy and the expensive and restricted supply of the primary energy source, fossil fuel, the global solar market is gradually expanding(Izam et al., 2022). It is now considered a major tool in advancing the economic standards of developing countries and sustaining the lives of many disadvantaged people because of the substantial, intensive research done to fasten its development. It is now inexpensive as a result of this. (Rathore & Panwar, 2022). It is important to emphasize that the solar industry would unquestionably profit from meeting future energy demand because it excels in terms of accessibility, affordability, capacity, and efficiency compared to other renewable energy sources. (de Almeida et al., 2022).

In solar energy research, solar radiation is a very important parameter. Solar radiation is a catch-all phrase describing the electromagnetic radiation that the sun emits. Other names for it include solar resources or just sunlight. Various kinds of devices may be employed to collect solar radiation and then transform it into usable forms of energy like heat and electricity. However, the technological viability and cost-effectiveness of these systems are based on the solar resource available at the particular location and in most cases, high cost and difficulty in measuring this parameter make it not readily available(Elminir et al., 2005). Depending on certain factors, every location on the earth receives its portion of the solar radiation at different parts of the year with certain times higher than others. These factors include geographical location, time of day, season of the year and weather conditions(Lopes et al., 2018). Therefore, alternative ways are needed to be developed to in generating this data. In this regard, Regression models based on sunshine duration were first applied to this problem Later, regression models incorporated with trigonometric functions were also used. Both methods had shown limitations when used to model nonlinear systems. Harmonic analysis techniques have also been used to describe radiation data which happens to be time-dependent. To overcome this, Artificial Neural Networks were then used due to their ability to learn from multidimensional data and because it has shown suitability in solving the problem of identifying noisy data(Elminir et al., 2005).

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Statement of the Problem

In developing nations, particularly African ones, solar energy can be used to generate electricity. Solar technologies convert sunlight into electrical energy through photovoltaic panels or mirrors that concentrate solar radiation, which can then be used as electricity in African countries. Solar energy can also be used as heat, cooling, lighting, and electricity for appliances. According to (Chakamera & Alagidede 2018), the majority of people living in remote regions of Africa do not have access to electricity. According to (Ogah (2002), the continent's development is hampered by the fact that nearly two-thirds of its estimated 620 million people do not have access to electricity.

In addition, only a small percentage of people in sub-Saharan Africa have access to electricity. A lot of people who have access live in homes, businesses, and industries with high incomes. Unfortunately, both rural and urban areas are losing value as a result of inadequate and poor electrical infrastructure maintenance and upgrade (Wolde-Rufael, 2006). The emergence of wind and solar energy as viable solutions to Africa's electricity shortage has led to an increase in energy demand. (Ramsami & Oree 2015) say that this raises the cost of fossil fuels and exacerbates climate change. In recent years, there has been an increase in the use of photovoltaic technologies, which convert solar radiation directly into electricity (Tripathi et al., 2022; Veisi and others, 2022) due to their abundance, cleanliness, and endless supply. Since solar energy has become the most popular alternative source of energy, researchers have been looking into all possible ways to make the most of it. As was mentioned earlier, the design of solar technologies in a particular location is heavily influenced by solar radiation. However, because solar radiation is unavailable and it costs a lot to get measured data, it is necessary to use other methods to get this data.

Aim of the Study

The aim of the study is to Predict the effects of Geographical Parameters in Predicting Solar Radiation Using Machine Learning Models in Global horizontal irradiance (GHI). The objectives of the study include the below inputs and models which were used to study the research. To fully understand the aims of this study, consider the table below:

Table 1

List of Input Parameters

Scenario 1	Scenario 2
Latitude	Year
Longitude	Surface Pressure (kPa)
Altitude	Temperature at 2 Meters (C)
Slope	Relative Humidity at 2 Meters (%)
Azimuth	Wind Speed at 2 Meters (m/s)
Year	Wind Direction at 10 Meters (Degrees)
Surface Pressure (kPa)	Wind Speed at 10 Meters (m/s)
Temperature at 2 Meters (C)	Dew/Frost Point at 2 Meters (C)
Relative Humidity at 2 Meters (%)	Wet Bulb Temperature at 2 Meters (C)
Wind Speed at 2 Meters (m/s)	Temperature at 2 Meters Maximum (C)
Wind Direction at 10 Meters (Degrees)	Temperature at 2 Meters Minimum (C)
Wind Speed at 10 Meters (m/s)	Cloud Amount (%)
Dew/Frost Point at 2 Meters (C)	Wind Speed at 10 Meters Maximum (m/s)
Wet Bulb Temperature at 2 Meters (C)	Wind Speed at 10 Meters Minimum (m/s)
Temperature at 2m Max (C)	Precipitation Corrected (mm/day)
Temperature at 2m Min (C)	Year
Cloud Amount (%)	
Wind Speed at 10m Max (m/s)	
Wind Speed at 10m Min (m/s)	
Precipitation Corrected (mm/day)	

From the above table, the aims of the study are:

1. To predict Global Horizontal Irradiance for the selected cities of Africa using machine learning models

2. To propose 2 scenarios with various input parameters as seen in the above table.

3. To compare and predict the accuracy of the models and to observe if there is any effect the geographical parameters latitude, longitude, altitude, slope and azimuth angle have on the models.

The proposed machine learning models:

- NARX regression neural network (NARXNN)
- Layer Recurrent Neural Networks (RNN)
- Cascade-forward neural network (CFNN)

However, to predict the accuracy of the proposed models and check the effects of the Parameters using the proposed ANN models. The test where slip into two scenarios where the first scenario was to run the models with latitude, longitude and altitude inclusive together with others parameters and see the effects of these geographical parameters on the outcome results of the ANN models while also the second scenario was tested without latitude, longitude and altitude to see the effects of these parameters to the proposed ANN models in prediction solar radiation.

Significance of the Study

1. Solar Technology Planning: predicting the GHI will bring about effective planning and assessing the potential of solar energy in Africa.
2. Energy Generation: by effectively predicting the GHI, energy generation and efficiency in Africa will be improved. In addition, by understanding the effect of these geographical parameters on GHI, this study will help in providing insights into having the optimal design of energy systems.
3. Environmental Impact: Solar energy has been an alternative source of energy and by predicting the GHI effectively, it will improve the use of solar energy which in return

will contribute to reducing greenhouse gas emissions. The findings can help to move Africa to a greener and more sustainable source of energy.

4. Research Advancement: this study can help in the area of machine learning and prediction of DNI. Also, the study will add to the existing knowledge and will help in advancing the understanding of solar energy resource assessment. The research results will surely inspire further investigations and research

Justification

Sunlight-based Energy has turned into a critical piece of Africa's reasonable turn of events and energy progress. As the landmass is confronting an ascent in an energy emergency and looks to limit the high reliance on fossil fuel, the requirement for satisfactory sun-based asset evaluation is principal. By zeroing in on the expectation of the GHI, which is a vital boundary in planning solar-based energy frameworks, this study resolves a basic issue in outfitting sun-powered energy possible in Africa.

Limitations of the Study

The only input data used in this study is from the NASA database. Accurately predicting the DNI of African cities and training and evaluating machine learning models may be difficult due to the limited availability of other data sources. In addition, the accuracy of geographical parameters like latitude, longitude, altitude, slope, and azimuth angle may vary depending on the data source. However, the majority of analyses to date have concluded that land will not significantly impede this transition, taking into account two key issues that are typically overlooked:

1) the requirement to deal with the fluctuation of the solar resource and

2) the actual occupation of land by solar technologies may also limit GHI research.

CHPATER II

Literature Review

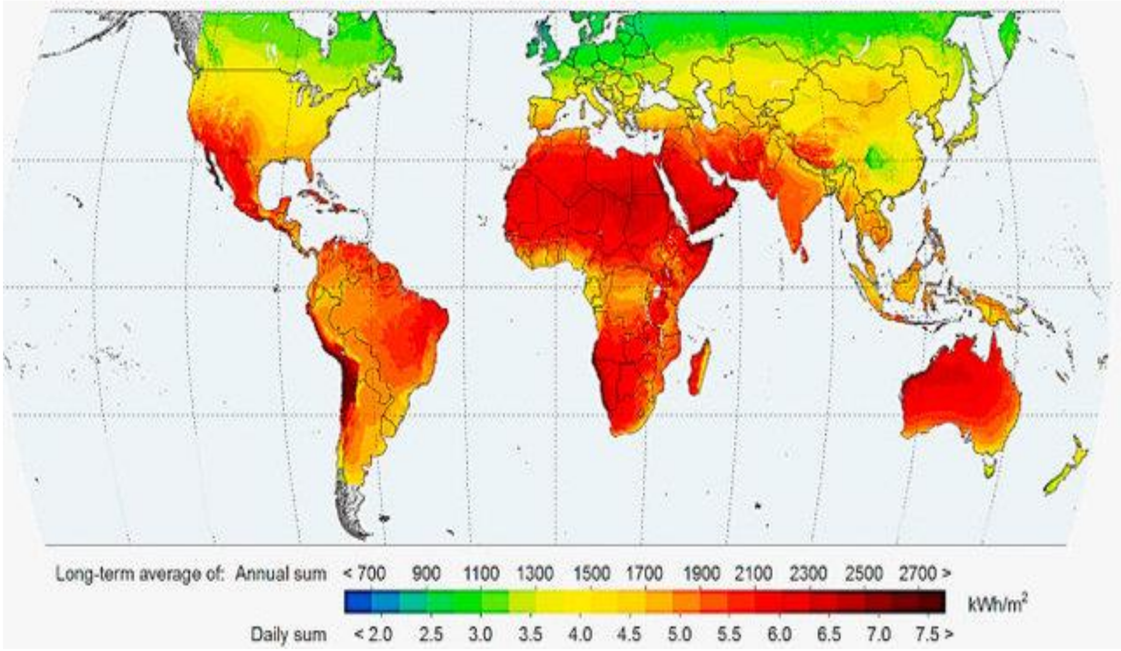
Introduction

Power is the energy which can be derived from a physical or chemical process in order to generate heat and light. Renewable energies such as wind and solar energy are emerging as an alternative energy source due to the growth of population and substituting the old fossils fuels, increasing energy demand and the rising cost of fossil fuel, and climate change (Ramsami and Oree 2015; Zhou et al. 2020). Renewable energy is made from natural resources which are renewed at a higher rate than the method used to use them. They can be used again for another purpose which might be different from their first purpose of use. Renewable energy sources are sunlight that is solar power and wind, which can be used through the use of wind turbines. The production of renewable energy produces less emissions than the burning of fossil fuels. It is possible to use renewable energy over and over again without depletion. Solar energy is the most abundant type of renewable source that we've ever had. Solar panels are used to capture solar energy from the Earth, which is about 10,000 times more than the rate of human consumption and can be used to generate solar power. Developing countries, particularly in Africa, can also exploit the sun's energy to generate electricity. In addition to heat, cold, lighting and electricity for hosting appliances it is also possible to use the sun's energy in other ways as well. Moreover, solar technologies change the sunlight into electrical energy through photovoltaic panels or through mirrors that concentrate solar radiation which then can be used as electricity in African countries. Electricity is not available to most people who live in remote areas of Africa, despite the fact that there a small fraction of those living in urban areas which have access to electricity. Lack of maintenance and poor investment in electricity infrastructure contribute to the depreciation of rural and urban areas, as a result of increased number of populations without electricity in African countries. Wind and solar energy are becoming alternative energy sources due to the lack of electricity in African countries, increasing energy demand, causing an increased cost of fossil fuel, and climate change (P. Ramsami and V. Oree, May 2015) As a result of the rapid growth and demand for electricity (PV) technologies which directly change solar radiation to energy have increased in recent years, due to their abundance, cleanness as well as inexhaustibility. As part of the planned use of Solar Energy as a new source of energy, further investigations are being undertaken in relation to different (PV) technologies and sun tracking systems. Recently, studies evaluating the potential of solar power to generate electricity have been carried out. For example, (H. Camur, Y. Kassem, and E. Alessi, 2021). assessed the performance of photovoltaic (PV) systems. It was found that, in order to satisfy the region's energy needs and reduce its electricity costs, yearly power generation could be made available. Using various machine learning models to take into account different input parameters such as those mentioned above (Mellit & Pavan, 2010; Tripathi et al., 2022) predicted that the solar photovoltaic system would generate its output power of a solar photovoltaic system using different machine learning models taking into consideration different input parameters such as temperature, relative humidity, solar radiation, on and time of the day. Similarly (Kassem, Cąmur, et al., 2021) performed a feasibility test of the use of different types of (PV) energy technology to connect smaller scale photovoltaic systems via an interconnected grid. The results of this study show that fossil fuel consumption and (CO_2) emissions would be significantly reduced by the use of power from renewable sources. Solar energy provides a significant boost to the growing demand and management of electricity from renewable sources. The precise identification of two key sun resources components, global horizontal irradiance (GHI) and direct normal irradiance (DNI) is essential in order to effectively operate (PV) and concentrated solar power plants. For both (PV) and nonconcentrated solar heating systems, accurate estimates of HICGHI are required since they're able to use both Direct and diffusion components of sunshine. However Atmospheric conditions may influence the measurement of solar irradiation. It is also apparent that a wide range of methods to measure the solar irradiance with varying inputs have been invented by numerous researchers.

A summary of some chosen studies and individual models and inputs can be found in Table 2. (Zazoum, 2022) examined the relationships between certain inputs and photovoltaic systems based on various machine learning models in his paper. The results revealed that the basic factor affecting the energy outputs of a photovoltaic system is these input parameters, which include ambient temperature, sunshine flux, daytime's humidity. Furthermore, machine learning models for forecasting (PV) system energy as a result of changing climatic conditions have been used in several further studies such as this one (Omubo-Pepple et al., 2009) Different machine learning models that depended on feed flow have estimated solar radiation from around 200 cities in Nigeria. And multi-layered network using different weather condition. (Teke et al., 2015) came up with a model using ANN to predict the solar radiation in Saudi Arabia. A different pattern of a multiple feed neural network was trained using an algorithm for back propagation. Taking account of the minimal absolute percentage error, the best result has been determined. Solar energy offers Africa an opportunity for economic growth and jobs, reducing its global carbon footprint and greenhouse gas emissions in a way that is conducive to the development of African countries. A major demand and increased use of solar power products is caused by the energy scarcity in African countries, such as solar geysers, solar cooking pots, etc.

Figure 1

World Solar Energy Map



Energy

Energy is the capacity to do work. Experimentally energy can be characterized as the capacity to do work or cause movement of an object. Current civilization is conceivable in light of the fact that individuals have figured out how to change energy starting with one structure then onto the next and afterward use it to do another work. Individuals use energy to walk and bike, move vehicles along streets and boats through water, cook food on ovens, make ice in coolers, light our homes and workplaces, fabricate items, and send space explorers into space.

There are many types of energy which include:

1. Heat
2. Light
3. Motion
4. Electrical

5. Compound
6. Gravitational

These types of energy can be assembled into two general sorts of energy for doing work:

1. Potential energy
2. Dynamic energy

Energy can be changed over starting with one structure and then onto the next. For instance, the food you eat contains synthetic energy, and your body stores this energy until you use it as motor energy during work or play. The put-away compound energy in coal or gaseous petrol and the dynamic energy of water streaming in streams can be changed over completely to electrical energy, which can be switched over completely to light and intensity.

Energy sources are sustainable which is renewable or non-renewable

There is a wide range of wellsprings of energy, yet they can be generally separated into two classifications:

1. Renewable Energy Sources
2. Non-Renewable Energy Sources

Sustainable and non-renewable energy sources can be utilized as essential energy sources to deliver valuable energy like intensity, or they can be utilized to create auxiliary energy sources like power and hydrogen.

Renewable Energy Sources

Renewable energy comes from sources that will not be used up in our lifetimes, such as the sun and wind. Renewable energy source can be used again and again for the same purpose or different purpose not harming the environment. Renewable Energy is from naturally replenishing but flow-limited sources is renewable energy. Although renewable resources have a limited amount of energy available per unit of time, their duration is nearly infinite.

The most common forms of renewable energy are, biogas from biofuels Hydropower from geothermal and dams solar, and wind energy.

Wind Energy

Wind energy keeps on making advances in Africa because of falling expenses and mechanical headways. Most African nations are arranging, exsiccating and associating their environmentally friendly power projects with public network frameworks giving high appropriateness to energy security, reasonable energy utilization, and low fossil fuel by-product use of wind energy by humans goes back a very long time. Ancient Egyptians made wind-powered boats five thousand years ago. Windmills were used to pump water and grind grain in China and the Middle East around 200 B.C.E. Today, wind turbines are used to harness the wind's energy. A windmill is like a turbine; It has a very high tower that has two or three blades that look like propellers at the top. The wind is what turns these blades. The generator inside the tower is turned by the blades, which generate electricity. This wind energy can improve Africa's ability to convey cleaner, less expensive, and harmless to the ecosystem energy by guaranteeing energy security, making an energy economy, and decreasing energy destitution (Sarker, 2019)

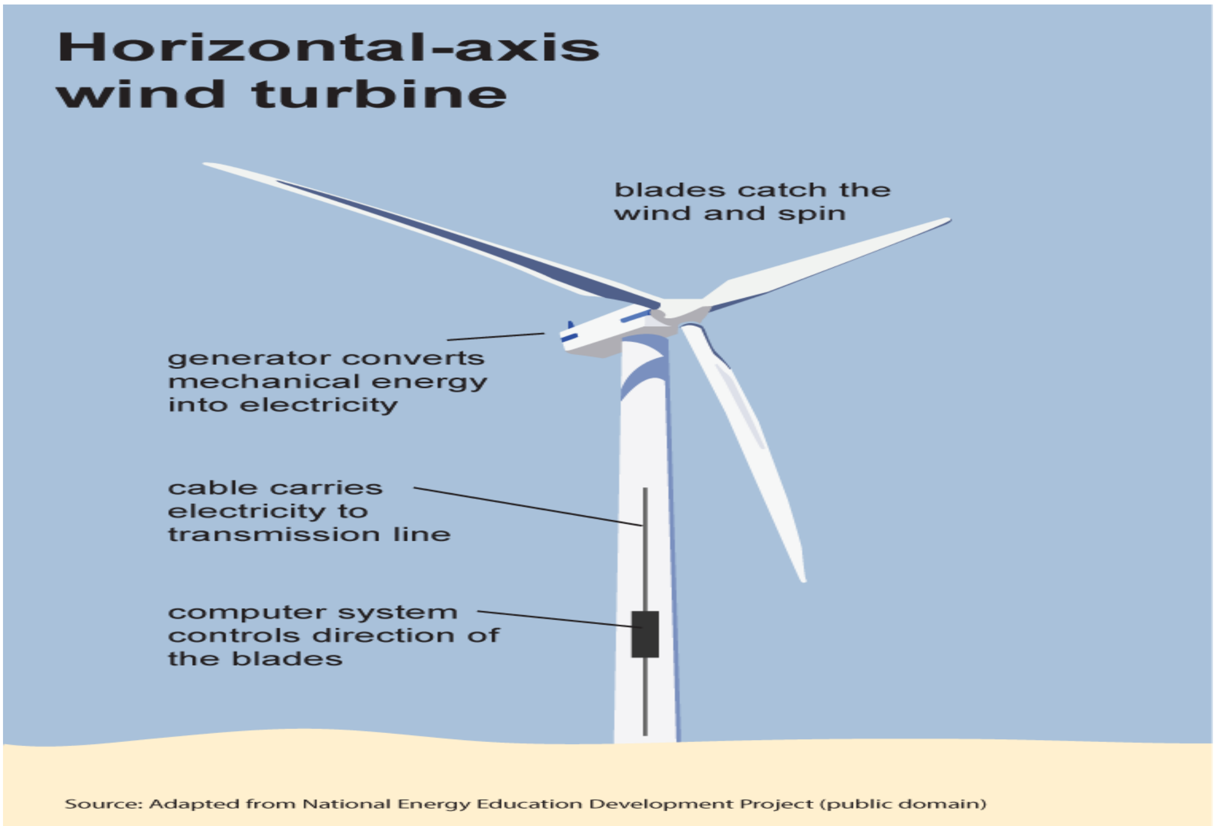
Table 2

Advantages and Disadvantages of wind energy

ADVANTAGES	**DISADVANTAGES**
Wind power can be very effective. The steady winds that blow along coasts and the Midwest in African countries can provide inexpensive and dependable electricity.	However, wind is not always a reliable energy source. The time of day, the weather, and where you are affecting the speed of the wind. At this time, it cannot meet all of our electricity requirements.
The fact that wind power is a "clean" energy source is yet another significant advantage. Wind turbines do not use fuel and do not produce any air pollution.	Bats and birds can also be at risk from wind turbines. These animals frequently collide with the blades without knowing how quickly they are moving.

Figure 2

Horizontal Wind Turbine.



Solar Energy.

Solar-based power is the transformation of this energy into power straightforwardly utilizing photovoltaic innovation or by implication utilizing concentrated sun-powered chargers (CSP) (Hayat et al., 2019)CSP uses mirrors, lenses, and other solar tracking systems to capture sunlight over a larger and wider area, whereas photovoltaic technology uses the photovoltaic effect to turn sunlight into electric current (Guney, 2016) .The amount of solar radiation received during a specific time period affects both systems' ability to generate electricity.

Photovoltaic System

Using a photovoltaic (PV) system, solar radiation may be converted into power. The photovoltaic effect is a principle that the PV system uses to convert sunlight into electrical power. The energy from photons is transferred to the charge carriers every time light strikes a photovoltaic cell. The electric field across the junction caused the charge carriers to divide into positively charged holes and negatively charged electrons at that point. If a closed channel is given to the circuit by attaching a load, current will flow as a result (Venkateswari & Sreejith, 2019).

Figure 3

Photovoltaic System

Concentrated Solar Power

The technology of concentrated solar power (CSP) harnesses heat produced by solar radiation that is focused on a tiny area to produce electricity. Sunlight is reflected off of mirrors and directed to a receiver, where heat is captured by a thermal energy carrier (primary circuit) and utilized either directly (in the case of water or steam) or indirectly (through a secondary circuit) to drive a turbine and produce electricity. Particularly in areas with high DNI, CSP is a viable technology

Figure 4

Concentrated Solar Power

Solar Irradiance

Solar irradiance is defined as the amount of solar radiation that reach a certain area. The unit of solar irradiance is watts per square meter (W/m^2). It is a representation of the intensity or power density of sunlight a specified location and time. The amount of solar irradiance in a given location is a key factor in determining how much energy is produced. As a result, a site with high solar irradiance will produce more energy, whereas a location with low irradiance will produce less energy.

Understanding this pattern is very crucial in designing and optimization of solar energy systems. By assessing this, engineers and designers can choose the best technology and establish ideal sizes and orientation of the solar panels. It also gives the ability to analyse and predict the energy production at a given time.

Factors affecting Solar Irradiance

Solar Irradiance is affected by many factors which include longitude, latitude, cloud cover, atmospheric conditions and seasonal variations(Rathod et al., 2017)

1. Atmospheric Conditions: factors such as cloud cover, air pollution dust particles and water vapour can impact the amount of solar irradiance at a given location. A location with clear skies tends to have higher amount of solar irradiance(Rathod et al., 2017).
2. Time of the year: Due to Earth's axial tilt, solar irradiance varies throughout the year. In summer, solar irradiance becomes higher and becomes lower during winter(Stanciu & Stanciu, 2014)
3. Time of the day: as the Sun's angle changes, the amount of solar irradiance also changes. In morning and evenings, the amount is very much lower and becomes peak at noon(Chu et al., 2015).
4. Geographical parameters: Latitude and longitude greatly affect solar irradiance. Locations that are closer to the equator will have higher amount and as locations move closer to the poles, the amount of solar irradiance decreases(Rathod et al., 2017)

Components of Solar Irradiance

Direct Normal Irradiance (DNI)

Direct normal irradiance (DNI) is the amount of solar radiation that a surface that is always held perpendicular (or normal) to the rays that arrive in a straight line from the sun's current location in the sky receives. By maintaining a normal angle with the incoming radiation, a surface may frequently receive the most irradiance annually. This parameter is particularly important to both installations that follow the sun's path and concentrated solar thermal plants (Boutahir et al., 2022). This component is measured with a pyrheliometer.

Diffuse Horizontal Irradiance (DHI)

Diffuse Horizontal Irradiance (DHI) is the quantity of radiation received by a surface (that is not in any shade or shadow) per unit area that is not arriving from the sun directly, but is instead evenly distributed from all directions by atmospheric molecules and particles(Haase, 2016). This component is measured using a device named Pyranometer

.

Global Horizontal Irradiance (GHI

A surface horizontal to the ground receives all of the shortwave radiation from above, which is known as global horizontal irradiance (GHI). Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI) are both included in that value, which is of particular significance to solar systems(Boutahir et al., 2022)

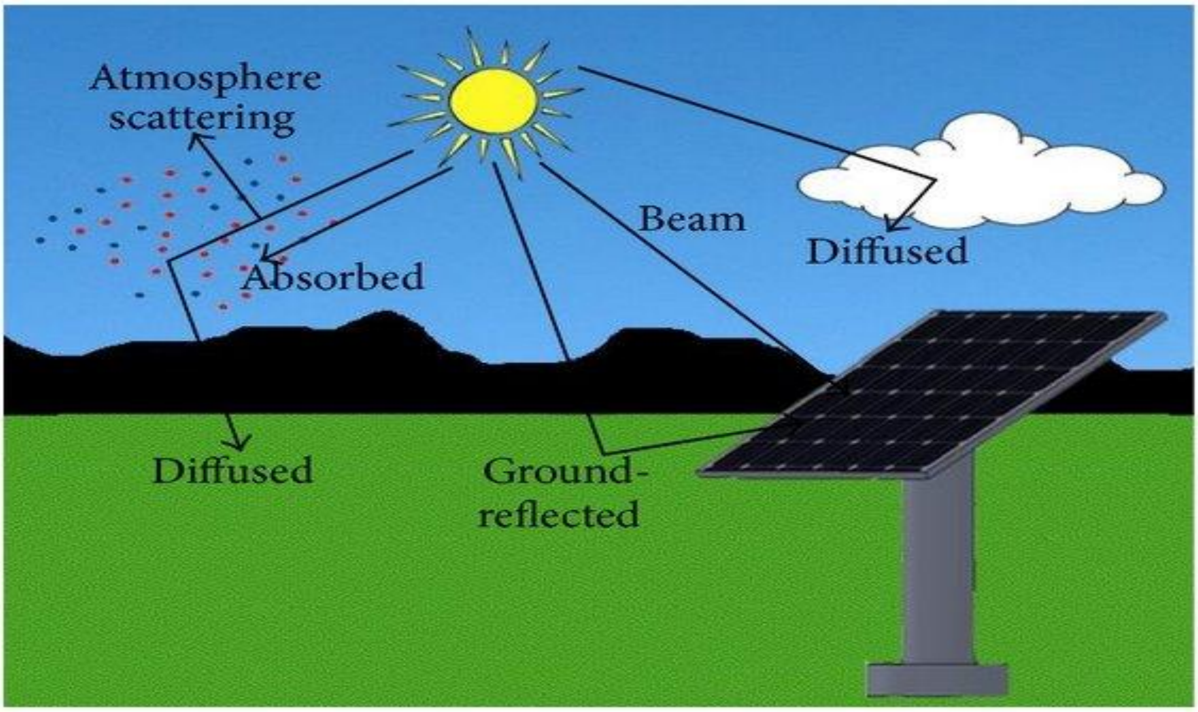
Table 3

Advantages and Disadvantages of GHI

ADVANTAGES	**DISADVANTAGES**
It’s cheap to develop compared to (DHI)	the increased in forecasting error with increments in the time horizon.
better performance than other models	
(GHI) has a close relationship with the sun position	
GHI forecasting to assess the performance of solar photovoltaic (PV) and thermal systems	

Figure 5

Global Horrizontal Irradiance



Africa

Africa is the second largest by land mass and the second most populated continent on earth. It has a land mass of about 11.72 million square miles (30.3 million km^2). It covers one-fifth of the total Earth land mass. It has boundaries from the west with Atlantic Ocean, from the north, Mediterranean Sea, from the east, Red Sea and from south, Atlantic and Indian Oceans. It is situated on a latitude and longitude of 9.1021^{0}N and 18.2812^{0}S. Africa has a population of about 1.3 billion as of 2019. This value represents 16% of the world's population. There are 54 countries in the African continent. From north to south, the continent is around 5,000 miles (8,000 km) long, and from east to west, it is about 4,600 miles (7,400 km). Africa typically has a humid and warm environment with the northern part mostly covered by dryness and very high temperature. Because of the Equator's almost equal division of the continent, the majority of Africa is located in a tropical area that is bordered on the north by the Tropic of Cancer and on the south by the Tropic of Capricorn. The majority of Africa's land is located north of the Equator due to the bulge that western Africa has created. The prime meridian (0° longitude) runs through Africa from north to south, passing close to Accra, Ghana, to the east.

Figure 6

Map of Africa

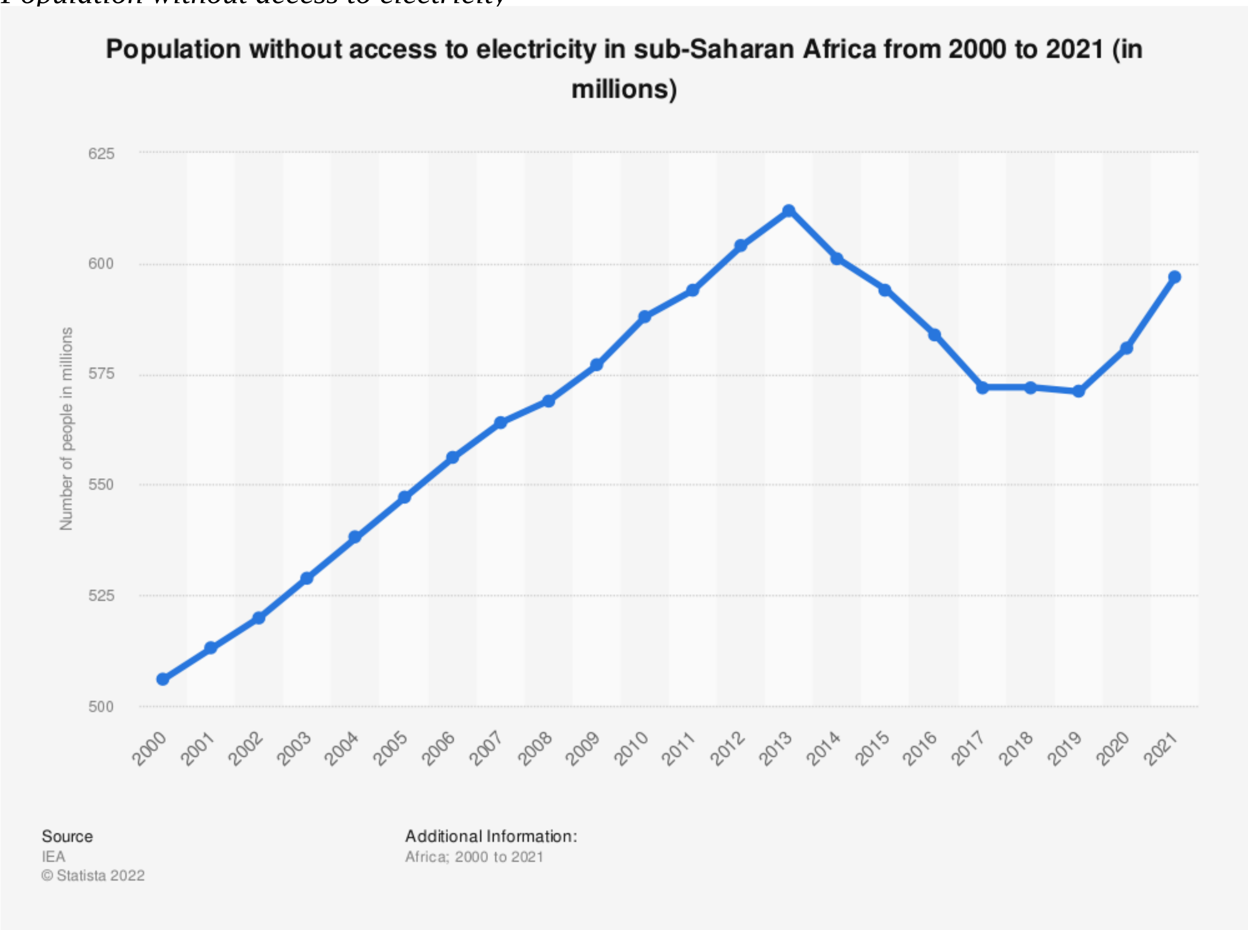
Energy Crisis in Africa

With the high population of about 1.3 billion, most of the people who stay in remote areas in Africa do not have access to electricity (Chakamera & Alagidede, 2018). It is on record that nearly two-thirds of Africa's population, which is estimated to be 620 million and increasing, lack access to electricity, which limits the continent's ability to develop (Ogah, 2022). Despite the fact that Africa as a continent normally has severe electrical problems, Sub-Saharan Africa is the area that suffers the most from these issues because it is presently home to more than two-thirds of the world's people who do not have access to power(*Africa Energy Outlook 2022 – Analysis - IEA*, n.d.). In addition, inadequate maintenance has rendered around 15% of Sub-Saharan Africa's installed capacity inoperable. Furthermore, because accessing the national electrical grid is expensive, an estimated 700 million individuals in Africa still generate their own electricity using traditional biomass(Adenle, 2020). Africa's anticipated population rise is a serious problem. By 2050, it is predicted that there will be 2 billion people living in sub-Saharan Africa alone. Despite this, the region's energy demand is expected to increase by 3% annually(Bugaje, 2006). Rising energy costs and the increased need for climate change mitigation strategies may also provide new difficulties(Maji et al., 2019). With all these issues only 1.48% of the world's capacity for solar energy is occupied by Africa, despite the continent having 40% of the world's solar power potential(*IRENA: Renewable Capacity Statistics 2019 - Google Scholar*, n.d.). This problem is mostly attributed to the following reasons:

1. Lack of Access to Electricity: like stated earlier, almost two third of Africa's population don't have access to electricity. The number is even more severe in rural areas with people mostly relying on expensive and insufficient sources (*Access to Electricity – SDG7: Data and Projections – Analysis - IEA*, n.d.)

Figure 7

Population without access to electricity



2. Insufficient Infrastructure: in Africa, the energy infrastructure in mostly in adequate and insufficient to fulfil the high and rising population demand. In most areas of the continent, there is power outages and blackout due to inadequate and poorly maintained distribution networks. The flow of energy effectively from production sites to end users is mostly hindered by this problem(Abdullahi, 2015)

3. Lack of funding: the funding of the energy sector in most African countries have been marred by lack of funding by most governments(González-Eguino, 2015). In cases where there is funding, it is mostly characterised by corruption and embezzlement which at long last, the aim is not achieved(Abdullahi, 2015)

Therefore, increasing solar power and using renewable energy sources to deliver power in Africa is a realistic choice

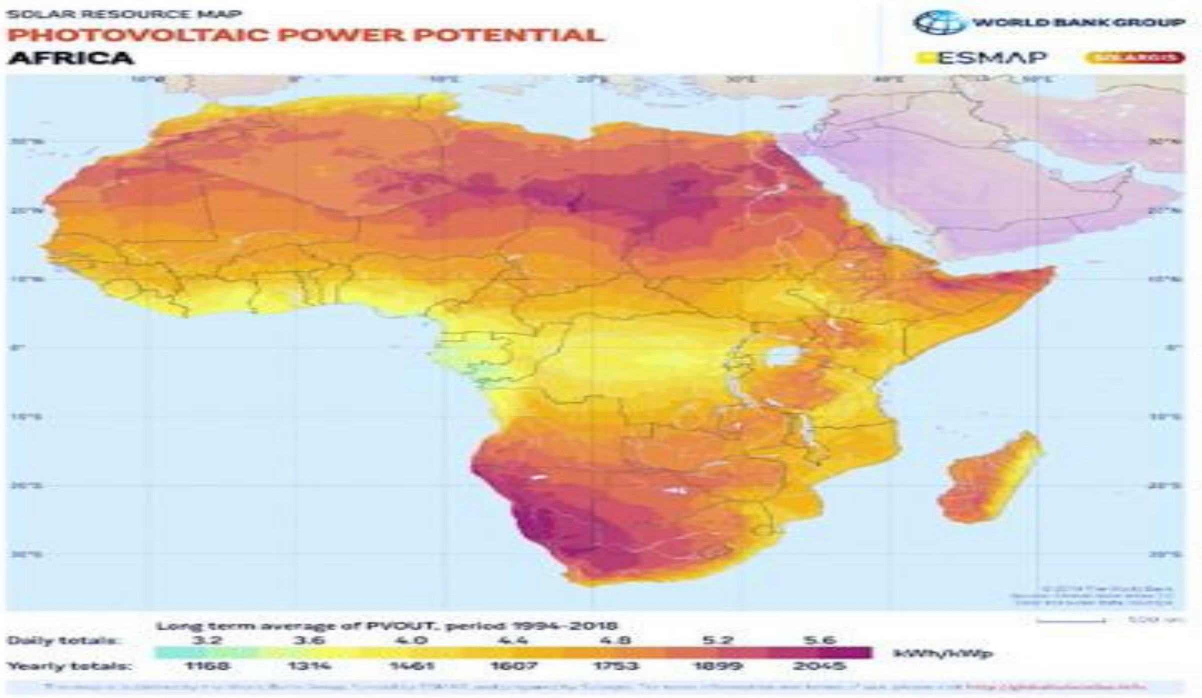
Solar Potential in Africa

Africa faces numerous obstacles and dangers, including its susceptibility to climate change, a rapidly increasing population compared to other nations, and insufficient electrification to support the shift towards renewable energy(Abdelrazik et al., 2022). To tackle these issues, renewable energy is a practical solution. To optimize solar power, comprehensive knowledge of solar resources is crucial in the midst of changing climatic conditions(Goliatt & Yaseen, 2023). Africa, due to its proximity to the equator and profusion of sunshine, Africa experiences high amounts of daily global solar radiation. Africa receives between 4 and 6 kWh/m2 of solar energy on average every day, with specific quantities varying throughout the continent's various areas. This enormous sun resource offers a big opportunity for solar energy harvesting and can aid in the continent's sustainable development(*IRENA: Renewable Capacity Statistics 2019 - Google Scholar*, n.d.).

Africa has enormous solar energy potential. This is brought about by a variety of elements, including its close closeness to the equator and its abundance of sunny, dry days (*The Solar Revolution in Africa*, n.d.) For instance, South Africa has a solar PV potential of 42,243 TWh/year and a concentrated solar potential of 43,275 TWh/year(Adenle, 2020). With an average insolation of 220 W/m2, most of South Africa experiences more than 2500 hours of sunlight annually(Ayodele & Munda, 2019). . In North Africa, solar power facilities occupy twice as much territory as the entire European Union of Africa, according to the German Aerospace Centre, a pioneer in the field of renewable energy technology. It is claimed that the power use may be met(*The Solar Revolution in Africa*, n.d.). Figure 8 illustrates how North Africa is advantageously situated in the Sunbelt area, where solar energy is abundant. The quantity of yearly solar radiation reflects this; for instance, the annual total solar radiation in Algeria, Morocco, Egypt, and Tunisia is 2700 KWh/m2, 2600 KWh/m2, and 2800 KWh/m2, respectively(Zhao et al., 2018).

Figure 8

Photovoltaic Potential in Africa

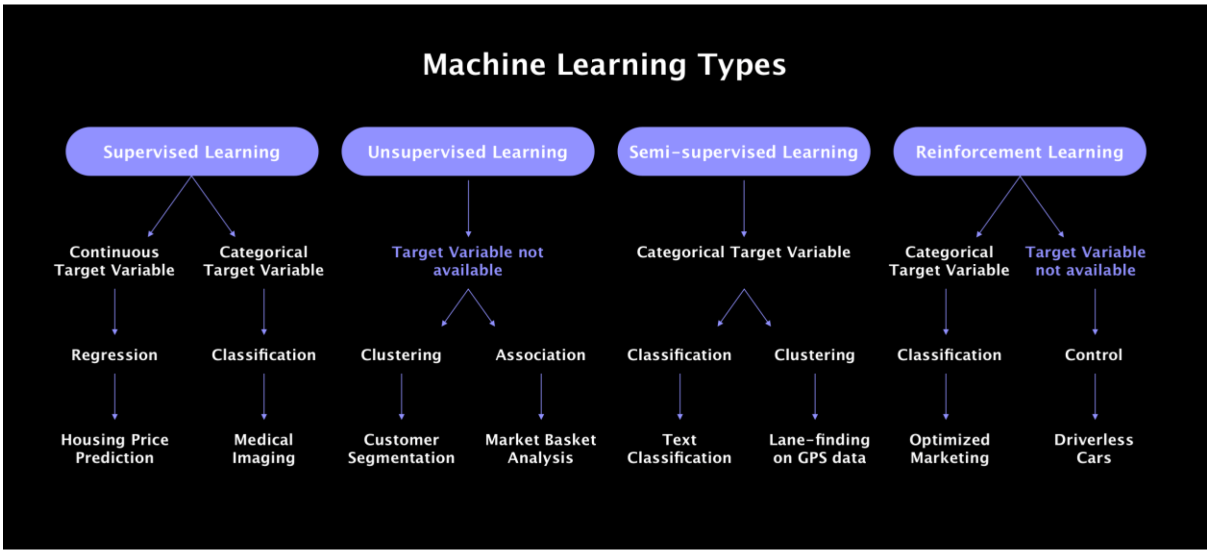


Machine Learning

Data are considered new life of the 21st century, amounting to significant information, insights and potential, and they are now a vital part of all entities that are driven by data. In a variety of areas, including research, health, industries, educational areas, financial services, cybersecurity, law enforcement, governance, and marketing, information may be extracted from data to develop varieties of smart applications(Sarker, 2019). As a result, there is an urgent demand for data management systems that can rapidly and shrewdly extract relevant insights from data. Machine Learning (ML), which is one of the most important tools for intelligently analyzing such data and creating related practical applications, has advanced significantly in recent years.(Koteluk et al., 2021; Sarker et al., 2020). The picture below shows the different type of machines learning.

Figure 9

Types of Machine Learning



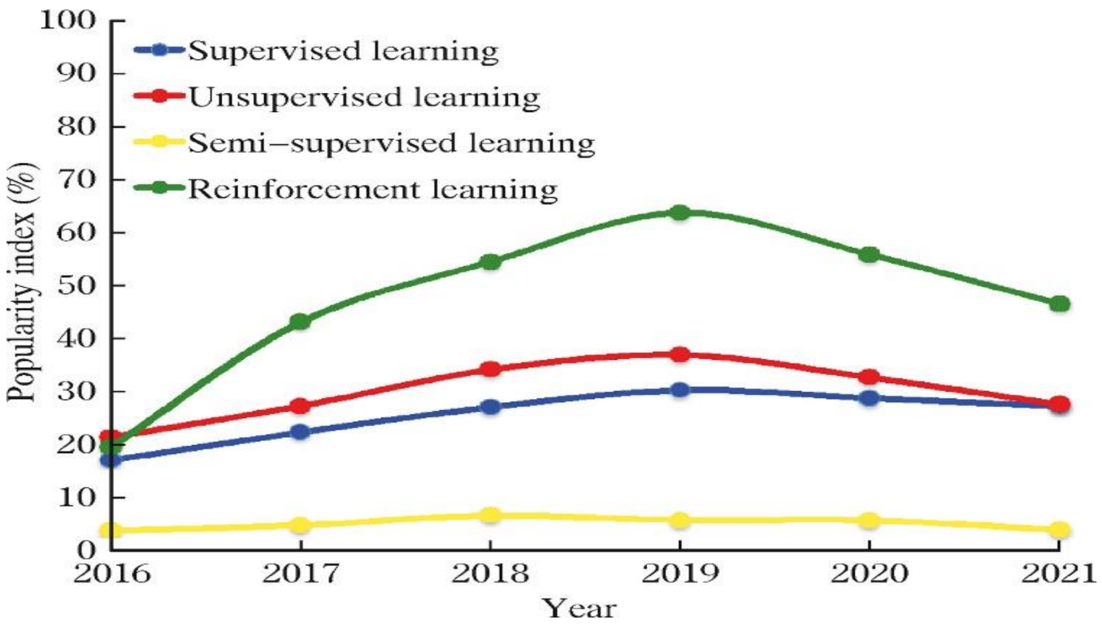
Types of Machine Learning

1. Supervised Learning: Base on test input to output pair, supervised learning uses Machine Learning tasks in training a function that translates inputs to outputs. As a result, this learning processes is founded on linking the derived outputs and projected outputs; hence, learning is the process of calculating the errors and modifying the errors to produce the desired outputs(Pugliese et al., 2021). The automatic response to incoming communications (valuable for large businesses), facial recognition for ATM security, surveillances areas, closed-circuits cameras, the criminals justice system, and picture tag on social networking platforms like meta's Facebook are examples of applications of this learning(Li et al., 2015; Pugliese et al., 2021).
2. Unsupervised Learning: Without human intervention, unsupervised learning examines unlabeled datasets. In this learning, the algorithms splits the sample into several class according to only the characteristic of data to be trained, without assigning matching labels(Jia et al., 2022; Pugliese et al., 2021).
3. Semi-supervised Machine Learning: Given that it use data that are both labeled and unlabeled, semi-supervised learning may be seen as a hybridization of supervised and unsupervised approach outlined above(Jia et al., 2022; Pugliese et al., 2021).
4. Reinforcement Learning: An environment-driven technique, or reinforcements learning, relies on collection of algorithms that generally run in sequence to analyze automatically

the ideal behaviors in certain environments and increase its effectiveness(Buşoniu et al., 2010).

Figure 10

Popularity Index of Machine Learning

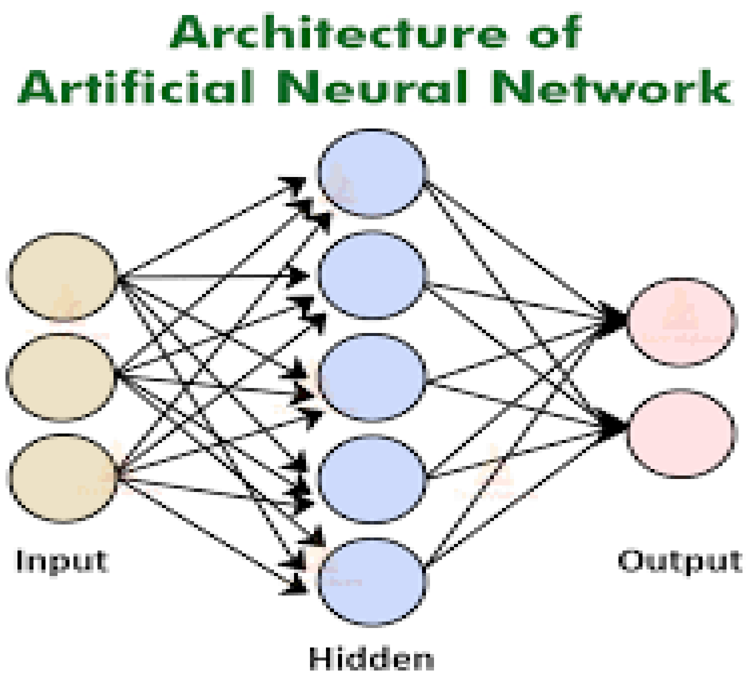


Types of Machine Learning Model

1. Artificial Neural Networks: an artificial neural networks are based on the ideas of a human neurons(Han et al., 2018). Artificial neurons, comprised of a group of cluster members that resemble the neurons found in a biological brain, make up the central component of an ANN. (Zakaria et al., 2014). Each link may communicate with surrounding neurons, much like the junctions in the human brain. A synthetic neuron takes inputs, analyses them, and then sends messages to neurons nearby(Rashid, 2016).

Figure 11

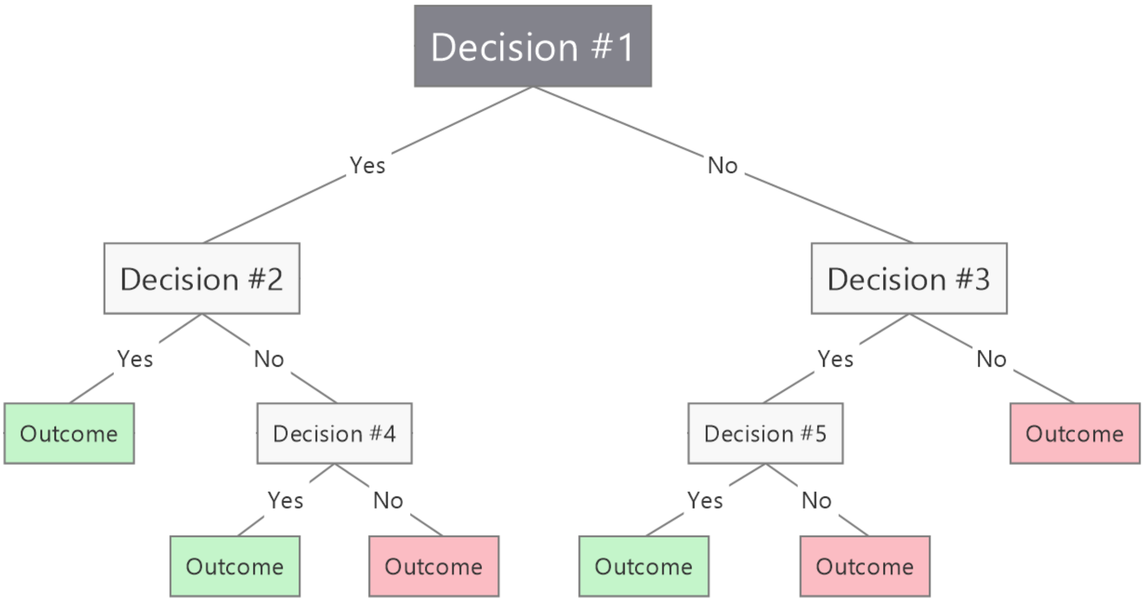
Architecture of ANN



2. Decision Tree: Two most common usage of the decisions tree approach are the creations of categorization system dependent on a number of different factors and the building of predictions algorithms for a target variables. (Song & Lu, 2015). In order to develop an inverted tree with a root nodes, internal node, and leaf node, this algorithm divides a population into segments that resemble branches. (Bhukya & Ramachandram, 2010). The methods, which are non-parametric, might successfully handle different, complicated dataset against generating a difficult parametric framework. Once the sample sizes are large enough, the research's data may be split into trainings and validations dataset. The best final model is produced by building a decisions tree model using the training datasets and choosing the optimum tree sizes using the validation dataset.(Loh, 2014).

Figure 12

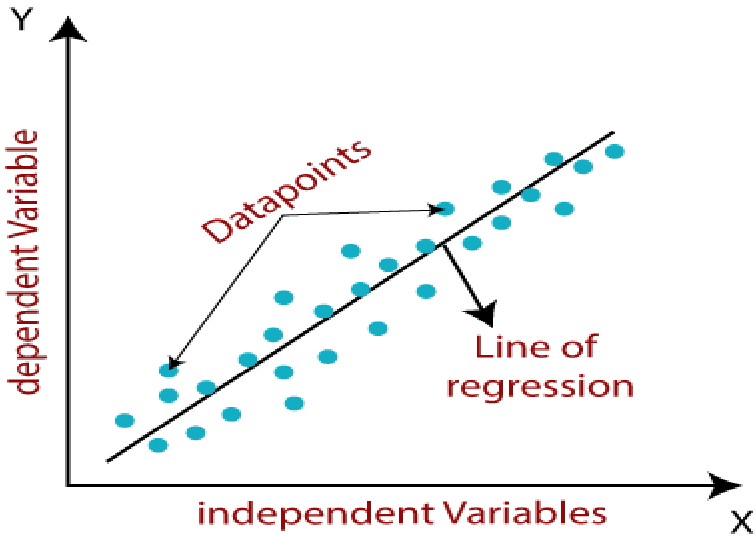
Architecture of Decision Tree



3. Linear Regression: A continuous target variable is predicted using linear regression using one or more input features. The model implies that the input and target variables have a linear relationship (Ray, 2019)

Figure 13

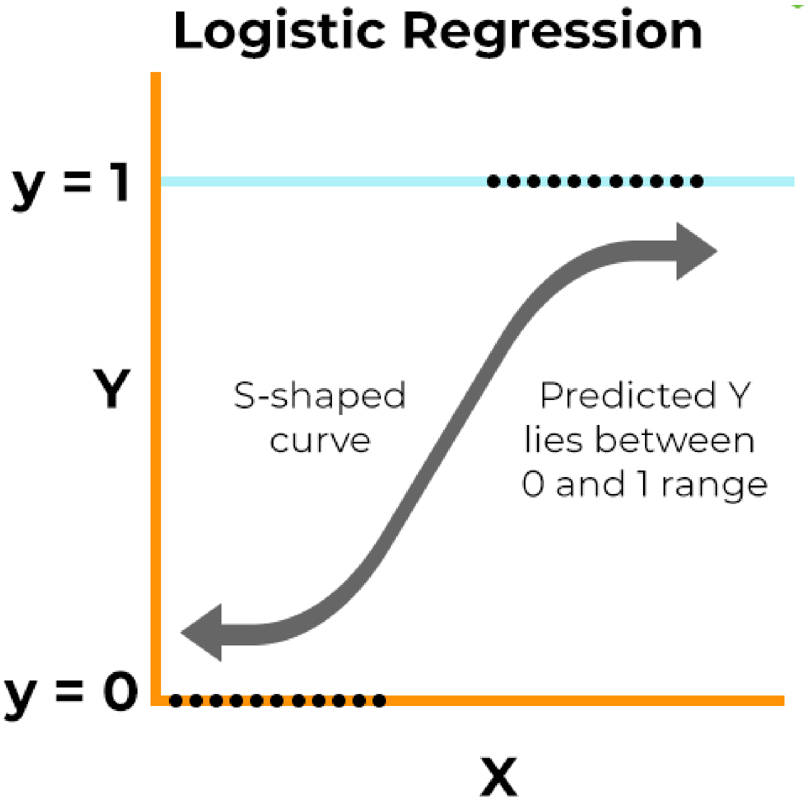
Architecture of Linear Regression



4. Logistic Regression: When the target variable has two classes, logistic regression is the model used to solve binary classification issues. Calculate the likelihood that a certain instance belongs to a certain class(Ray, 2019)

Figure 14

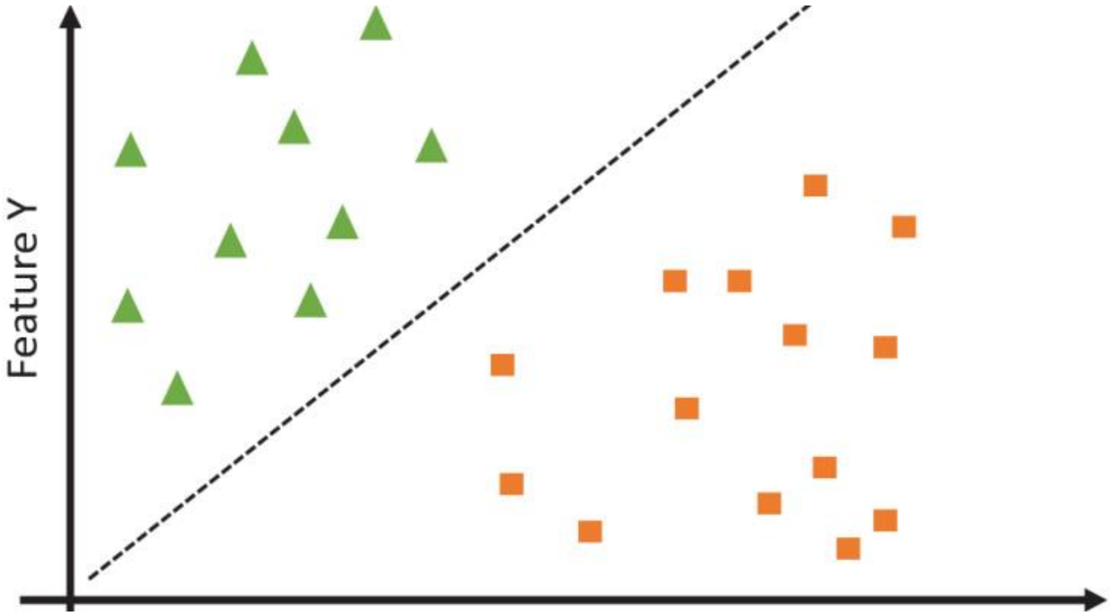
Logistic Regression



5. Support Vector Machine (SVM): SVM is a well-liked model for both regression and classification tasks. Find the ideal hyperplane with the biggest margin of separation between data points from distinct classes(Ray, 2019).

Figure 15

Architecture of SVM



Review of existing Literature on the Prediction of Solar Radiation Using Machine Learning Models

The switch from conventional to renewable energy (RE) resources has been prompted by the sharply rising global energy desire, the sharp decline in fossil fuels reserves, global warming, climate change, and energy security concerns (Fang et al., 2018). More than 75% of China's power is still produced using "dirty" coal, which emits large amounts of NOx, CO_2, and SO_2 into the atmosphere(Bi et al., 2018). Researchers are looking for alternative energy sources that can both provide energy and preserve the environment as a result of the environmental issues brought on by the growing use of fossil fuels.(Kassem, Cąmur, et al., 2021). Due to its economic viability and few negative effects on the environment, renewable energy sources like solar energy are quickly expanding (Kassem, Gökçekuş, et al., 2021). Also, due to its sustainability and financial advantages, solar energy has become one of the most popular alternative energy sources. Additionally, it has been determined that the quantity of solar energy on the earth is 157 times greater than coal reserves and 516 times greater than the world's oil reserves(Nordell, 2003). In modern years, studies have evaluated solar energy potentials as a good power source for electric generations. For example, taking Nahr El-Bared, Lebanon as a case study, (Camur et al., 2021) assessed the performances photovoltaic (PV) systems. The findings showed that the yearly generation of power might meet the area's energy needs and lower its electricity costs. (Tripathi et al., 2022) predicted the resulted output power of a solar photovoltaic system using different machine learning models taking into consideration different input parameters such as temperature, relative humidity, solar radiation, on and time of the day. Their study concluded that of all the models employed, the multiple linear regression algorithm demonstrated better performances considering mean squared error and mean absolute error. Similarly, (Kassem, Cąmur, et al., 2021) tested the viability of a small-scale grid-connected Photovoltaic system using various technology in Amman, Jordan. The result of their study showed that the power obtained would significantly reduce the consumption of fossil fuels and emissions of CO_2. In another study of (Jia et al., 2022), machine learning model was used to estimate the daily global and diffuse solar radiation. Their result from the models employed indicated that the SVM models showed reliability in the prediction of radiation under slight pollutions and weather condition. In his paper, (Zazoum, 2022) explored the relationships between certain inputs and Photovoltaic systems using different machine learning model. The result indicated that these input parameters which included ambient temperature, solar flux, day time and relative humidity are basic factors that influence the energy outputs of a Photovoltaic system. Additionally several of other studies have employed machine learning models to forecast PV system power as a function of variations in climate (Omubo-Pepple et al., 2009). The solar radiation of about 200 cities in Nigeria were estimated using different machine learning models that are dependent of feed forward and multilayered network using different weather condition(Teke et al., 2015). came up with a model using ANN to predict the solar radiation in Saudi Arabia. Using back propagation algorithm, the various patterns of the multilayer feed neural network were trained. The best result was determined considering the minimum mean absolute percentage error.

Table 4

Summary of some existing Literature

Reference	Area of Study	Aim	Data Used	Models Used
(Kassem & Othman, 2022b)	Amman, Jordan	-the developed models for predicting the output power of 68 kW grid-connected PV system	- the mean daily average temperature, -minimum and Maximum temperatures, -wet-bulb temperature -relative humidity, -global solar radiation - wind speed	-MFFNN -CFNN -RBFNN -ENN -QM -MLR
(Veisi et al., 2022)	Mashhad(capital of Khorasan Razavi province of Iran)	-Application of machine learning for solar radiation modelling	-maximum temperature - minimum temperature -maximum city heights -minimum city heights	-GPR -ANN -SVM -ANFIS -MLR -RBF

Table 4 (Continued)

(Demir & Citakoglu, 2023)	Turkey	- to make Solar Radiation prediction with different machine learning approaches.	-max. temperature -min. temperature -wind speed - max relative humidity	-SVMR -LSTM -GPR -ELM -KNN
(Kisi et al., 2020)	Antakya/Adana Turkey	-for estimating monthly solar radiation	-maximum temperature -maximum temperature -sunshine hours -wind speed -relative humidity	-ANN -ELM -RBF -WANN -WRBF -BMA -WELM
(Belmahdi et al., 2022)	Tetouan, Morocco			-ARIMA -FFNN-BP -k-NN -SVM

Table 4 (Continued)

(Banerjee et al., 2022)	Eastern India	- the net radiation, global solar radiation (GSR) and canopy temperature (CT) were measured over five different types of crops, namely cowpea, maize, rice, chickpea and mustard.	-thermometer -Canopy temperature	-DNN -RR -SR -RF -GBR
(Sohani et al., 2022)	-Tehran, Iran	-an enhanced design for the solar still system, which was originally introduced by Sohani , is investigated, and the experimental data for that are employed as the input data for obtaining different types of ANN model.	-water temperature - hourly distillate production -Wind speed -Depth of water in the basin, -Ambient temperature -The radiation received from the sun	-FF -BP -RBF
(de Amorim Neto et al., 2022)	-Ceará, Brazil	-predicting the thermal response of a solar wall.	- ambient temperature -solar radiation temperature -date -time -direct difuse -	-kNN -MLM -SVM -RF

Table 4(Continued)

(García-Cuesta et al., 2022)	-Iberian Peninsula	- to extract features and reduce dimensionality in renewable energy.	-Cloud mixing ratio -Relative humidity -Soil Temperature -component of wind	-SLMVP -PCA -LPP -LOL -SNMF
(Verma & Patil, 2021)	-France	-the estimation of ground solar radiation based on satellite images	-altitude - latitude - longitude - month -day - time -solar zenith angle - solar azimuth angle -viewing zenith angle -viewing azimuth angle	-ANN -SVM -EVM
(Demir & Citakoglu, 2023)	-Turkey.	- investigated the potential of new ensemble method, Bayesian model average-ing (BMA), in modelling monthly solar radiation based on climatic data	-minimum temperature -maximum temperature -sunshine hours -wind speed -relative humidity-	-ELM -RBF - WANN -WELM -WRBF -BMA

Table 4 (Continued)

(Janković et al., 2021)	-China	- develop the prediction models of the EF.	-natural gas sources, -coal sources, - oil sources - wind Sources -solar photovoltaic sources, -hydropower sources -nuclear sources	-KNNR -RFR
(Ofori-Ntow Jnr et al., 2022)	Ghana	- handling long-term photovoltaic power Forecasting	-wind speed -air temperature -sun height -	-BPNN -GMDH -ENN -LSSVM -RBFNN
(Muhammad Ehsan et al., 2017)	Tiruchirappalli India	- the profile of power output of a grid-connected 20-kWp solar power plant	- Atmospheric Temperature - Relative Humidity - Wind speed -Earth Temperature - solar radiation - wind direction - rainfall	

Table 4 (Continued)

(Park et al., 2021)	- Korea	- RNN model for predicting solar PV power generation using the neural network toolbox function of MATLAB.	-outdoor air temperature -humidity, -direct solar radiation -diffuse solar radiation - wind speed	- RNN
(Kumar et al., 2020)	-India	- A 5 kWp grid-connected PV system is installed at rooftop of the laboratory	-irradiance incident -cell temperature -Linke turbidity - wind speed	- GWO –MLP
(Arora et al., 2021)	-India	- to improve ANN based prediction model by incorporating technique to normalise input dataset.	- temperature, -relative humidity, -precipitation, -sunshine hours, -clearness index, -pressure, -wind speed	- FFD -
(Shah et al., 2021)	-India	- T to find out the best model for estimation from RBF and MLP	-sunshine duration -relative humidity -temperature, -atmospheric pressure	- RBF -MLP

Table 4 (Continued)

(Dikmen et al., 2014)	-Turkey	-The thermal performance of the evacuated tube solar collector	-Ambient temperature -Solar radiation -Collector tilt-angl -Mean temperature -Thermal performance	-LM
(Natsheh et al., 2014)	-Manchester	-The solar irradiance and temperature data are gathered from a 28.8 kW solar power system	- Solar irradiance, -temperature	-LM

Table 5

Information of Data Used by Previous Studies

Common Data	**Few Data**	**New Data**
Pressure	Solar Zenith Angle	Sunrise Hour Angle
Relative Humidity	Maximum City Heights	Extra-Terrestrial
Wind Speed	Longitude	Radiation On A
Wind Direction	Latitude	Horizontal Surface
Sunshine Hours	Temperature Ratio	Temperature Ratio
The Mean Daily Average Temperature	Max Sea Surface Pressure,	Component Of Wind
Minimum Temperatures	Min Sea Surface Pressure	Viewing Zenith Angle
Maximum Temperatures	Mean Sea Surface Pressure	Viewing Azimuth Angle
Wet-Bulb Temperature	Mean Vapour Pressure	Year
Global Solar Radiation	Max Cloudiness	Irradiance Incident
Rainfall	Mean Cloudiness	Cell Temperature

Table 5 (Continued)

	Evaporation	
	Mean Dew Point Temperature,	
	Mean Wet Point Temperature,	
	Maximum Air Pressure,	
	Minimum Air Pressure,	
	Mean Air Pressure,	
	Mean Vapour Saturation Pressure	
	Canopy Temperature	
	Minimum Humidity	Cloud Mixing Ratio
	Mean Humidity	Soil Temperature
	Sunshine Hours,	Component Of Wind

Table 6

Models used by previous studies

COMMON MODELS	FEW MODELS
SVR	GWO
DTR	MLP
RFR	RR
GBR	SR
LSTM	RF
GPR	RR
SVM	SR
ANFIS	RF
MLR	BPNN
RBF	FFNN
SVMR	DNN
LSTM	MANN
ELM	ENN
KNN	QM
WANN	CC
WRBF	RMSE
BMA	NS
WELM	
MLM	
SVM	
MLM	
MLM	

CHAPTER III

Materials and Methods

In this section, the effects of geographical parameters in prediction of solar radiation using machine learning methods were studied utilizing three models of ANN for predicting the results.

Description of the Dataset

The patterns of solar radiation in the region are influenced by a number of climatic factors in Africa, the second-largest continent Earth. There are significant variations in the amount of solar radiation present on Earth because of its large size and diverse geography, with some regions getting high quantities while others receive low levels.

Solar radiation forecasting is crucial for the development of renewable energy projects in Africa, especially in remote and rural areas with little access to grid electricity. Latitude, altitude cloud cover, air pollution, and land cover are just a few of the factors that affect how much solar radiation is received in different parts of Africa.

In order to accurately predict solar radiation in Africa, it is essential to take into account these factors and develop reliable models that take into account the local conditions. Thanks to the rapid advancement of renewable energy technology in Africa, accurate estimates of solar radiation can aid in the deployment of solar power plants and ease the transition to a more sustainable energy future on the continent. In this study, 91 major cities were selected for to check the effect of this parameters in the prediction of the solar radiation of the region.

Cities that were used for training include Cairo Egypt, the Kinshasa Democratic Republic of the Congo, Lagos Nigeria, Giza Egypt, Luanda Angola, Dar es Salaam Tanzania, Khartoum Sudan, Johannesburg South Africa, Abidjan Côte d'Ivoire, Alexandria Egypt Addis Ababa Ethiopia, Nairobi Kenya, Cape Town South Africa, Kano Nigeria, East Rand South Africa, Douala Cameroon, Casablanca Morocco, Ibadan Nigeria, Antananarivo Madagascar, Abuja Nigeria, Kampala Uganda, Kumasi Ghana, Dakar Senegal, Durban South Africa, Lusaka Zambia, Algiers Algeria, Bamako Mali, Omdurman Sudan, the Mbuji-Mayi Democratic Republic of the Congo, Lubumbashi Democratic Republic of the Congo, Accra Ghana, Brazzaville Republic of the Congo, Mogadishu Somalia, Lomé Togo, Benin City Nigeria, Matola Mozambique, Monrovia Liberia, Kananga Democratic Republic of the Congo, Harare

Zimbabwe, Onitsha Nigeria, N'Djamena Chad, Nouakchott Mauritania, Mombasa Kenya, Niamey Niger, Gqeberham South Africa, Fez Morocco, Mwanza Tanzania, Lilongwe Malawi, Kigali Rwanda, the Bukavu Democratic Republic of the Congo, Abomey-Calavi Benin, Nnewi Nigeria, Kaduna Nigeria, Aba Nigeria, Bujumbura Burundi, Maputo Mozambique, Hargeisa Somalia, Bobo Doulas, Burkina Faso, Shubra el-Kheima Egypt, Ikorodu Nigeria, Asmara Eritrea, Marrakesh Morocco, Ilorin Nigeria, Blantyre Malawi, Agadir Morocco, Misratah Libya, Jos Nigeria, Bangui Central African Republic, Nampula Mozambique, Lubango Angola, Cabinda Angola, Libreville Gabon, Maiduguri Nigeria, Enugu Nigeria, Lokoja Nigeria, Benguela Angola For testing data, the data for; Oran Algeria, Ouagadougou Burkina Faso, Owerri Nigeria, Pointe-Noire Republic of the Congo, Port Harcourt Nigeria, Pretoria South Africa, Rabat Morocco, Tangier Morocco, Tripoli Libya, Tshikapa Democratic Republic of the Congo, Tunis Tunisia, Umuahia Nigeria, Uyo Nigeria, Warri Nigeria, Vereeniging South Africa, West Rand South Africa and Yaoundé.

Table 7

Information of the Selected Cities

Location	Latitude [N°]	Longitude [E°]	Altitude [m]
Cairo	30.033	31.562	350
Kinshasa	-4.322	15.313	277
Vereeniging	-26.558	27.908	1526
Giza	29.987	31.212	19
Luanda	-9.518	13.536	201
Dar es Salaam	-6.816	39.28	15
Khartoum	15.603	32.526	387
Johannesburg	-26.205	28.05	1746
Abidjan	5.409	-4.042	105
Alexandria	30.943	29.766	18
Addis Ababa	9	38.750	2315
Nairobi	-1.303	36.826	1657
Cape Town	-33.299	18.417	35

Table 7 (Continued)

Yaoundé	3.869	11.521	715
Kano	11.985	8.536	454
East Rand	-26.395	27.396	1590
Umuahia	5.532	7.492	154
Douala	36.634	4.085	614
Casablanca	33.263	-7.964	189
Ibadan	7.378	3.897	223
Antananarivo	18.985	46.739	1205
Abuja	9.064	7.489	473
Kampala	0.318	32.581	1237
Kumasi	6.698	-1.623	260
Dakar	14.74	-17.334	6
Port Harcourt	4.768	7.019	18
Durban	-29.862	31.01	13
Ouagadougou	12.37	-1.533	299
Lusaka	-15.358	29.165	1149
Algiers	36.775	3.06	31
Bamako	12.649	-8	335
Omdurman	15.645	32.478	391
Mbuji-Mayi	-6.119	23.568	678
Pretoria	-25.746	28.188	1338
Kananga	-5.895	22.409	636
Harare	-17.857	31.06	1483
Onitsha	6.133	6.792	51

Table 7 (Continued)

N'Djamena	12.119	15.05	297
Nouakchott	18.079	-15.978	8
Mombasa	-4.039	39.684	10
Niamey	13.525	2.11	207
Pointe-Noire	-4.816	11.887	16
Gqeberha	-33.962	25.621	52
Cabinda	-5.056	12.321	103
Fez	33.833	-4.856	971
Uyo	5.032	7.925	71
Mwanza	-2.455	32.713	1134
Lilongwe	-14.041	33.735	1071
Kigali	-1.886	30.13	1575
Bukavu	-2.498	28.887	1533
Abomey	6.415	2.303	30.02
Nnewi	5.96	6.981	163
Tripoli	32.773	13.332	31
Kaduna	10.382	7.853	661
Aba	5.113	7.364	64
Bujumbura	-3.349	29.363	798
Maputo	-25.966	32.568	14
Hargeisa	9.562	44.062	1267
BoboDioulass	11.176	-4.296	420
Shubra el-Kheima	30.124	31.238	28
Ikorodu	6.619	3.505	36

Table 7 (Continued)

Asmara	15.339	38.933	2342
Marrakesh	31.626	-7.989	468
Tshikapa	-2.981	23.822	505
Ilorin	8.496	4.548	318
Blantyre	-15.78	35.01	698
Agadir	30.703	-9.570	454
Misratah	32.375	15.092	9
Lubumbashi	-11.664	27.483	1262
Accra	5.81	0.1	39
Brazzaville	-2.981	23.822	505
Monrovia	6.328	-10.798	6
Tunis	33.844	9.4	43
Rabat	33.967	-6.843	87
Lomé	6.13	1.216	14
Benin City	6.333	5.622	90
Owerri	5.48	7.022	74
Warri	5.517	5.75	5
Jos	9.918	8.898	1182
Bangui	4.378	18.554	355
Nampula	-15.119	39.262	430
Oran Algeria	35.622	-0.702	162
West Rand	-26.223	27.513	1589
Lubango	-14.919	13.49	1774

Artificial Neural Network

ANN is the most commonly utilized model to solve non-linear functions and describe a complex system (de Amorim Neto et al., 2022; García-Cuesta et al., 2022) An artificial neural network (ANN) is a network of linked nodes that is used to solve complicated issues and show the intricate relationship between causes and effects(Kassem, Gökçekuş, et al., 2021). A "black box" of linked artificial neurons makes up an artificial neural network (ANN), a type of computer model. These neurons, which can be organized in one or more layers, don't function linearly. An ANN's operation is modelled after how the human brain functions. It has input, hidden, and output layers, with nodes connecting each neuron. Data is sent from input nodes to hidden neurons, integrated, and processed by activation functions, and finally it is delivered to the output neurons. This is how information flows in an ANN. Different ANN approach have been created and used in a variety of sectors, including engineering and research. Long short-term memory, feed-forward neural networks, multi-layered perceptron neural networks, generalized regression neural networks, support vector machines, K-nearest neighbor algorithms, and extreme learning machines are a few examples. In this study, three machine learning models, **feed-forward neural network, NARX regression neural network and Layer Recurrent Neural Network,** were used for predicting the yearly of the African countries. The performance of these models was tested on 91 cities in Africa with the six main climate zones, namely, Equatorial, Humid Tropical, Tropical, Semi-desert (Sahalian), Mediterranean, and Desert, which are subject to the high solar radiation zone.

Feed Forward Neural Network:

The term "FFNN" stands for "Feed-Forward Neural Networks," and it refers to a model that is widely used for issue analysis across many different fields(Iravanian et al., 2022). Using this model, the Levenberg-Marquardt algorithm and the backpropagation approach are frequently employed. (Meshram et al., 2019). Trials and error is used to determine the number of hidden layers and numerous neurons. The training algorithm's effectiveness is evaluated using mean squared error. The data are normalized between 0 and 1, so take note of that. In this research, the learning algorithm is the backpropagation algorithms. The structure of the proposed model is given in figure 16 (Kassem & Othman, 2022a).

Figure 16

Architecture of FFNN

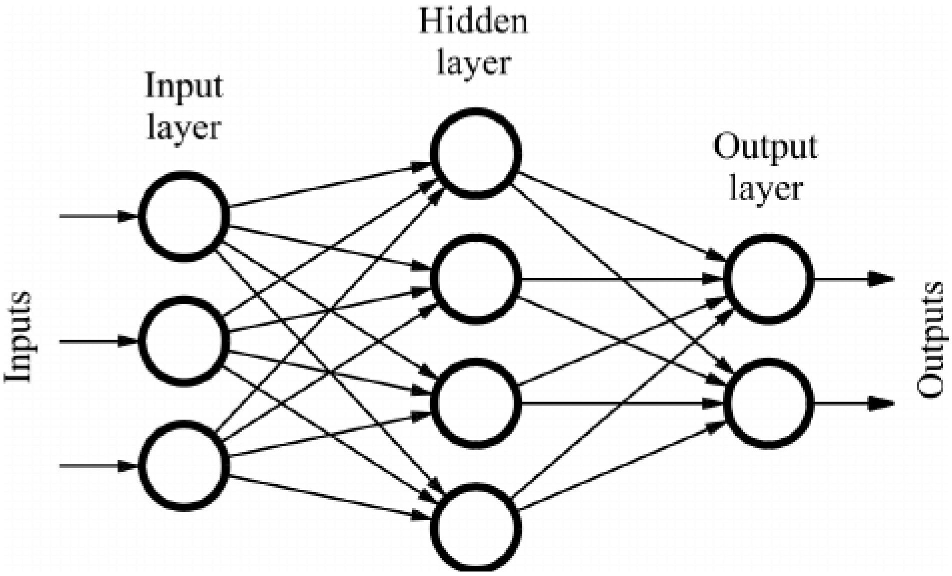
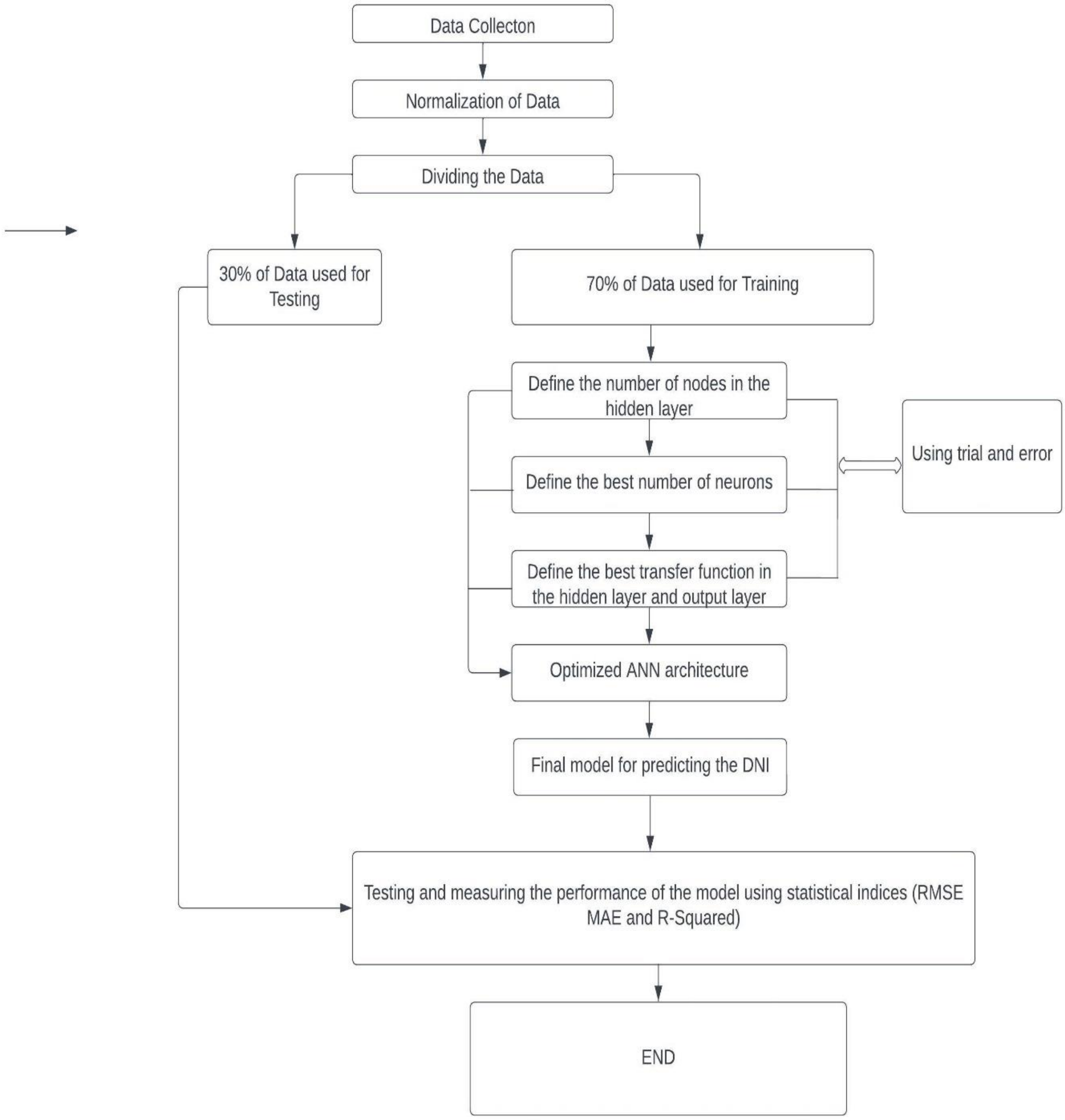


Figure 17

Flowchart of FFNN



Cascaded Forward Neural Network

Cascade for-ward neural network (CFNN) and FFNN are comparable in general. An input layer, one or more hidden layers, and an output layer make up its three layers. Weights derived from the input are included in the top layer. Weights from the input and all earlier levels are also included in each succeeding layer. Biases exist on every layer. The output layer is the final one. Weights and biases for each layer must be set up. For the purpose of assessing the model's performance during the training phase, the mean squared error was determined.

Figure 18

Architecture of CFNN

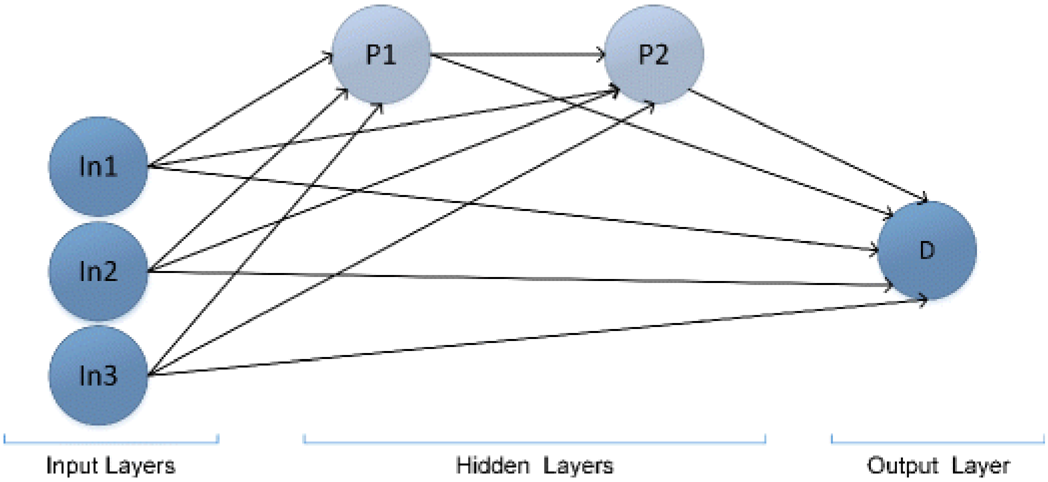
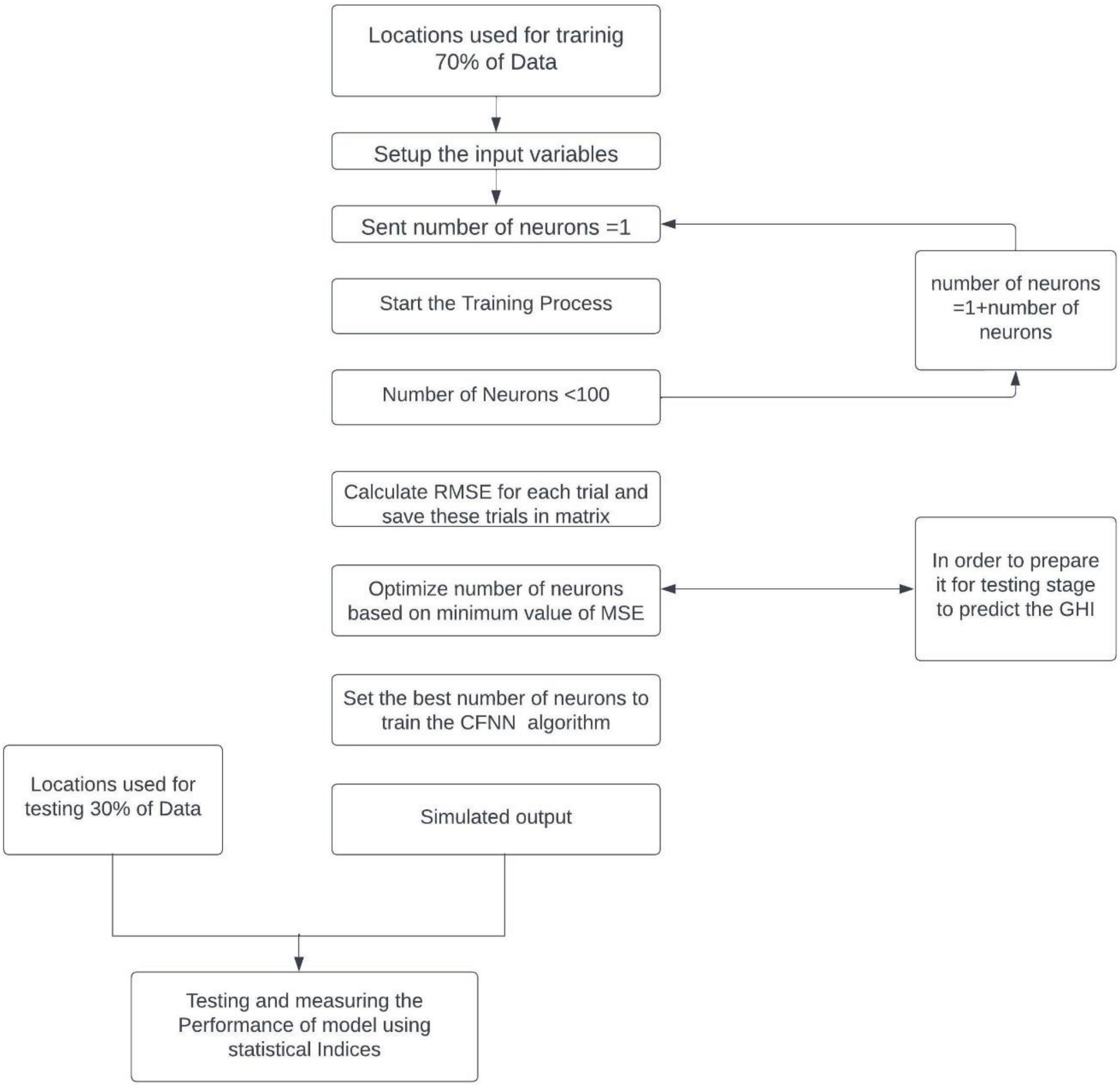


Figure 19

Flowchart of CFNN



NARX regression neural network

The default NARXNN functions as a parallel neural network. Given the continuity of the time series, the output of the prediction is fed back as a one-dimensional input of the following instant to add the historical series' effect on the anticipated value of the following moment. As a result, the NARXNN is converted into a pure forward neural network in series-parallel neural network mode. Determining whether the network training result is positive or negative is based on the performance function, which is specified as the training result detection function. Although adding additional hidden layer nodes improves network accuracy, it also causes a discordant fit that impairs the network's performance.

Figure 20

Architecture of NARX

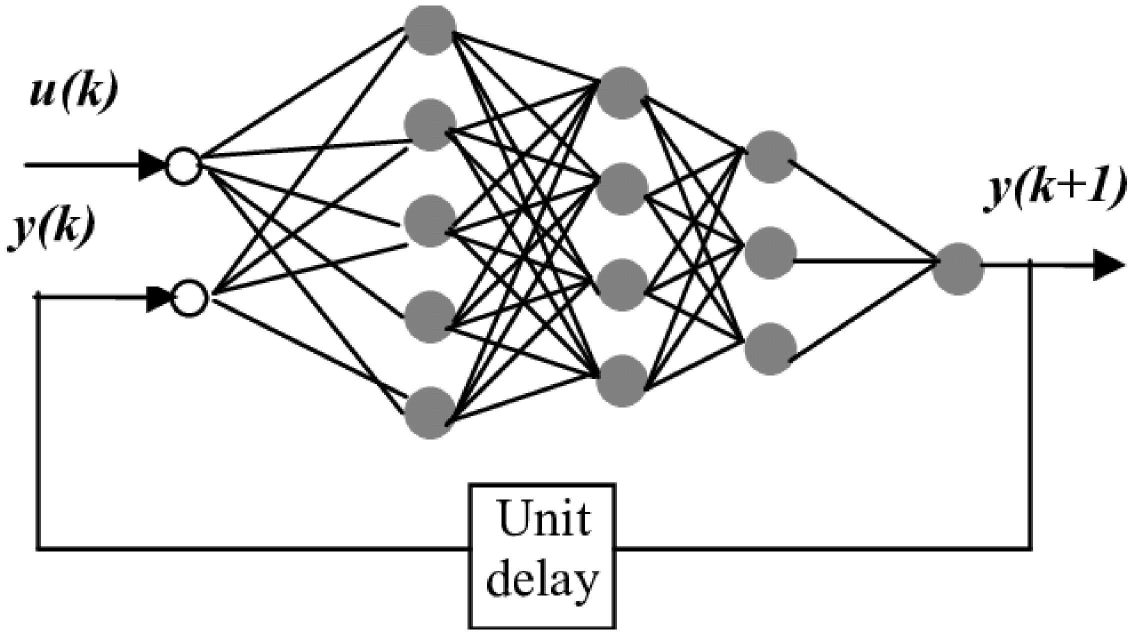
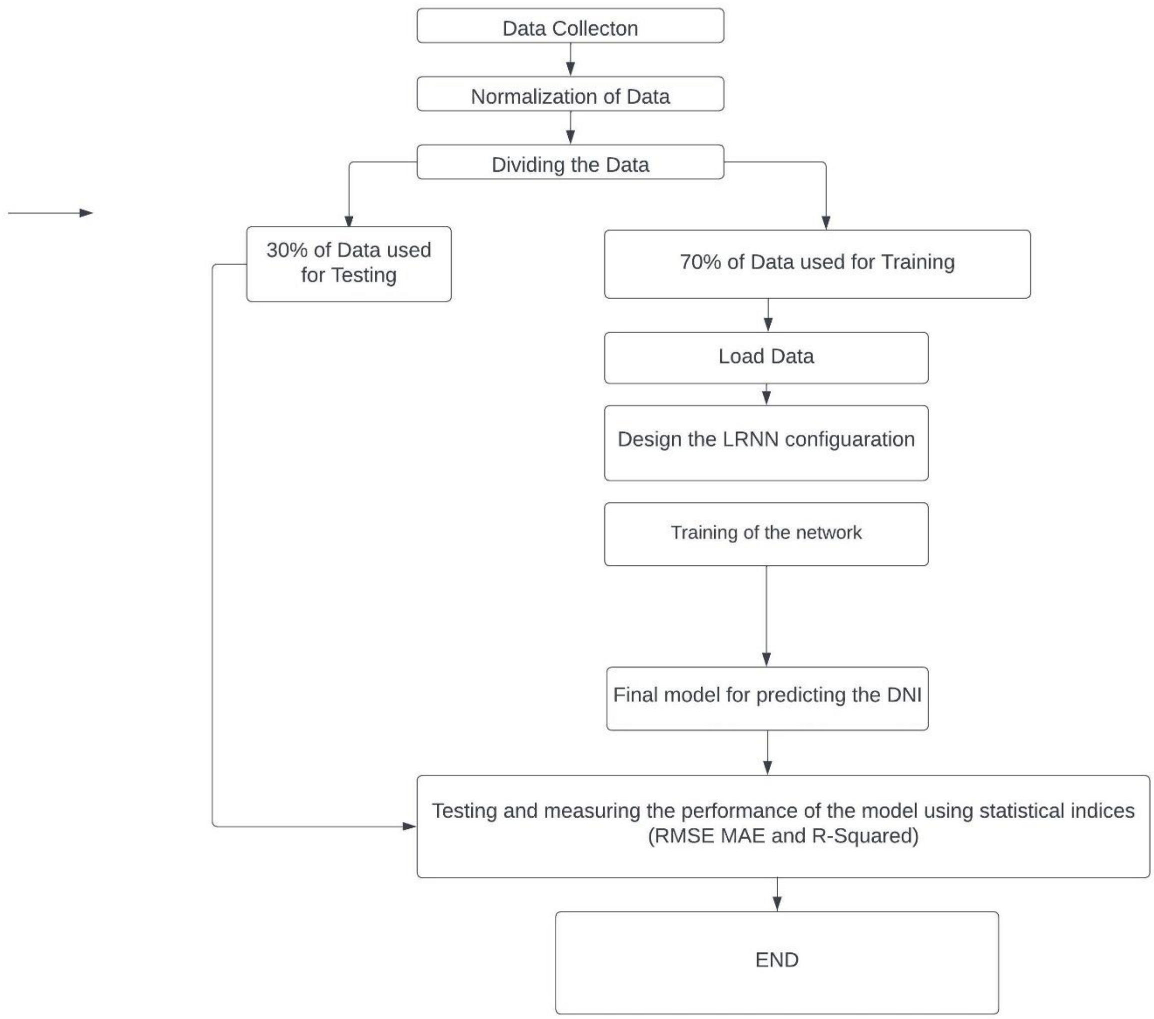


Figure 21

Flowchart of NARX



Dataset

The NASA POWER (Prediction of Worldwide Energy Resource) dataset is a comprehensive collection of solar and meteorological data. It provides information on various parameters that are crucial for studying and analysing renewable energy resources and their potential. The dataset covers locations worldwide, allowing researchers and analysts to access solar and meteorological data for virtually any location on Earth. The NASA POWER dataset includes a wide range of parameters related to solar radiation and meteorological conditions. These data are solar radiation including Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), Diffuse Horizontal Irradiance (DHI), and Clear Sky GHI as well as meteorological data including: temperatures, relative humidity, wind speed, wind directions, precipitation, clouds cover, atmospheric pressures, and more. The dataset offers both hourly and daily temporal resolutions. Hourly data is available for certain parameters, allowing for a more detailed analysis of solar and meteorological conditions throughout the day. Daily data provides aggregated values for each parameter. The spatial resolution of the NASA POWER dataset varies depending on the specific parameter and the data source used. Generally, the dataset provides information at a spatial resolution of approximately 1 km. The dataset integrates data from various sources, including satellite observations, ground measurements, and atmospheric models. NASA incorporates data from multiple sensors and instruments to provide accurate and reliable information. The NASA POWER dataset is freely accessible to the public through the NASA POWER web portal (https://power.larc.nasa.gov/).

Therefore, the annual data including Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), Surface Pressure, average, maximum and minimum temperature, Relative Humidity, Wind Speed at 2m height, average, maximum and minimum wind speed at 10m height, Wind Direction at 10m height, Dew/Frost Point, Wet Bulb Temperature, cloud amount, and precipitation were collected for all selected cities in Africa.

Figure 22

NASA Power Access Data Viewer

Data Normalization

A preprocessing method used in machine learning to normalize the range of features or variables is known as data normalization, often referred to as feature scaling. Data normalization aims to scale all characteristics uniformly while preserving their individual distinctions and interrelationships(Ali et al., n.d.).

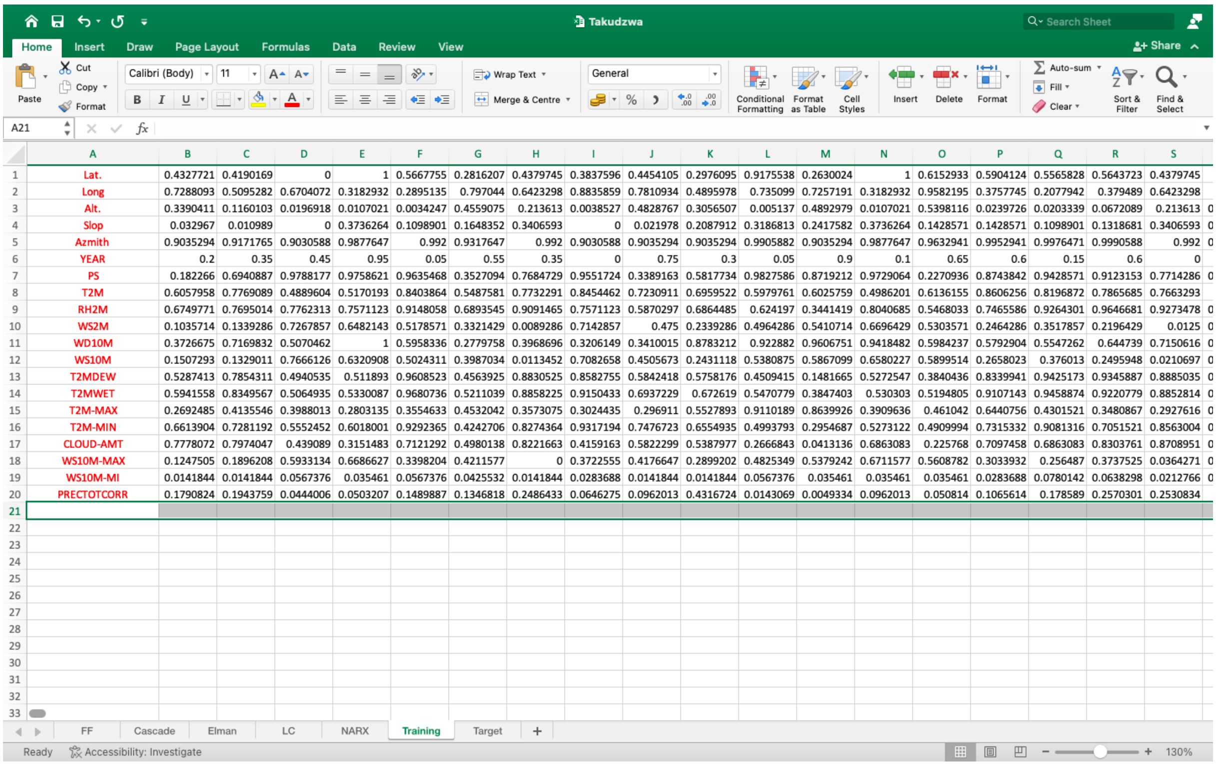
Normalization is crucial since it aids in preventing the dominance or distortion of particular characteristics in the learning algorithm. When the input data is of similar scale, several machine learning algorithms operate more effectively or converge more quickly(Singh et al., n.d.).

It is calculated mathematically using the formula:

$$\frac{X - X_{minimum}}{X_{maximum} - X_{minimum}}$$

Figure 23

Normalized Data in Excel Sheet



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	Lat.	0.4327721	0.4190169	0	1	0.5667755	0.2816207	0.4379745	0.3837596	0.4454105	0.2976095	0.9175538	0.2630024	1	0.6152933	0.5904124	0.5565828	0.5643723	0.4379745
2	Long	0.7288093	0.5095282	0.6704072	0.3182932	0.2895135	0.797044	0.6423298	0.8835859	0.7810934	0.4895978	0.735099	0.7257191	0.3182932	0.9582195	0.3757745	0.2077942	0.379489	0.6423298
3	Alt.	0.3390411	0.1160103	0.0196918	0.0107021	0.0034247	0.4559075	0.213613	0.0038527	0.4828767	0.3056507	0.005137	0.4892979	0.0107021	0.5398116	0.0239726	0.0203339	0.0672089	0.213613
4	Slop	0.032967	0.010989	0	0.3736264	0.1098901	0.1648352	0.3406593	0	0.021978	0.2087912	0.3186813	0.2417582	0.3736264	0.1428571	0.1428571	0.1098901	0.1318681	0.3406593
5	Azmith	0.9035294	0.9171765	0.9030588	0.9877647	0.992	0.9317647	0.992	0.9030588	0.9035294	0.9035294	0.9905882	0.9035294	0.9877647	0.9632941	0.9952941	0.9976471	0.9990588	0.992
6	YEAR	0.2	0.35	0.45	0.95	0.05	0.55	0.35	0	0.75	0.3	0.05	0.9	0.1	0.65	0.6	0.15	0.6	0
7	PS	0.182266	0.6940887	0.9788177	0.9758621	0.9635468	0.3527094	0.7684729	0.9551724	0.3389163	0.5817734	0.9827586	0.8719212	0.9729064	0.2270936	0.8743842	0.9428571	0.9123153	0.7714286
8	T2M	0.6057958	0.7769089	0.4889604	0.5170193	0.8403864	0.5487581	0.7732291	0.8454462	0.7230911	0.6959522	0.5979761	0.6025759	0.4986201	0.6136155	0.8606256	0.8196872	0.7865685	0.7663293
9	RH2M	0.6749771	0.7695014	0.7762313	0.7571123	0.9148058	0.6893545	0.9091465	0.7571123	0.5870297	0.6864485	0.624197	0.3441419	0.8040685	0.5468033	0.7465586	0.9264301	0.9646681	0.9273478
10	WS2M	0.1035714	0.1339286	0.7267857	0.6482143	0.5178571	0.3321429	0.0089286	0.7142857	0.475	0.2339286	0.4964286	0.5410714	0.6696429	0.5303571	0.2464286	0.3517857	0.2196429	0.0125
11	WD10M	0.3726675	0.7169832	0.5070462	1	0.5958336	0.2779758	0.3968696	0.3206149	0.3410015	0.8783212	0.922882	0.9606751	0.9418482	0.5984237	0.5792904	0.5547262	0.644739	0.7150616
12	WS10M	0.1507293	0.1329011	0.7666126	0.6320908	0.5024311	0.3987034	0.0113452	0.7082658	0.4505673	0.2431118	0.5380875	0.5867099	0.6580227	0.5899514	0.2658023	0.376013	0.2495948	0.0210697
13	T2MDEW	0.5287413	0.7854311	0.4940535	0.511893	0.9608523	0.4563925	0.8830525	0.8582755	0.5842418	0.5758176	0.4509415	0.1481665	0.5272547	0.3840436	0.8339941	0.9425173	0.9345887	0.8885035
14	T2MWET	0.5941558	0.8349567	0.5064935	0.5330087	0.9680736	0.5211039	0.8858225	0.9150433	0.6937229	0.672619	0.5470779	0.3847403	0.530303	0.5194805	0.9107143	0.9458874	0.9220779	0.8852814
15	T2M-MAX	0.2692485	0.4135546	0.3988013	0.2803135	0.3554633	0.4532042	0.3573075	0.3024435	0.296911	0.5527893	0.9110189	0.8639926	0.3909636	0.461042	0.6440756	0.4301521	0.3480867	0.2927616
16	T2M-MIN	0.6613904	0.7281192	0.5552452	0.6018001	0.9292365	0.4242706	0.8274364	0.9317194	0.7476723	0.6554935	0.4993793	0.2954687	0.5273122	0.4909994	0.7315332	0.9081316	0.7051521	0.8563004
17	CLOUD-AMT	0.7778072	0.7974047	0.439089	0.3151483	0.7121292	0.4980138	0.8221663	0.4159163	0.5822299	0.5387977	0.2666843	0.0413136	0.6863083	0.225768	0.7097458	0.6863083	0.8303761	0.8708951
18	WS10M-MAX	0.1247505	0.1896208	0.5933134	0.6686627	0.3398204	0.4211577	0	0.3722555	0.4176647	0.2899202	0.4825349	0.5379242	0.6711577	0.5608782	0.3033932	0.256487	0.3737525	0.0364271
19	WS10M-MI	0.0141844	0.0141844	0.0567376	0.035461	0.0567376	0.0425532	0.0141844	0.0283688	0.0141844	0.0141844	0.0567376	0.035461	0.035461	0.035461	0.0283688	0.0780142	0.0638298	0.0212766
20	PRECTOTCORR	0.1790824	0.1943759	0.0444006	0.0503207	0.1489887	0.1346818	0.2486433	0.0646275	0.0962013	0.4316724	0.0143069	0.0049334	0.0962013	0.050814	0.1065614	0.178589	0.2570301	0.2530834

Data Randomization

The process of randomizing the order of data instances inside a data collection is referred to as data randomization, also known as shuffling. It is frequently used in machine learning to prevent data during training from being distorted or biased by innate ordering or patterns(Adams & Anthony, 1996).

Because some machine learning algorithms might be sensitive to the sequence of training samples, the random order of data examples is crucial. The ordering of the data might lead to biased or inefficient learning.

Figure 24

Data Randomization in Excel Sheet

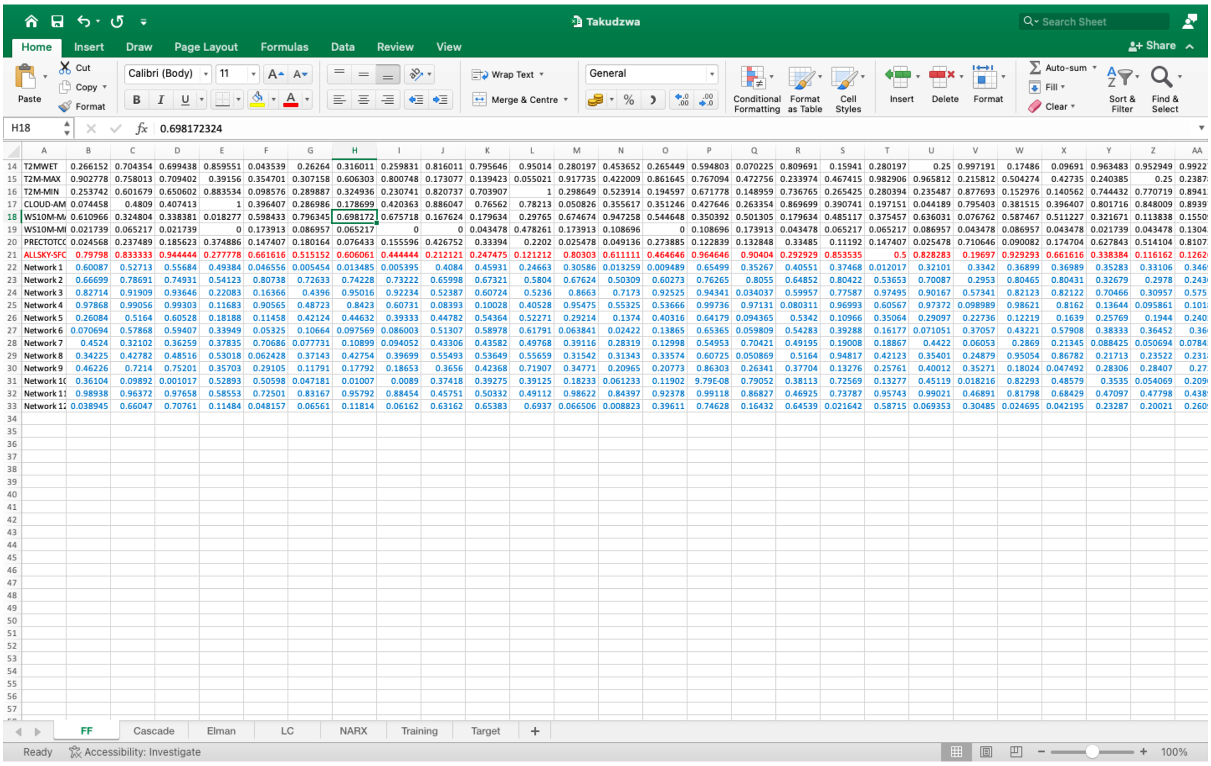


Table 8

Descriptive Statistics of the Training Datasets

Variable	Mean	Median	SD	Minimum	Maximum
Long	3.618	6.131	16.951	-33.962	36.775
Long	16.257	14.543	16.087	-17.334	46.739
Alt.	555.7	352.5	597.6	6.0	2342.0
Slop	17.619	16.000	15.724	-1.000	90.000
Azimuth	930317	-2	7842303	-2099	66988885
YEAR	2011.0	2011.0	6.06	2001.0	2021.0
PS	96.063	97.950	5.636	81.400	101.700

Table 8 (Continued)

RH2M	68.820	71.910	15.201	23.810	89.190
WS2M	2.4182	2.3000	1.1292	0.4500	6.0500
WD10M	195.17	211.25	94.24	0.44	359.50
WS10M	3.4027	3.2750	1.2156	1.0200	7.1900
T2MDEW	15.994	15.440	5.570	4.120	24.300
T2MWET	19.810	19.755	3.923	7.190	25.670
T2M-MAX	36.476	36.105	4.942	25.250	46.940
T2M-MIN	11.895	12.120	5.895	-8.700	23.520
CLOUD-AMT	54.354	55.755	15.929	11.360	86.880
WS10M-MAX	10.045	10.050	3.603	2.810	22.850
WS10M-MI	0.06226	0.05000	0.06463	0.00000	1.41000
PRECTOTCORR	2.8400	2.6350	1.9214	0.0100	20.2800
ALLSKY-SFC-SW-DNI	4.2669	4.3000	1.3801	1.9700	7.7400
ALLSKY-SFC-SW-DWN	5.2555	5.2450	0.6825	2.5800	6.8000

Table 9

Descriptive Statistics of the Testing Datasets

Variable	Mean	Median	SD	Minimum	Maximum
Long	8.77	5.50	20.85	-26.56	35.62
Long	11.410	8.662	11.565	-6.843	31.238
Alt.	403.9	120.5	528.1	5.0	1589.0
Slop	19.765	17.000	11.415	0.000	34.000
Azimuth	-131.1	1.0	427.8	-1871.0	18.0
YEAR	2011.0	2011.0	6.06	2001.0	2021.0
PS	97.158	99.925	5.223	84.700	101.580
T2M	22.427	23.125	3.410	15.800	28.580
RH2M	70.830	71.685	15.565	39.250	90.250
WS2M	2.0017	2.0000	1.0286	0.0800	4.3600
WD10M	228.72	235.22	101.01	0.94	360.00
WS10M	2.9572	3.0700	1.1067	0.6600	5.3200

Table 9 (Continued)

T2M-MAX	36.992	35.905	4.785	29.050	47.770
T2M-MIN	8.881	10.235	7.843	-6.200	21.190
CLOUD-AMT	54.298	49.990	18.914	22.770	84.550
WS10M-MAX	9.883	9.500	4.379	1.730	20.880
WS10M-MI	0.05415	0.05000	0.04694	0.01000	0.47000
PRECTOTCORR	3.028	2.175	2.337	0.030	11.020
ALLSKY-SFC-SW-DNI	4.2447	4.5450	1.6901	1.8300	7.0900
ALLSKY-SFC-SW-DWN	5.0012	4.9500	0.5872	3.9800	5.9600

CHAPTER IV

Results and Discussion

Description of the Dataset

The data obtained for the 91 cities of different part of Africa from the NASA database were divided into training and testing with the training data taking 70% of the cities while testing was 30% of the cities. Data of 21 years (2000 to 2020) were utilized for this study. To start the training process, three (3) networks were created with different configurations. The training process was done by trial and error and were utilized to find the best neural network model and the best combination of input variables and hidden layer neurons. In this regard, the number of layers, neurons and iterations were between the range of 1-2, 5-15 and 10000-100000. Also, the, transfer function was changed between TANSIG and LOGSIG while the Training Function and Adaption Learning function was kept constant for all different configuration of networks. After the training, the optimal best network was then selected and the testing data was inputted to simulate the network.

Table 10

Optimum network configuration

ANN model	Scenario	Number of hidden layers	Number of neurons	Transfer function
FFNN	1	1	15	TANSIG
	2	1	15	TANSIG
ENN	1	2	5	LOGSIG
	2	1	15	TANSIG
LRNN	1	1	5	TANSIG
	2	2	10	LOGSIG

Results of the ANN

For every configuration, the input was varied with the first case including geographical parameters while the second scenario has no geographical parameters. To assess the best model, various statistical indices were employed such as the R^2, MAE, and RMSE. These statistical equations have been described as widely used when determining the best model (Arora et al., 2021; Kumar et al., 2020; Park et al., 2021). A model with a value of the R^2 that is close to 1 and RMSE and MAE close to 0 indicates the best model (Kassem & Gökçekuş, 2021). When comparing to other statistical indices, the R^2 is the most informative and thereby employed as the best when determining the performance of a model (Chicco et al., 2021). For models with a 0.5 R^2, the value is considered to be moderated and ca be accepted (Van Liew et al., 2003) The mathematical expressions for the indices are given below:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}$$

Where n is Number of Datasets, Y_i is Actual Datasets and $\hat{Y}_i$ is the Predicted Datasets and $\bar{Y}$ is the mean of actual values.

First Scenario

Based on the calculated results for the first scenario, the R^2 values for all the cities was between the range of 0.50 to 0.9 The values show that the models can be used to predict the GHI for the selected locations. FFNN was found to be the best models with the highest value of the R^2 of 0.8372. The values of RMSE and MSE for all the cities that was calculated closest to 0 was CFNN.

For Ouagadougou, Owerri, Pointe Noire, Port Harcourt, Pretoria, Rabat, Shubra El Kheims, Tangier, Tripoli, Tshikapa, Tunis, Umuahia, Uyo, Warri and Yaoundé, the values of R^2 for all the models used was found to be less than 0.5 which according to (Van Liew et al., 2003) is a poor R^2 value. The Calculated R^2 values Cities Oran, Vereeniging and West Rand indicated that the best models for the prediction are CFNN and FFNN.

For Ouagadougou, Owerri, Pointe Noire, Port Harcourt, Umuahia and Uyo the value of R^2 range from 0.01 to 0.49 but in this case, all values were below 0.5 and is concluded that the models employed in the prediction did not predict the values for this particular city thus unacceptable (Van Liew et al., 2003)

The calculated RMSE and MAE for cities Oran, Owerri, Tshikapa, Tunis, Umuahia and Uyo indicated that the least value of this indices was calculated in the model CFNN. Similarly, cities Ouagadougou, Port Harcourt, Shubra El Kheims, Tangier, Tripoli, and Warri were having FFNN as the model with the least value of RMSE and MAE.

The least values of RMSE and MAE for cities Pointe Noire, Pretoria, Rabat, Vereeniging, West Rand and Yaoundé was calculated and found in the model of NARX

Second Scenario

Results of the GHI prediction for the second scenario indicated that all the models used in this study have had a favourable value of the R^2 making the models good (Veisi et al., 2022). Of the three models employed, the FFNN was the best model with a value of 0.8526.

The result also indicated that no model predicted accurately the GHI for cities Ouagadougou, Owerri, Point Noire, Port Harcourt, Tshikapa. Tunis, Umuahia, Uyo, Warri West Rand and Yaoundé. For the listed cities, all value of R^2 was below 0.5 and was considered not good for prediction(Van Liew et al., 2003). For cities Tangier, Tripoli, Vereeniging and Oran, FFNN was the best model with a high R^2 value. CFNN was the model having the highest R^2 value for Shubra El Kheims while cities Pretoria and Rabat was NARX.

Based on the calculated RMSE and MAE, the results for all cities combined, Ouagadougou, Rabat, Shubra El Kheims and Tangier indicated that the FFNN was the model having the least error. But for cities Owerri, Point Noire, Port Harcourt, Pretoria, Tripoli, Tunis, Umuahia, Uyo, Vereeniging, Warri, West Rand and Yaounde were having NARX as the models that predicted their values with least error. For Tshikapa, the CFNN was the model with lowest value of the RMSE and MAE.

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Table 11

Calculated Results

Location	Case	Statistical Index	FFNN	CFNN	NARX
All Cities	1	R2	0.8372	0.5898	0.6610
		RMSE	0.1793	0.1157	0.3974
		MAE	0.1662	0.0974	0.3941
	2	R2	0.8521	0.8489	0.8029
		RMSE	0.2283	0.4206	0.4317
		MAE	0.2183	0.4196	0.4276
Oran	1	R2	0.5456	0.6388	0.4305
		RMSE	0.1793	0.1157	0.3974
		MAE	0.1662	0.0974	0.3941
	2	R2	0.5223	0.8184	0.3277
		RMSE	0.2283	0.4206	0.4317
		MAE	0.2183	0.4196	0.4276
Ouagadougou	1	R2	0.0021	0.0188	0.1070
		RMSE	0.0812	0.1036	0.5077
		MAE	0.0684	0.0819	0.4962
	2	R2	0.0421	0.0201	0.0038
		RMSE	0.0486	0.0620	0.0626
		MAE	0.0379	0.0495	0.0511
Owerri	1	R2	0.0002	0.0203	0.0627
		RMSE	0.1542	0.0843	0.1500
		MAE	0.1513	0.0744	0.1452
	2	R2	0.0747	0.0076	0.0073
		RMSE	0.2412	0.1257	0.0611
		MAE	0.2370	0.1050	0.0493

Table 11(Continued)

Pointe Noire	1	R2	0.0111	0.0133	0.0002
		RMSE	0.2543	0.2396	0.0658
		MAE	0.2507	0.2354	0.0531
	2	R2	0.1932	0.1449	0.1304
		RMSE	0.2888	0.1847	0.0451
		MAE	0.2855	0.1809	0.0387
Port Harcourt	1	R2	0.0202	0.0114	0.0782
		RMSE	0.0439	0.2596	0.0652
		MAE	0.0355	0.2562	0.0554
	2	R2	0.0332	0.0034	0.0291
		RMSE	0.3684	0.2984	0.1674
		MAE	0.3653	0.2878	0.1613
Pretoria	1	R2	0.4513	0.1663	0.4129
		RMSE	0.1181	0.2221	0.1057
		MAE	0.1029	0.2109	0.0933
	2	R2	0.5377	0.3604	0.6805
		RMSE	0.1456	0.1381	0.0509
		MAE	0.1282	0.1236	0.0365
Rabat	1	R2	0.4264	0.4637	0.0557
		RMSE	0.2773	0.2627	0.0918
		MAE	0.2725	0.2579	0.0732
	2	R2	0.1180	0.4285	0.6190
		RMSE	0.1334	0.1543	0.1757
		MAE	0.1160	0.1468	0.1695
Shubra el Kheims	1	R2	0.0839	0.0661	0.1016
		RMSE	0.0734	0.1010	0.1143
		MAE	0.0649	0.0946	0.1088
	2	R2	0.3525	0.5561	0.1381
		RMSE	0.0615	0.1291	0.0748
		MAE	0.0550	0.1239	0.0646

Table 11 (Continued)

Tangier	1	R2	0.4428	0.0336	0.4454
		RMSE	0.0902	0.3076	0.1917
		MAE	0.0744	0.2923	0.1785
	2	R2	0.6364	0.1095	0.0277
		RMSE	0.2410	0.3030	0.4320
		MAE	0.2357	0.2733	0.4250
Tripoli	1	R2	0.3158	0.0826	0.3223
		RMSE	0.0820	0.2848	0.1002
		MAE	0.0648	0.2408	0.0870
	2	R2	0.6270	0.1999	0.2032
		RMSE	0.1509	0.2321	0.1569
		MAE	0.1462	0.2125	0.1379
Tshikapa	1	R2	0.0366	0.1328	0.0109
		RMSE	0.2364	0.1787	0.3250
		MAE	0.2290	0.1688	0.3060
	2	R2	0.1011	0.0053	0.0332
		RMSE	0.1529	0.0702	0.1274
		MAE	0.1446	0.0606	0.1128
Tunis	1	R2	0.0142	0.0050	0.0012
		RMSE	0.1552	0.0446	0.1725
		MAE	0.1525	0.0392	0.1709
	2	R2	0.0867	0.0005	0.0151
		RMSE	0.1518	0.1805	0.1007
		MAE	0.1491	0.1789	0.0977
Umuahia	1	R2	0.0093	0.0134	0.0303
		RMSE	0.1612	0.0835	0.1457
		MAE	0.1587	0.0748	0.1416
	2	R2	0.0600	0.0000	0.0001
		RMSE	0.2571	0.1379	0.0638
		MAE	0.2537	0.1251	0.0532

Table 11(Continued)

Uyo	1	R2	0.0272	0.0661	0.0394
		RMSE	0.1590	0.0835	0.1372
		MAE	0.1565	0.0766	0.1328
	2	R2	0.0126	0.0029	0.0080
		RMSE	0.3023	0.2086	0.0452
		MAE	0.2958	0.1891	0.0354
Vereeniging	1	R2	0.6459	0.2405	0.1821
		RMSE	0.1215	0.1597	0.0857
		MAE	0.1109	0.1441	0.0665
	2	R2	0.5586	0.3319	0.3541
		RMSE	0.1389	0.1830	0.1020
		MAE	0.1260	0.1670	0.0858
Warri	1	R2	0.0238	0.0766	0.0530
		RMSE	0.0570	0.1233	0.0688
		MAE	0.0435	0.1163	0.0558
	2	R2	0.0208	0.0275	0.0249
		RMSE	0.3252	0.1821	0.0715
		MAE	0.3227	0.1667	0.0616
West Rand	1	R2	0.5334	0.2136	0.2951
		RMSE	0.1043	0.1945	0.1000
		MAE	0.0960	0.1768	0.0802
	2	R2	0.0436	0.2784	0.3796
		RMSE	0.1413	0.1657	0.1197
		MAE	0.1198	0.1528	0.1029
	1	R2	0.0023	0.0265	0.1196
		RMSE	0.1733	0.2813	0.0536
Yaounde		MAE	0.1702	0.2785	0.0445
	2	R2	0.0069	0.0009	0.0023
		RMSE	0.2223	0.1592	0.0526
		MAE	0.2188	0.1538	0.0425

Comparison of the Calculated Values for All Cities

The calculated results indicated that all the models employed for predicting the Global Horizontal Irradiance have a very good R^2. According to (Veisi et al., 2022), an R^2 value above 0.5 is considered good for models. To compare the results, it was observed that all the R^2 values for scenario 2 are larger than that of scenario 1. For FFNN, scenario 2 result was 0.8521 against 0.8372, CFNN was 0.8489 against 0.5898 and NARX was 0.8029 against 0.6610.

Percentage Error

To understand the effect of these changes and determine the accuracy of the models, the percentage error was calculated.

The formular for percentage error is given as:

$$\delta = \frac{v_A - v_E}{v_E} x\ 100$$

Where v_A is actual value observed

v_E is expected value

For FFNN: $\frac{0.8521-0.8372}{0.8372} x\ 100$ = 1.78%

For CFNN: $\frac{0.8489-0.5898}{0.5898} x\ 100 = 43.93\%$

For NARX: $\frac{0.8029-0.6610}{0.6610} x\ 100 = 21.46\%$

Based on the above errors, it was observed that for the conventional FFNN, the geographical parameters have a very negligible effect on the accuracy of the model. For CFNN and NARX, the geographical parameters have affected the accuracy of the model by a significant.

CHAPTER V

Conclusion and Recommendations

Base on the findings, it can be concluded that:

1. Global horizontal radiation predictions for Africa are significantly impacted by geography. In this note, GHI levels are significantly influenced by the climate, latitude, longitude, and altitude of different geographical areas.
2. Effective machine learning algorithms can forecast her GHI in Africa. These models offer precise predictions of solar irradiance and support effective planning and utilization of solar energy resources by utilizing geographic characteristics and climatic data.
3. Geographic characteristics and machine learning models trained on previous GHI data may recognize these fluctuations and produce accurate forecasts for specific places.
4. The performance of various machine learning methods in forecasting GHI for Africa varies. It's crucial to assess and contrast several models in order to choose the most precise and reliable strategy for a certain area.

Recommendations

1. By adding other parameters including atmospheric conditions, cloud cover, and aerosol index, research should continue to focus on improving the precision and accuracy of DNI predictions. This may be accomplished by collaborating with organizations that deal with meteorology and remote sensing experts.
2. To improve the performance of machine learning models, the DNI dataset must be updated and increased on a regular basis. In order to collect and distribute DNI data across Africa, cooperation is crucial.
3. Frameworks for designing and deploying solar energy systems may use newly created machine learning models. Governments, energy organizations, and renewable energy companies could utilize these models to identify high-potential locations for solar energy projects, boost energy output, and create intelligent policy decisions.

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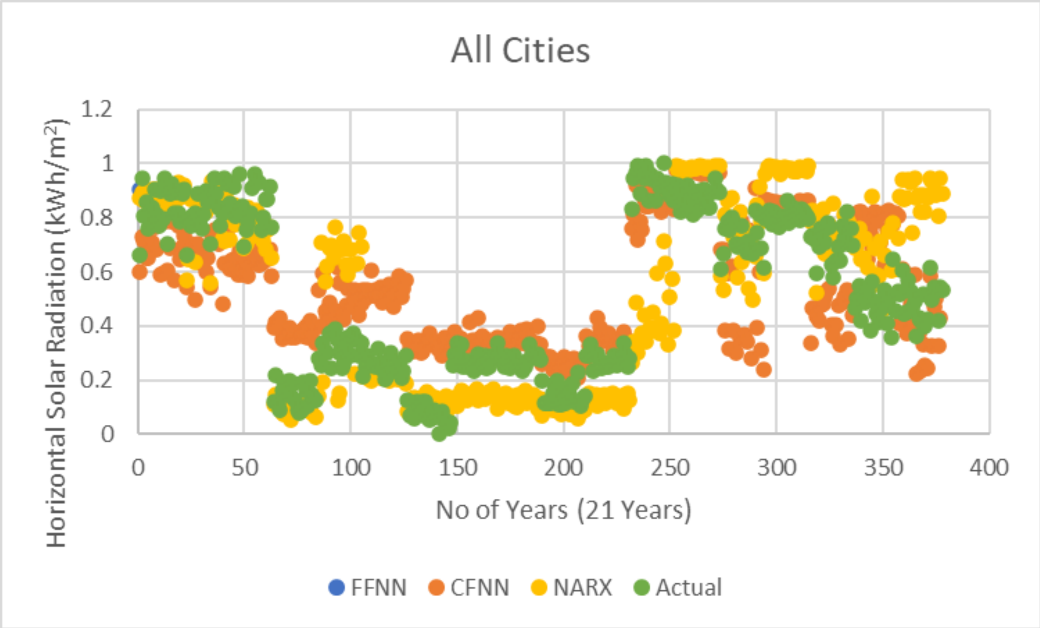
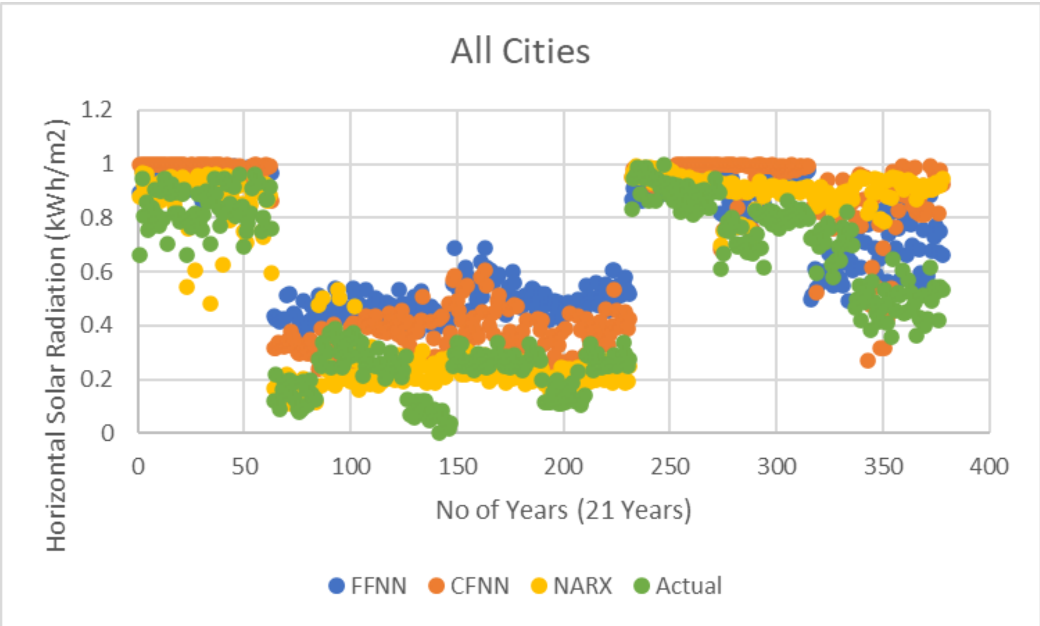
APPENDIX I

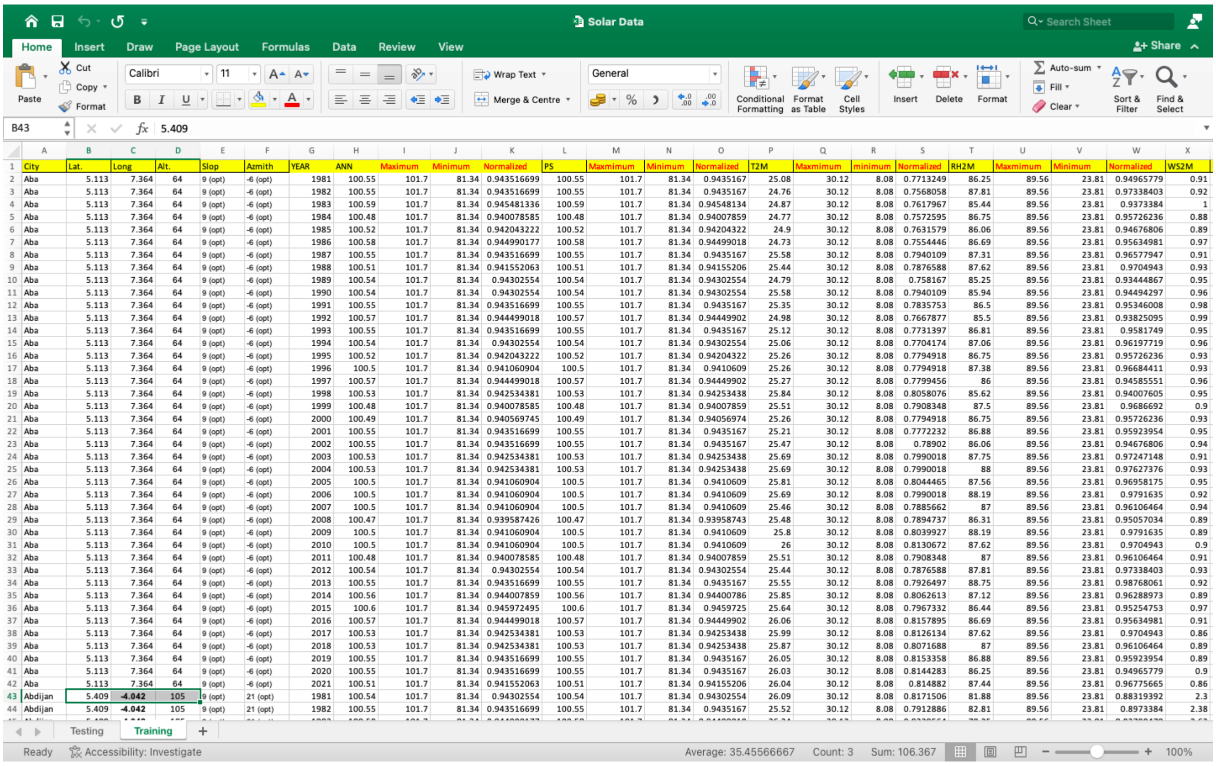
Time Series Plot for All Cities with Geographical Parameters



Time Series Plot for All Cities with nongeographical parameters



Excel sheet of all cities normalised



	City	Lat.	Long	Alt.	Slop	Azmith	YEAR	ANN	Maximum	Minimum	Normalized	PS	Maxmimum	Minimum	Normalized	T2M	Maxmimum	minimum	Normalized	RH2M	Maxmimum	Minimum	Normalized	WS2M
2	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1981	100.55	101.7	81.34	0.943516699	100.55	101.7	81.34	0.9435167	25.08	30.12	8.08	0.7713249	86.25	89.56	23.81	0.94965779	0.91
3	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1982	100.55	101.7	81.34	0.943516699	100.55	101.7	81.34	0.9435167	24.76	30.12	8.08	0.7568058	87.81	89.56	23.81	0.97338403	0.92
4	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1983	100.59	101.7	81.34	0.945481336	100.59	101.7	81.34	0.94548134	24.87	30.12	8.08	0.7617967	85.44	89.56	23.81	0.9373384	1
5	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1984	100.48	101.7	81.34	0.940078585	100.48	101.7	81.34	0.94007859	24.77	30.12	8.08	0.7572595	86.75	89.56	23.81	0.95726236	0.88
6	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1985	100.52	101.7	81.34	0.942043222	100.52	101.7	81.34	0.94204322	24.9	30.12	8.08	0.7631579	86.06	89.56	23.81	0.94676806	0.89
7	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1986	100.58	101.7	81.34	0.944990177	100.58	101.7	81.34	0.94499018	24.73	30.12	8.08	0.7554446	86.69	89.56	23.81	0.95634981	0.97
8	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1987	100.55	101.7	81.34	0.943516699	100.55	101.7	81.34	0.9435167	25.58	30.12	8.08	0.7940109	87.31	89.56	23.81	0.96577947	0.91
9	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1988	100.51	101.7	81.34	0.941552063	100.51	101.7	81.34	0.94155206	25.44	30.12	8.08	0.7876588	87.62	89.56	23.81	0.9704943	0.93
10	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1989	100.54	101.7	81.34	0.94302554	100.54	101.7	81.34	0.94302554	24.79	30.12	8.08	0.758167	85.25	89.56	23.81	0.93444867	0.95
11	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1990	100.54	101.7	81.34	0.94302554	100.54	101.7	81.34	0.94302554	25.58	30.12	8.08	0.7940109	85.94	89.56	23.81	0.94494297	0.96
12	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1991	100.55	101.7	81.34	0.943516699	100.55	101.7	81.34	0.9435167	25.35	30.12	8.08	0.7835753	86.5	89.56	23.81	0.95346008	0.98
13	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1992	100.57	101.7	81.34	0.944499018	100.57	101.7	81.34	0.94449902	24.98	30.12	8.08	0.7667877	85.5	89.56	23.81	0.93825095	0.99
14	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1993	100.55	101.7	81.34	0.943516699	100.55	101.7	81.34	0.9435167	25.12	30.12	8.08	0.7731397	86.81	89.56	23.81	0.9581749	0.95
15	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1994	100.54	101.7	81.34	0.94302554	100.54	101.7	81.34	0.94302554	25.06	30.12	8.08	0.7704174	87.06	89.56	23.81	0.96197719	0.96
16	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1995	100.52	101.7	81.34	0.942043222	100.52	101.7	81.34	0.94204322	25.26	30.12	8.08	0.7794918	86.75	89.56	23.81	0.95726236	0.93
17	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1996	100.5	101.7	81.34	0.941060904	100.5	101.7	81.34	0.9410609	25.26	30.12	8.08	0.7794918	87.38	89.56	23.81	0.96684411	0.93
18	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1997	100.57	101.7	81.34	0.944499018	100.57	101.7	81.34	0.94449902	25.27	30.12	8.08	0.7799456	86	89.56	23.81	0.94585551	0.96
19	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1998	100.53	101.7	81.34	0.942534381	100.53	101.7	81.34	0.94253438	25.84	30.12	8.08	0.8058076	85.62	89.56	23.81	0.94007605	0.95
20	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	1999	100.48	101.7	81.34	0.940078585	100.48	101.7	81.34	0.94007859	25.51	30.12	8.08	0.7908348	87.5	89.56	23.81	0.9686692	0.9
21	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2000	100.49	101.7	81.34	0.940569745	100.49	101.7	81.34	0.94056974	25.26	30.12	8.08	0.7794918	86.75	89.56	23.81	0.95726236	0.93
22	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2001	100.55	101.7	81.34	0.943516699	100.55	101.7	81.34	0.9435167	25.21	30.12	8.08	0.7772232	86.88	89.56	23.81	0.95923954	0.95
23	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2002	100.55	101.7	81.34	0.943516699	100.55	101.7	81.34	0.9435167	25.47	30.12	8.08	0.78902	86.06	89.56	23.81	0.94676806	0.94
24	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2003	100.53	101.7	81.34	0.942534381	100.53	101.7	81.34	0.94253438	25.69	30.12	8.08	0.7990018	87.75	89.56	23.81	0.97247148	0.91
25	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2004	100.53	101.7	81.34	0.942534381	100.53	101.7	81.34	0.94253438	25.69	30.12	8.08	0.7990018	88	89.56	23.81	0.97627376	0.93
26	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2005	100.5	101.7	81.34	0.941060904	100.5	101.7	81.34	0.9410609	25.81	30.12	8.08	0.8044465	87.56	89.56	23.81	0.96958175	0.95
27	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2006	100.5	101.7	81.34	0.941060904	100.5	101.7	81.34	0.9410609	25.69	30.12	8.08	0.7990018	88.19	89.56	23.81	0.9791635	0.92
28	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2007	100.5	101.7	81.34	0.941060904	100.5	101.7	81.34	0.9410609	25.46	30.12	8.08	0.7885662	87	89.56	23.81	0.96106464	0.94
29	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2008	100.47	101.7	81.34	0.939587426	100.47	101.7	81.34	0.93958743	25.48	30.12	8.08	0.7894737	86.31	89.56	23.81	0.95057034	0.89
30	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2009	100.5	101.7	81.34	0.941060904	100.5	101.7	81.34	0.9410609	25.8	30.12	8.08	0.8039927	88.19	89.56	23.81	0.9791635	0.89
31	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2010	100.5	101.7	81.34	0.941060904	100.5	101.7	81.34	0.9410609	26	30.12	8.08	0.8130672	87.62	89.56	23.81	0.9704943	0.9
32	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2011	100.48	101.7	81.34	0.940078585	100.48	101.7	81.34	0.94007859	25.51	30.12	8.08	0.7908348	87	89.56	23.81	0.96106464	0.91
33	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2012	100.54	101.7	81.34	0.94302554	100.54	101.7	81.34	0.94302554	25.44	30.12	8.08	0.7876588	87.81	89.56	23.81	0.97338403	0.93
34	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2013	100.55	101.7	81.34	0.943516699	100.55	101.7	81.34	0.9435167	25.55	30.12	8.08	0.7926497	88.75	89.56	23.81	0.98768061	0.92
35	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2014	100.56	101.7	81.34	0.944007859	100.56	101.7	81.34	0.94400786	25.85	30.12	8.08	0.8062613	87.12	89.56	23.81	0.96288973	0.89
36	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2015	100.6	101.7	81.34	0.945972495	100.6	101.7	81.34	0.9459725	25.64	30.12	8.08	0.7967332	86.44	89.56	23.81	0.95254753	0.97
37	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2016	100.57	101.7	81.34	0.944499018	100.57	101.7	81.34	0.94449902	26.06	30.12	8.08	0.8157895	86.69	89.56	23.81	0.95634981	0.91
38	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2017	100.53	101.7	81.34	0.942534381	100.53	101.7	81.34	0.94253438	25.99	30.12	8.08	0.8126134	87.62	89.56	23.81	0.9704943	0.86
39	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2018	100.53	101.7	81.34	0.942534381	100.53	101.7	81.34	0.94253438	25.87	30.12	8.08	0.8071688	87	89.56	23.81	0.96106464	0.89
40	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2019	100.55	101.7	81.34	0.943516699	100.55	101.7	81.34	0.9435167	26.05	30.12	8.08	0.8153358	86.88	89.56	23.81	0.95923954	0.89
41	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2020	100.55	101.7	81.34	0.943516699	100.55	101.7	81.34	0.9435167	26.03	30.12	8.08	0.8144283	86.25	89.56	23.81	0.94965779	0.9
42	Aba	5.113	7.364	64	9 (opt)	-6 (opt)	2021	100.51	101.7	81.34	0.941552063	100.51	101.7	81.34	0.94155206	26.04	30.12	8.08	0.814882	87.44	89.56	23.81	0.96775665	0.86
43	Abdijan	5.409	-4.042	105	9 (opt)	21 (opt)	1981	100.54	101.7	81.34	0.94302554	100.54	101.7	81.34	0.94302554	26.09	30.12	8.08	0.8171506	81.88	89.56	23.81	0.88319392	2.3
44	Abdijan	5.409	-4.042	105	9 (opt)	21 (opt)	1982	100.55	101.7	81.34	0.943516699	100.55	101.7	81.34	0.9435167	25.52	30.12	8.08	0.7912886	82.81	89.56	23.81	0.8973384	2.38

APPENDIX II

Thesis

ORIGINALITY REPORT

14%	7%	9%	4%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	profound-answers.com Internet Source	<1%
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5	Zhang, H.L., J. Baeyens, J. Degrève, and G. Cacères. "Concentrated solar power plants: Review and design methodology", Renewable and Sustainable Energy Reviews, 2013. Publication	<1%
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Assoc. Prof. Dr. Youssef Kassem