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# Assessment of sustainable electricity generation scenarios in Burundi using multi-criteria approaches.

Igiraneza, Nice Leslie
*School of Computing and Engineering Sciences*
*Strathmore University*

# ASSESSMENT OF SUSTAINABLE ELECTRICITY GENERATION SCENARIOS IN BURUNDI USING MULTI-CRITERIA APPROACHES

**NICE LESLIE IGIRANEZA**

**ADMN. NO: 152495**

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**OF**

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**2025**

## DECLARATION

I so certify that my work has never before been accepted as a degree submission by this university or any other university. Except for the references that are appropriately listed in the proposal, the dissertation, to the best of my knowledge and belief, does not contain any previously published or authored works by other authors. No part of this thesis may be reproduced without the author's and Strathmore University's consent.

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**Approval**

I have given my permission in my capacity as the academic advisor for Nice Leslie Igiraneza's submission of this thesis proposal to the School of Computing and Engineering Sciences.

Signed:

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Date: 1st April 2025

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**Dr.Eng. Fenwicks S. Musonye., P.E., PhD**

**Strathmore University, Kenya**

# DEDICATION

To my parents, who taught me that nothing is impossible if I put my mind to it. They have also been my support system for many years. I am very grateful to my lecturers, who walked this journey with us. I praise the Almighty God for his strength, grace, and never-ending love.

## ACKNOWLEDGEMENT

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Above all, I want to express my sincere gratitude to my family and friends for their constant encouragement, understanding, and support. Their confidence in me has continuously motivated me and kept me engaged and focused.

This research would not have been possible without God’s grace, strength, wisdom, and guidance, for which I am eternally grateful.

## ABBREVIATIONS

| | |
|---|---|
| kW | Kilowatt |
| kWh | Kilo-watt Hour |
| MW | Megawatt |
| RE | Renewable Energy |
| BAU | Business As Usual |
| IRR | Internal Rate of Return |
| NACOSTI | National Commission for Science, Technology, and Innovation |
| LCOE | Levelized cost of energy |
| NREL | National Renewable Energy Laboratory |
| PV | Photovoltaic |
| CSP | Concentrated Solar Power |
| UNFCCC | United Nations Framework Convention for Climate Change |
| NDC | Nationally Determined Contributions |
| SDG | Sustainable Development Goals |
| LEAP | Low Emissions Analysis Platform |
| TIMES | The Integrated MARKAL_EFOM System |
| GDP | Gross Domestic Product |
| NOTC | Nominal Operating Cell Temperature |
| STC | Standard Test Conditions |
| AC | Alternating Current |
| DC | Direct Current |
| DoD | Depth Of Discharge |
| PSH | Pumped storage hydropower |
| AI | Artificial Intelligence |
| ML | Machine Learning |
| ARIMA | Autoregressive Integrated Moving Average |
| AR | Autoregressive |

| | |
|---|---|
| MA | Moving Average |
| ANN | Artificial Neural Network |
| AFINN | Fuzzy Inference Neural Network |
| MTP | Medium-Term Plan |
| LTP | Long-Term Plan |
| LPG | Liquified Petroleum Gas |
| REGIDESO | Water and Electricity Production and Distribution Authority |
| MINHEM | Ministry of Hydraulics, Energy and Mines |
| WASP | Wien automatic System Planning |

## ABSTRACT


With an 11% electrification rate, Burundi is one of the countries in the sub-Saharan region still facing significant energy access challenges in the region. This has considerably impacted the economic development, energy security and technical advancement of the country. The country primarily relies on hydroelectric power, with 49MW installed out of a potential 1700MW, as well as diesel thermal plants, solar, biomass, peat, firewood, coal, bagasse, although on a smaller scale. Due to a poor energy mix and inadequate maintenance of existing hydro infrastructure, technical issues, like insufficient capacity, supply disruptions lead to low-quality electrical supply. Moreover, the increasing reliance on traditional biomass has led to deforestation, and environmental degradation.

There have been nevertheless attempted initiatives to close the energy supply and demand imbalance, while promoting renewable energy integration. Burundi is boosting energy generation through public and private initiatives, including rehabilitating existing hydropower infrastructure, developing rural electrification with mini-hydro, solar, and wind power, extending electric networks and building regional plants with neighbors. Feasibility studies for solar and wind power investments are also in progress. Despite this, there is no data and structured modeling tool available to support evidence-based decisions about these investments.

This study aimed to assess the pathways to electricity generation by developing and testing an energy planning tool, that integrated available resources and the future energy demand in Burundi, to close the existing gap between supply and demand. It will serve as a resource for the relevant stakeholders as they tackle the issues of energy access, affordability, security, decarbonization and decentralization, and support potential investors in their decision making.

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# CHAPTER ONE INTRODUCTION

## 1.1 Background of Study

Burundi is one of the countries in sub-Saharan Africa still facing major energy access challenges in the region. With only roughly 11% of the country's 11 million residents enjoying access to electricity, Burundi is among the least electrified countries in the world (Burundi - Lighting Global, 2022). The vast majority of people with access to electricity live in cities, whereas most rural households, which constitute 86% of the population as of 2022, and some urban regions rely on conventional biomass. Seventy percent of these biomass sources come from firewood, with the remaining 18% supplied by agricultural waste, 6% coming from coal, and 1% from bagasse (Macumi & Tacer, 2020). The excessive use of fuel wood as a primary energy source has a severe environmental impact and highlights the need for quick, sustainable energy solutions.

Burundi relies on hydroelectric power, which has the biggest energy resource potential, with 49MW installed out of a total of 1700MW. On a smaller scale, the country also uses diesel-powered thermal plants, solar energy, biomass, firewood, peat, bagasse, coal and wind power (Macumi & Tacer, 2020). Nevertheless, some of the hydro power plants are on the brink of meltdowns due to inadequate maintenance. The energy sector is grappling with low-quality electrical supply, attributed to technical, administrative, as well as institutional issues. Some of the technical causes are: inadequate installed capacity, an ageing and inefficient transmission and distribution network, and inadequate plant maintenance. The administrative and institutional variables include governance frameworks, subsidy redistribution schemes, and political influence over public energy supply (Nsabimana, 2020). This has an impact on the chances for expanding the nation's energy resources and limits the scope for effective policymaking and the design and operation of institutions that produce, sell, and use energy.

There are rising initiatives, both from the public and private sector, to augment energy generation in the country. The Burundi government intends to rehabilitate existing non-functioning power plants, renovate existing hydroelectric plants, expand both urban and rural electric networks, build regional power plants in collaboration with neighboring countries, and develop rural electrification through the construction of mini-hydro plants, solar PV, and wind power. Currently, there are also feasibility studies ongoing in various areas of the country for hydroelectric and solar photovoltaic power exploitation.

## 1.2 Problem Statement

The prevailing energy landscape in the country is marked by an imbalance between power supply and demand. This is particularly evident in insufficient energy access, especially in rural regions, which slows down economic growth. It is predominantly reliant on hydro power and traditional biomass sources. The output of the former is reliant on seasonal variations, while the latter leads to deforestation, and environmental degradation. Nonetheless, attempts have been launched to address the energy supply and demand mismatch, including the restoration of existing hydropower infrastructure, the development of new hydroelectric sites, and solar mini-grid projects.

Despite the above-mentioned initiatives, energy access is still low. There have been suggestions to fully exploit the existing energy resources and tap into other technologies. For example, Burundi has a hydroelectric potential, estimated at 1700MW that remains untapped. Similarly, solar energy represents a significant opportunity, with an estimated potential of 2000kWh/m2/year (African Development Bank Group, 2020). Further, a recent study found the Bujumbura region to have a great potential in wind energy harvesting (Desai et al., 2022). This notwithstanding, there is no available data that can support evidence-based decision making on investments in renewable energy in Burundi. There is a need to develop planning tools that incorporate all energy market variables, which include energy efficiency and all the available resources. This work aimed to develop an Energy Resource Planning tool for Burundi. It will serve as a resource for the relevant stakeholders as they tackle issues related to energy access, affordability, energy security, decarbonization and decentralization, as well as potential investors in their decision making.

## 1.3 Research Objectives

### 1.3.1 General Objectives

This research aimed to assess sustainable electricity generation scenarios in Burundi using multi-criteria approaches.

### 1.3.2 Specific objectives

1. Conduct an energy resource assessment for Burundi.
2. Forecast energy demand for Burundi.
3. Model energy investments scenarios considering the demand and supply side characteristics for Burundi.

### 1.3.3 Research Questions

The research will seek to answer the following research inquiries:

1. What are the available energy resources in Burundi, and how can they be assessed in terms of their sustainability, availability, capital expenditure required, operational costs and potential to contribute to the national energy mix?
2. What is the projected energy demand in Burundi over the next 15 years, considering variables like population increase, urbanization, economic development, and technological improvements?
3. What cost-effective renewable energy investment scenarios could be pursued to optimize resource use?

## 1.4 Justification

Developing an Energy Resource Planning tool for Burundi is key due to the current energy insecurity, environmental degradation, and socio-economic challenges. The country's reliance on intermittent hydro power plants and traditional biomass worsens energy poverty, while inefficient energy practices contribute to environmental harm. Access to reliable, affordable, and sustainable energy is essential for promoting economic growth, achieving social development goals (SDGs), and mitigating climate change risks.

As part of the efforts to boost the attainment of the United Nation's Sustainable Development Goal 7, to "ensure access to affordable, reliable and modern energy for all by 2030"(Team & Roser, 2023), Burundi has set itself the target of increasing the national rate of access to electricity to 30% by 2030 (Ministère de l'Energie et des Mines, Burundi, 2013). These research findings will serve as a roadmap to utility planners and the government in their attempts to maintain an optimal energy mix, while promoting energy efficiency to achieve environmental and economic goals. It can also be used by the Ministry of the Environment in prioritizing programs and policy options.

Burundi, as a participant in United Nations Framework Convention for Climate Change (UNFCCC), submitted its NDCs (Nationally Determined Contributions) in 2021. According to NDC, (2021), the government outlined its goal of the battle against climate change as follows: "A state that promotes development that is resilient to the harmful effects of climate change.". The updated submitted NDC has an unconditional emissions reduction target of 3.04% and a conditional target of 12.61% by 2030, as part of their commitment to lower greenhouse gas emissions. Additionally, the carbon market presents itself as a source of revenue through carbon financing. This study will assist policy makers and government officials in coming up with carbon friendly guidelines and protocols while maintaining a stable grid.

## 1.5 Scope of Study

This research focused on designing an energy planning tool for sustainable power generation in Burundi and aimed to develop a model that will guide potential energy investors, private and public on the factors to consider as they assess the performance rate and economic viability of power generation projects. This study assumed that energy transportation will be done via the forthcoming transmission lines and considered technical losses due to transmission as negligible.

## CHAPTER TWO LITERATURE REVIEW

### 2.1 Introduction

This literature review chapter delves into a comprehensive exploration of both theoretical frameworks and empirical studies relevant to this research. In the first section, a theoretical review explores the fundamental concepts of the main intended electricity sources for exploitation in Burundi, namely solar, hydro, and wind. This section also introduces the carious existing energy demand forecasting models. The second section presents an empirical review that highlights a few studies that have been done within the area of research. The aim is to identify the study gaps, limits, and areas for further exploration. The last part of this chapter includes a summary of these study gaps, providing grounds for investigating the research problem at hand.

### 2.2 Theoretical Review

#### 2.2.1 Solar PV Technology Fundamentals

The environmental advantages and falling costs of solar energy have made it a popular renewable and sustainable energy source that is reducing dependency on fossil fuels. It is, however, an intermittent energy source and is usually integrated with other power sources. Despite the recent considerable price reductions, the initial investment for installation is still relatively high. On the other hand, compared to conventional energy sources, solar modules present significantly lower operation costs and demand less maintenance after installation. Rooftop, ground, or floating installations are possible for solar PV panels. Large-scale solar installations are mostly ground mounted and require significant land area, which may not be feasible in densely populated or metropolitan locations and could result in disputes over land use. In some cases, solar projects may intrude on agricultural land, natural habitats, or territories belonging to indigenous communities, raising concerns about environmental justice and the rights of affected communities.

The process of transforming light (photons) into electricity (voltage) is known as the solar photovoltaic effect, and it is how solar energy is captured. A voltage or electric current is produced in the cell upon exposure to sunlight. Fig. 1 is a representation of several solar PV cells, which, when combined form a PV panel.

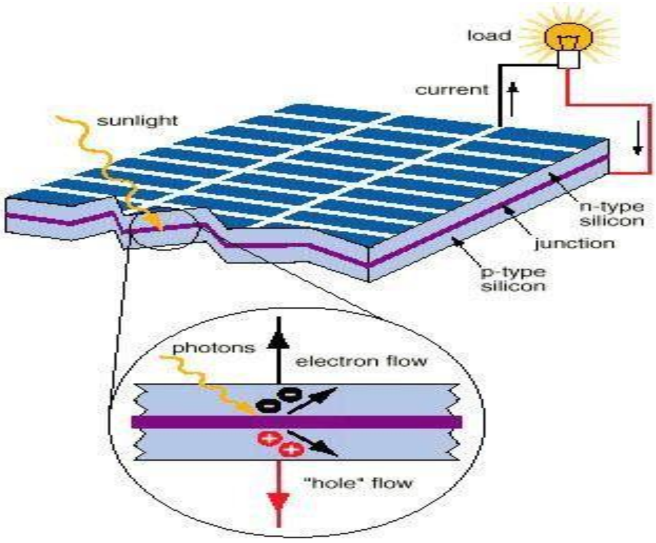


Figure 2.1 The photovoltaic effect in a solar cell (A. Khalil, 2015)

Solar cells are up of two different types of semiconductors, p-type and n-type, connected to form a p-n junction. When the two are joined, this junction produces an electric field that makes it easier for electrons to move freely, traveling toward the positive side (p) and holes toward the negative side (n). As a result, particles with a positive charge migrate in the opposite direction from the ones with a negative charge due to this field. The cell generates an electric current as a result of this operation. The size of individual cells and the intensity of the light affect this current (A. Khalil, 2015). Photovoltaic cells are available in many different semiconductor materials. The most prominent materials are copper-indium selenide, amorphous silicon, polycrystalline silicon, and monocrystalline silicon. Depending on the voltage or current required, the individual solar cells are usually combined in series and in parallel.

To increase the power output of a PV array, solar panels are also interconnected in series or parallel. When multiple panels are connected in series, they produce a PV module string, with the positive and negative terminals of each other interconnected, increasing the voltage of the PV array. The number of panels on the string is determined by the required voltage level. A parallel connection, on the other hand, increases the current by connecting the negative and positive terminals of one module to the respective modules' negative and positive terminals. The necessary current level for the system is then obtained by connecting numerous PV strings in parallel (Yusof & Baharuddin, 2020). The output of a solar PV system also depends on a few other factors, such as solar irradiance, temperature, panels mounting tilt and orientation, shading, system design and components, among others.

#### 2.2.1.1 Factors Affecting the Output of Solar PV Systems.

Solar irradiance is referred to as the power of solar radiation collected from the sun, per unit area at a specific location on Earth's surface. It is a gauge of how much sunlight is reaching the surface of the Earth at any one time. Solar irradiance is measured perpendicular to the direction of sunlight and is commonly given in watts per square meter ($W/m^2$). Seasons, air quality, and sun angle are some of the variables that can cause variations in solar irradiance values during the day. A solar PV panel's current rises proportionately to increased irradiance (Majid et al., 2013)

Solar panels also operate less efficiently at higher temperatures. While sunlight is essential for solar PV production, excessively high temperatures can reduce the efficiency of the panels, affecting electricity output. Similarly, an increase in temperature at the cell level affects the PV module output. The industry standard test settings known as Standard Test conditions (STC) are used to evaluate all solar PV panels in order to ascertain their rated power and other attributes. Nominal Operating Cell Temperature (NOCT) is a standard measurement used in the solar energy industry to rate the operating temperature of photovoltaic (PV) modules under specific settings. These are a standard sunlight intensity of 800 $W/m^2$, 20°C air temperature and 1m/s wind conditions for NOTC and cell 25°C temperature, 1000 $W/m^2$ irradiance and air mass value of 1.5 for STC. Tsai & Tsai (2012) further differentiates the NOTC and STC.

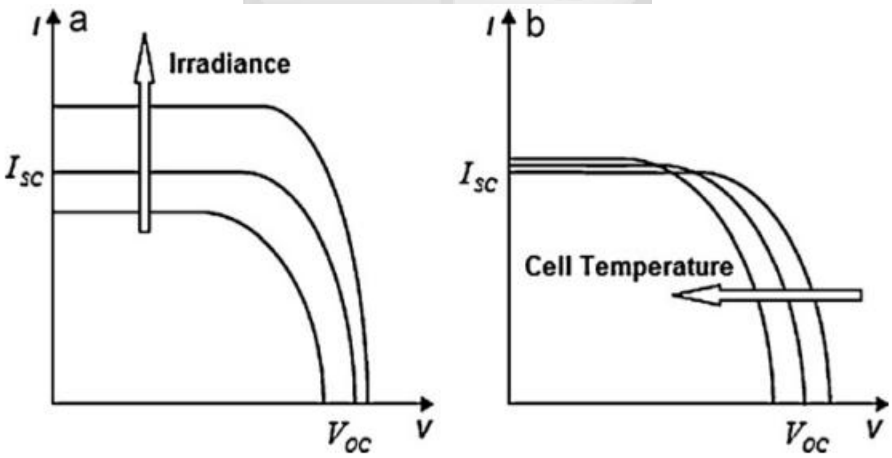


Figure 2.2 Temperature and irradiance effect on cell properties (A. Khalil, 2015)

Figure 2(a) illustrates how a rise in solar radiation causes the VOC (open circuit voltage) to rise and the ISC (short circuit current) to rise linearly. The effects of temperature on cell characteristics are shown in Figure 2(b). Reduced efficiency results from the open circuit voltage decreasing linearly with increasing cell temperature. A slight increase in short circuit current is observed when the cell temperature rises (A. Khalil, 2015).

Other factors that affect a solar PV array's production include azimuth, tilt, and shading. Reduced sunlight exposure from buildings, trees, and other barriers can lower the electricity production of solar modules. When connecting a solar module, two main angles are considered to have an impact on PV module performance. These are the module's tilt angle and orientation angle, or azimuth. Generally, solar panels should be positioned to face the true south for sites located in the northern hemisphere and true north for the ones in the southern hemisphere. The mounting location's angle with respect to the equator should serve as guidance for the panels' tilt (Dewi et al., 2019).

#### 2.2.1.2 Components of a Solar PV System

In addition to solar panels, the second component of a typical solar system is an inverter. Inverters in PV applications fall under two categories:

- Grid-tie inverters in grid tied systems.
- Hybrid/ Stand-alone inverters in off grid systems.

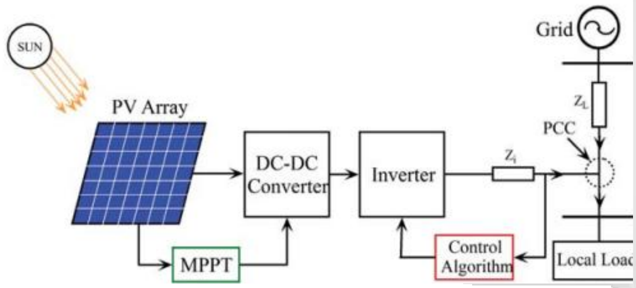


Figure 2.3 Grid Tie PV System(Karchi & Kulkarni, 2022)

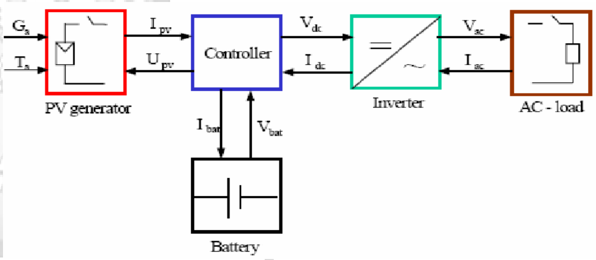


Figure 2.4 Stand-alone PV System (Fara & Craciunescu, 2017)

Figure 3 is a schematic for a simple grid-tied PV installation. The DC electricity from the solar panels is fed into an inverter, which converts it into alternating current (AC) electricity. For such systems, the grid-tied inverter is connected to the utility grid, which allows the system to inject surplus electricity generated by the solar PV array back into the grid, where that option is available. These systems do not typically incorporate energy storage, relying instead on the grid to provide power when sunlight is insufficient.

In contrast, standalone PV systems, also known as off-grid systems, hybrid/ stand-alone inverters operate independently of the grid and allow integration with battery storage to store surplus energy produced during sunny periods for use during periods of low or no solar production. A typical stand-alone system should also have an AC engine generator to supply power to the AC loads and allow the batteries to charge when the PV system is producing less than the required demand (Mayfield, 2010). Standalone systems are commonly used in remote areas where grid connection is impractical or expensive, providing a reliable and sustainable source of electricity.

A battery bank makes up the third important part. Batteries keep energy in reserve to provide energy throughout the night or on autonomous days (also known as no-sun days or dark days) when the sun does not provide enough radiation. Battery autonomy, which refers to how long a battery can operate without being recharged by solar panels or another source matters when sizing the battery capacity required in a solar system. It depends on factors such as battery capacity, energy consumption, solar generation, depth of discharge (DoD), efficiency losses, and temperature. These batteries, which can be lead-acid, lithium-ion, Nickel-Cadmium or Ni-Metal hydride batteries are made to be progressively discharged and recharged hundreds of times up to 80% of their capacity. (Al-Shamani, 2015). Lifetime depends on factors such as the number of charging and discharging cycles, temperature, and other relevant parameters.

### 2.2.2 Hydro Technology Fundamentals

According to Singh & Singal (2017) research, impulse momentum is the basic idea underlying the production of hydropower. Through a turbine's rotation, water potential is transformed into mechanical energy. A generator is then used to further convert this mechanical energy into electrical energy. Because they can produce continuously as long as there is a consistent supply of water and can react quickly to changes in the demand for electricity, hydroelectric power plants provide operational flexibility. Because of this, hydroelectric plants are well-suited to deliver base load power since they can continuously produce electricity to fulfill the grid's minimal need (Lejeune, 2012).

Hydroelectric power generation is regarded as cost-effective in terms of cost per kilowatt-hour (kWh) in comparison to other RE sources including geothermal, biomass, solar, and wind (I. U. Khalil et al., 2020). On the flip side, hydro projects, even those considered nominally successful, frequently come with adverse environmental impacts. These can manifest as loss of biodiversity, interference with fish migration patterns, significant land inundation, displacement of human communities, and various other consequences (Tahseen & Karney, 2017).

Fig 2.5 presents the basic components of a hydro powerplant.

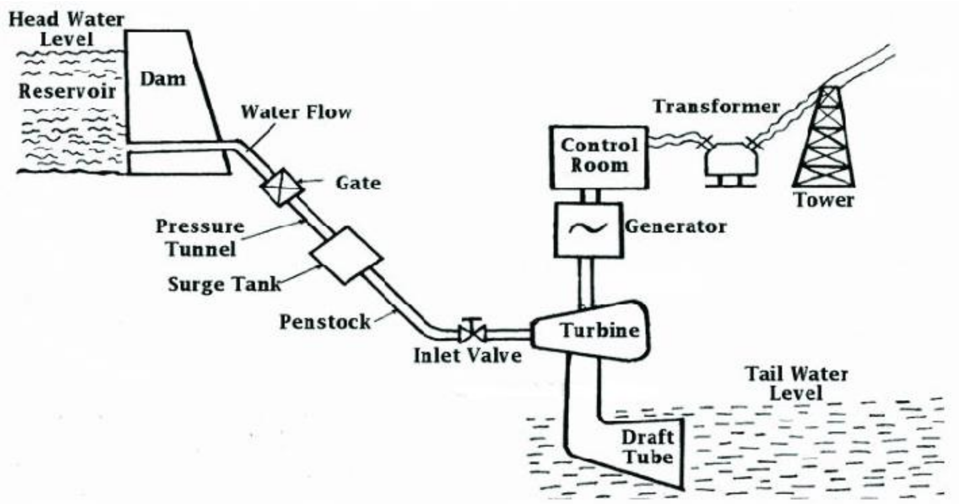


Figure 2.5 A hydroelectric power plant and its basic components (I. U. Khalil et al., 2020)

The process of producing hydroelectric electricity entails gathering or storing water at one location and directing it downward to a lower level via enormous pipes or tunnels known as penstocks. The head is the vertical distance that separates these two altitudes. When the water reaches the bottom of its course through the pipes, it causes turbines to rotate. Generators are then powered by the turbines, converting the mechanical energy from the turbines into electrical energy. The alternating voltage produced by the generators is stepped up by transformers for long-distance transmission. The powerhouse is the building that houses the generators and turbines and provides access for the pipes or penstocks (Singh & Singal, 2017).

There are three categories of hydropower plants: impoundment, diversion or "run of the river," and pumped storage. The latter is the most prevalent kind of hydroelectric power plant; it is usually a large hydroelectric system that stores river water in a reservoir using a dam. When the reservoir's water is discharged, it passes through a rotating turbine, starting a generator that generates energy (Tkáč, 2018).

A diversion or run-of-the-river facility for hydropower plants relies on a river’s natural flow rather than a big reservoir. These hydroelectric facilities direct a portion of the water flow either through a penstock, or through a canal. Diversion facilities have the option to utilize a dam for the purpose of redirecting water, although it is not mandatory. While they may possess a limited capacity for storage, known as pondage, their ability to store water is far lower compared to an impoundment facility. Typically, storage only affects short-term changes in water flow and does not significantly impact the flow of rivers downstream (Tsuanyo et al., 2023).

Pumped storage hydropower is a large energy storage mechanism. Such a plant can store electricity generated from non-renewable energy sources, like solar, wind, and nuclear power, for later use. Pumped hydro storage facilities store energy by using a system of two connected reservoirs, one higher than the other in altitude. Water is pumped to the upper reservoir when there is an excess of energy available. On the other hand, in periods of excess demand, water is released from the higher to the lower reservoir via reversible Francis turbines, producing energy along the way. The process is then repeated, resulting in a cycle efficiency of about 80% overall. Pumped-storage facilities are highly suitable for effectively handling surges in energy demand and ensuring backup power generation (Lejeune, 2012).

#### 2.2.2.1 **Hydropower Systems Design**

A hydroelectric project necessitates the availability of a river. The energy that can be extracted from the river is subject to two factors: the water's flow rate of and the vertical distance between the riverbed and the water surface, commonly referred to as the head of water. According to Breeze, (2005) a river with a high flow rate would generate more electricity compared to a river with a low flow rate, even if they are of the same size.

After identifying a suitable location for a hydropower project, there are typically two methods for harnessing its potential. One approach is to construct a dam and establish a reservoir behind it, which will be used to extract water for powering hydraulic turbines in the powerhouse. The other approach, known as a run-of-river plan, operates with no need for a reservoir, but it typically includes a barrage of some kind. Instead, it directly extracts water from the river and transports it to the powerhouse, where the turbines are erected (Breeze, 2005).

The main components required to convert the potential energy of the river into electricity are turbines, which transform kinetic and potential energy into mechanical energy, and a generator, which transforms mechanical energy into electrical energy. The monthly hydropower output can be determined using an equation that takes into account the water volume released, gross head, and efficiency of the turbine generator, which typically ranges between 0.7 and 0.85 (Jeyalitha et al., 2008).

### 2.2.3 Wind Energy Fundamentals

Kalmikov (2017) defines wind as atmospheric air in motion. It is caused by temperature fluctuations in different places. The temperature properties of land and sea differ due to their respective compositions. Generally, there is more wind in the water than on land. Wind turbines convert wind power into electricity.

A wind turbine converts the wind's kinetic energy into rotational motion in the shaft, generating electricity. The amount of power that can be harnessed from the wind is determined by both its velocity and the area covered by the turbine's moving blades. Hence, a higher wind speed or larger rotor blades result in greater wind energy extraction (Stephanie Cole, 2022). Figure 6 illustrates the primary components of a wind turbine, including the tower, the rotor blades, high speed shaft, drive shaft, generator, and gearbox.

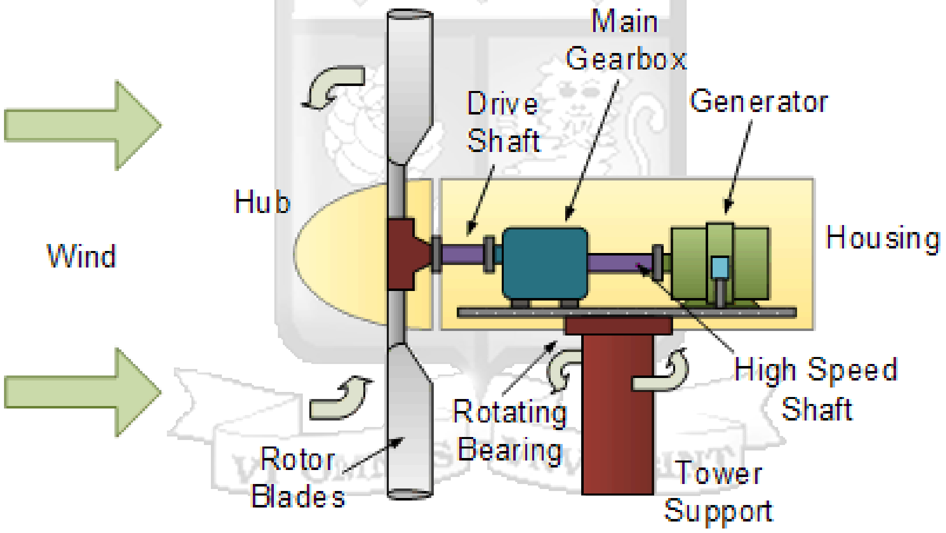


Figure 2.6: Typical wind turbine generator design (Stephanie Cole, 2022)

The wind speed fluctuates hourly, although the overall average remains constant throughout the day. The average wind velocity is utilized for the analysis of performance and power output. Wind power is usually exploited in conjunction with another power source to provide a consistent production (Zafar, 2018). The efficiency and safety of the wind turbine are determined by the wind speed. There are three different types of wind speeds used to evaluate performance and reliability of a wind turbine. These are: the cut-in speed, rated output wind speed and cut-out speed.

The cut-in speed refers to the threshold velocity at which a wind turbine’s blades initiate rotation and subsequently produce electrical energy. Wind turbine blades are unable to function at extremely low wind speeds because of their substantial weight and insufficient power supply. Nevertheless, as the velocity increases, the turbine produces enough torque to revolve and generate electricity. The normal cut-in speed ranges between 3 and 4 m/s. (Stephanie Cole, 2021)

The electrical output power quickly increases as the wind speed surpasses the cut-in speed. Nonetheless, the power output reaches the electrical generator's maximal capacity between 12 and 17 m/s. The generator's rated power output is its maximum power output, and the rated output wind speed is the wind speed at which this maximum output is reached (Stephanie Cole, 2021).

The maximum speed at which a wind turbine can function is known as the cut-out speed. Beyond this point, the turbine is exposed to extraordinarily strong stresses that could jeopardize its stability. Turbines are usually equipped with a braking system that can be operated manually or automatically. The braking system kicks in and brings the object to a stop when the speed hits the cut-out threshold. About 25 m/s is the usual threshold velocity, according to Stephanie Cole, (2021).

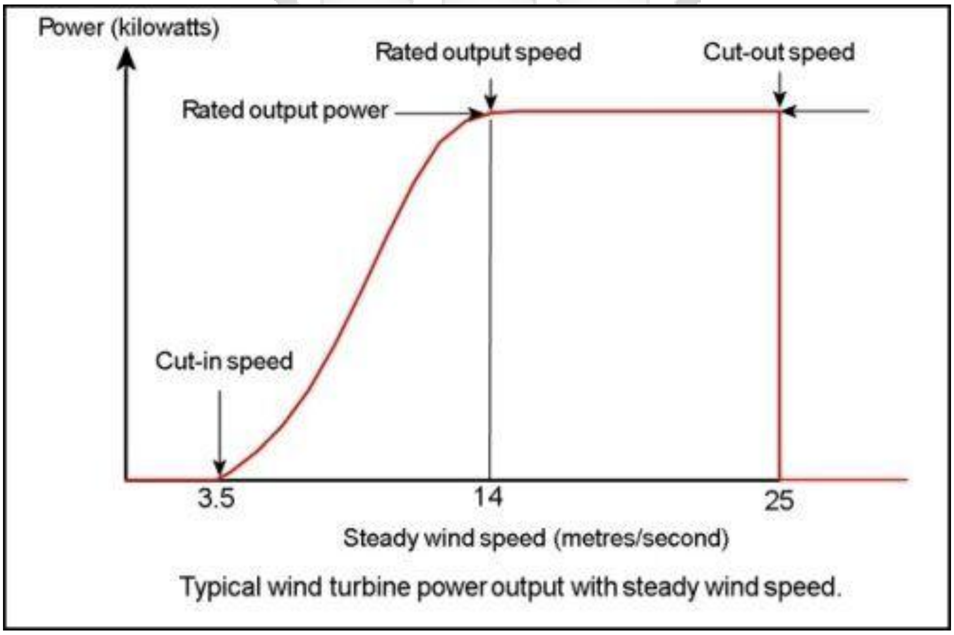


Figure 2.7 Typical wind turbine power output curve (Stephanie Cole, 2022)

Pfaffel et al., (2017) notes a few performance indicators of wind turbines. The most common metric, the capacity factor, represents the proportion of the turbines' actual electrical output over a specific timeframe to its ideal (or rated) power output. It depends heavily on the available wind conditions. Among other performance indicators the author highlights are the time-based availability, energetic availability, technical availability, failure rate, and average down time.

Betz's Limit, which establishes the highest theoretical efficiency of a wind turbine, is a key concept in wind energy conversion. According to this theory, which was put forth by German physicist Albert Betz in 1919, no wind turbine is capable of converting more than 59.3% of the wind's kinetic energy into mechanical energy. The reason for this limit is that if all of the wind's energy were extracted, it would cease to move at all, which would halt more air from passing through the turbine. Depending on variables including wind speed, system losses, and blade design, contemporary wind turbines can reach efficiencies of anywhere between 35% and 45% in real-world applications. In order to maximize wind turbine performance and raise the viability of wind energy systems overall, it is essential to comprehend Betz's Limit.

Wind resources can be classified in two main categories based on their geographical location: onshore and offshore wind power. Offshore wind power refers to the production of energy using wind farms placed in bodies of water, usually in the sea, whereas onshore wind farms are normally constructed on land. The reason offshore farms produce more power is because wind speeds are higher offshore compared to onshore. Because of their location, offshore conversion technologies need a more durable bearing structure than onshore systems. Additionally, the transmission of electric power requires the use of specialized cables, and equipment both for installation and maintenance, which makes offshore wind power much more expensive compared to onshore wind power. However, offshore wind farms are less impactful on the environment and people, making them less controversial. (Desalegn et al., 2023).

### 2.2.4 Demand Forecasting Techniques

Forecasting involves predicting future trends by analyzing patterns in past and present data. It consists of three key components: input variables, which encompass historical and current data; forecasting methods, which rely on trend analysis; and output variables, which represent future projections. As illustrated in Figure 2.8, a typical energy demand forecasting process begins with a well-organized and accessible historical energy database, serving as the foundation for accurate predictions.

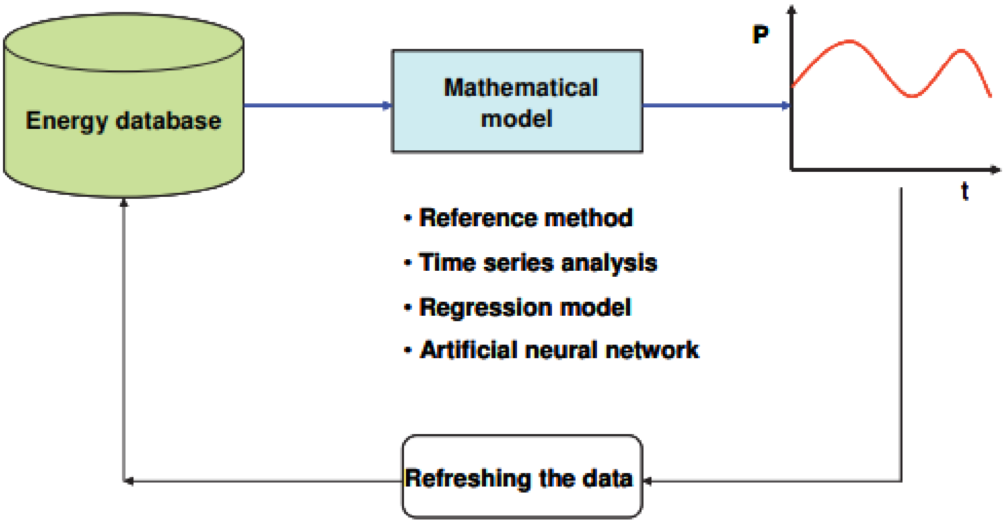


Figure 2.8 Forecasting Method (Schellong, 2011)

The database should contain energy demand data and other factors influencing energy use. This data is fed into a forecast model, which generates a prediction of energy demand. This is typically an ongoing process, in which new data is added to update the energy database and continually provide new forecasts with time.

#### 2.2.4.1 **Forecasting Methods**

The choice of the ideal forecasting technique is dependent on the availability of data, the objectives of the forecasting tool, and the planning processes. Debnath & Mourshed (2018) categorize demand forecasting strategies into two primary groups: stand-alone and hybrid methods. This classification is based on the number of methodologies employed for pattern analysis. Stand-alone approaches employ a singular strategy for analyzing trends, while hybrid methods incorporate multiple stand-alone techniques. Hybridization is primarily used to streamline and enhance the accuracy of forecast output, resulting in more dependable projections.

Energy demand forecasting methods include a variety of techniques utilized to predict future energy consumption patterns, crucial for effective energy resource planning, infrastructure development, and policy formulation. Conventional tools include time series analysis, such as regression analysis and moving averages, which examine historical consumption data to detect trends and patterns. Econometric models integrate economic indicators and demographic variables to forecast energy demand based on economic activity and population changes. Additionally, advanced techniques like artificial intelligence and machine learning algorithms utilize complex data sets to enhance accuracy and adaptability in forecasting. These methods account for dynamic factors such as weather patterns, technological advancements, and policy shifts, enabling more robust and precise predictions of energy demand at various temporal and spatial scales, essential for informed decision-making in the energy sector.

Suganthi & Samuel (2012) categorize energy demand forecasting models into various categories. In the field of economics, different models are used, including regression, time series, econometric, cointegration, and decomposition models. Other approaches include AutoRegressive Integrated Moving Average (ARIMA) models, artificial systems such as expert systems and Artificial Neural Network (ANN) models, grey prediction models, input-output models, and fuzzy logic models. Additionally, integrated models such as support vector regression, autoregressive models, and particle swarm optimization models are utilized. Lastly, bottom-up models like MARKAL, The Integrated MARKAL-EFOM System (TIMES), and the Long-range Energy Alternatives Planning System (LEAP) are also employed.

A time series energy demand forecasting model utilizes historical energy consumption data to predict future demand patterns based on observed trends and seasonality. This model usually employs numerical approaches such as autoregressive integrated moving average (ARIMA) or exponential smoothing to discover and extrapolate trends in time series data. The model can catch repeating trends, such as daily and seasonal variations, and project them into the future by analyzing previous energy consumption data at regular time intervals (hourly, daily, monthly). Additionally, integrating exogenous variables like weather data or economic indicators can improve prediction accuracy by accounting for external factors that influence energy demand changes (Ghalehkhondabi et al., 2017). A study by García-Ascanio & Maté (2010) shows that using interval time series forecasting models can lower operational risk and improve power system planning.

Regression models establish a forecasting function by computing the value of a dependent variable using one or multiple independent variables. The terms "response variable" and "predictor variable" refer to the dependent and independent variables, respectively. The Simple linear regression predicts the Y variation as X varies by a specific amount. With regression, the Y variable is predicted from X using a linear equation: Y=b0+b1X. In this equation, b0 is the intercept (or constant), and b1 is the slope of X. Because it is dependent on X, the Y variable is referred to as the response. The X variable is either the independent variable or the predictor. The machine learning experts commonly refers to Y as the target and X as the feature (Peter Bruce, Andrew Bruce, and Peter Gedeck, 2020).

Econometric models for energy demand forecasting use economic theory and statistical methods to assess the link between energy use and major economic variables including GDP, industrial output, and population growth. These models typically utilize time-series or regression analysis to identify the effect of economic factors on energy demand. By incorporating key determinants of energy consumption, econometric models provide insights into the underlying drivers of energy demand and enable policymakers to forecast future energy consumption levels under different economic scenarios. Rao & Parikh (1996) demonstrated that econometric models are ideal in energy demand forecasting for developing countries.

AutoRegressive Integrated Moving Average (ARIMA) models are mostly utilized to forecast energy demand because of their ability to detect temporal trends and seasonality in past energy consumption data. In an ARIMA model, the historical values of the energy demand series are regressed on lagged values and error terms, which include autoregressive (AR) and moving average (MA) modules. The "integrated" component represents differencing to attain stationarity in time series data. Fattah et al. (2018) argue that when the seasonal adjustment order is large or diagnostics fail to prove that the time series is stable after seasonal adjustment, the ARIMA approach becomes expensive and, in many circumstances, impossible to create a model. In such instances, the static variables of the standard ARIMA model are viewed as the primary barrier to forecasting highly fluctuating seasonal demand. Another limitation of the standard ARIMA approach is that it necessitates a high number of observations to obtain the best fit model for a given dataset.

Olivencia Polo et al., (2015) by the form and function of biological neural networks that learn patterns and relationships from historical energy consumption data via training methods while dealing with complicated non-linear behaviors. Figure 8 illustrates the basics of ANN, which comprises of three distinct layers: input layer, hidden layer, and output layer.

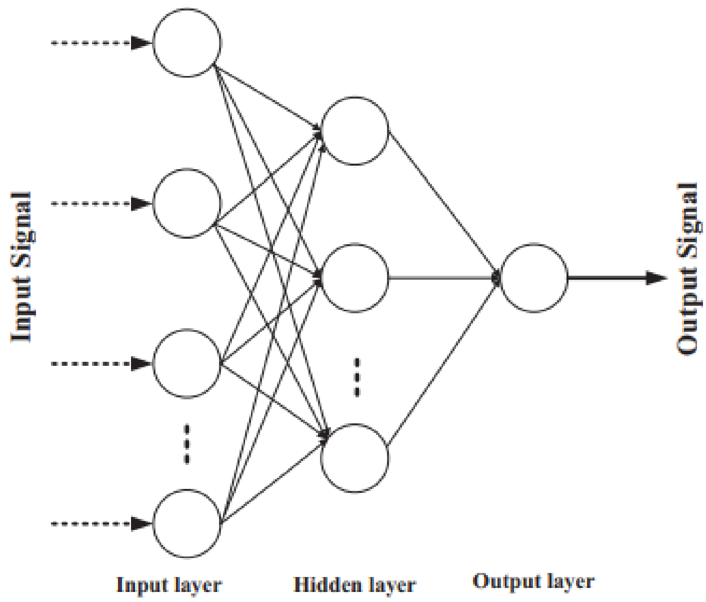


Figure 2.9 Basics of artificial neural network structure (Sobri et al., 2018)

Artificial Neural Network (ANN) models are increasingly utilized in demand forecasting due to their ability to handle complex data as well as nonlinear relationships (MALCOLM et al., 1999).These models can capture complex interactions between various factors influencing energy demand, including socio-economic variables, weather patterns, and technological advancements. These are then utilized to predict productivity, giving the ability to foresee current and potential problems (including fault, failure, production losses, etc.) based on data collected from sensors (Ferrero Bermejo et al., 2019). This provides more accurate and adaptive forecasts compared to traditional statistical methods. According to Miller et al. (1990), one of the key disadvantages of ANN models is the necessity for extensive information and sufficient data quality, which is not frequently available or affordable.

The Grey Prediction Model, a subset of Grey System Theory, offers a forecasting technique particularly suitable for situations with limited data or when traditional statistical methods may not be applicable. This notion is referred to as "grey" due to the existence of unclear data. In energy demand forecasting, the Grey Prediction Model utilizes a small dataset to establish the underlying relationships between energy consumption and influential factors (Julong, 2018.). Grey prediction is commonly employed due to its attribute of higher forecasting accuracy than other methods and the typically lower requirement in terms of data pieces to develop a forecasting model. It employs a Grey Differential Equation to model the dynamic evolution of energy demand over time, effectively capturing both linear and nonlinear trends.

Fuzzy sets are used to make decisions based on ambiguous data, interact with human cognitive processes, and assess uncertainty at different stages of a process. Fuzzy sets theory allows systems to express their principles using "if-then" statements, eliminating the requirement for mathematical analysis in modelling (Haji & Assadi, 2009). A study by Iyatomi & Hagiwara (2004) proves that fuzzy logic use fewer analytical observations than a number of other approaches and yields anticipated values from imperfect data, however their output is not always satisfactory. When the number of input dimensions increases, conventional fuzzy systems frequently fail to complete the task effectively. In the same study, Iyatomi & Hagiwara, (2004) offer an adaptive fuzzy inference neural network (AFINN) that can construct itself, estimate parameters, and extract rules. Fuzzy sets enable modelers to condense large quantities of data into fewer variable rules, which are then used by fuzzy forecasting models.

Forecasting is an indispensable tool, even in operations management, enabling organizations to anticipate future demand and optimize decision-making processes. The Forecasting Fundamentals, a study on Mighty Mechanical provides a systematic exploration of forecasting techniques, emphasizing their application in demand prediction. A critical distinction is drawn between qualitative methods, which rely on expert judgment and subjective inputs, and quantitative methods, which leverage historical data and mathematical models for objective analysis. Given the operational focus of demand forecasting, quantitative approaches, particularly time-series models, are often prioritized for their ability to extract meaningful patterns from past.

Time-series forecasting encompasses several techniques, each suited to different demand characteristics. The naïve method, for instance, uses the most recent observation as the forecast, offering simplicity but limited accuracy in volatile environments. Conversely, moving averages smooth out fluctuations by averaging past data points, with the option to weight recent observations more heavily, using weighted moving averages or equally as in simple moving averages. Exponential smoothing further refines this approach by applying exponentially decreasing weights to older data, controlled by a smoothing constant, $\alpha$. Lower $\alpha$ values enhance stability, while higher values improve responsiveness to recent changes. Trend projection, a regression-based technique, is highlighted for its effectiveness in modeling steady growth or decline, and this is done through an equation which forecasts demand based on a linear trend.

The study also highlights a significant challenge in forecasting which is accounting for seasonality. The study addresses this through decomposition and seasonal indices. By isolating trend, seasonal, cyclical, and random components, forecasts can be adjusted to reflect periodic demand variations. For example, quarterly forecasts derived from annual projections are refined using seasonal indices such as 0.80 for Q1, 1.20 for Q2, ensuring alignment with historical patterns. This approach is contrasted with applying separate trend lines to each quarter's data, illustrating how methodological choices influence forecast precision.

Finally, the study also underscores the importance of evaluating forecast accuracy through metrics such as Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percent Error (MAPE). MAD measures average error magnitude, while MSE penalizes larger errors more severely, making it useful for high-stakes applications. MAPE, expressed as a percentage, facilitates cross-comparisons across datasets. A hypothetical comparison of two forecasting methods reveals that identical MFE or MAD values may mask critical differences in consistency, which MSE and MAPE can uncover. This aligns with broader literature emphasizing the need for multi-metric assessment to balance bias, precision, and practicality (Hyndman & Koehler, 2006).

#### 2.2.4.2 Energy Modeling Tools

The transition toward renewable energy systems necessitates robust modeling tools to address challenges such as grid stability, variable renewable energy (VRE) integration, and decarbonization pathways. The flowchart as illustrated in Figure 2.10 provides a structured framework for selecting an appropriate energy modeling tool based on various criteria. It begins with the general logic of available models, which are categorized by approach, purpose, and methodology. The resolution of the model is then considered in both temporal and spatial dimensions. Additionally, the inclusion of technical and economic parameters, such as conventional and renewable generation, energy storage, grid management, demand elasticity, and market factors, plays a crucial role in model selection. Finally, the availability of the model—whether it is open-source, commercial, or defined by a specific software type—guides the final model choice.

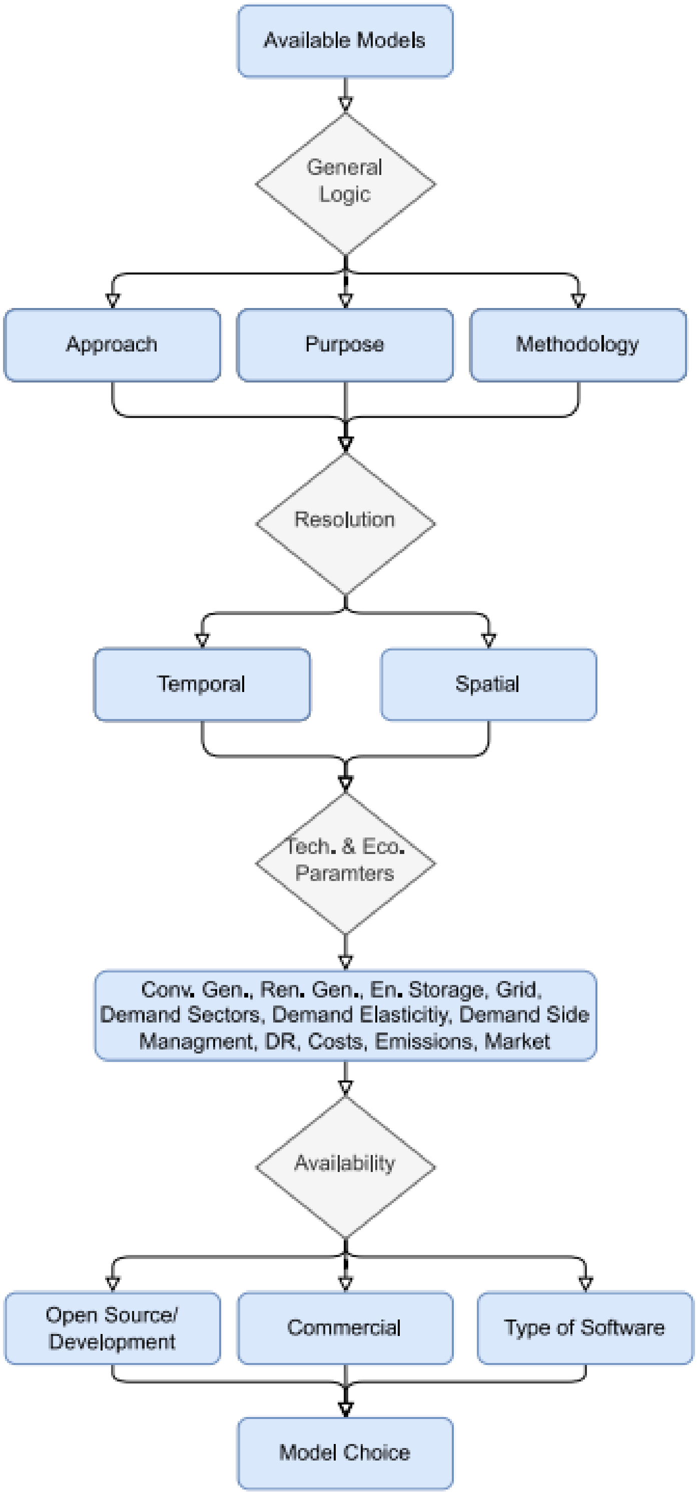


Figure 2.10 Classification for model choice, adapted from (Ringkjøb et al., 2018)

Sommer, (2023) highlights several open-source and commercial tools that facilitate these analyses, each with distinct methodological approaches and applications. Among these, Python for Power System Analysis (PyPSA) emerges as a prominent tool for optimizing power systems with high shares of VRE. Utilizing linear programming (LP), PyPSA enables cost-effective grid expansion and sector coupling, such as electricity, heat, hydrogen, while maintaining hourly temporal resolution. However, its limitations in non-linear power flow analysis restrict its utility for detailed grid stability assessments (Brown et al., 2018).

For technical grid analysis, pandapower offers specialized capabilities, including non-linear power flow calculations and short-circuit analysis, making it indispensable for distribution system studies. Its open-source nature and Python integration enhance accessibility, though its focus on operational rather than long-term economic modeling narrows its scope (Thurner et al., 2018). In contrast, RAPSim employs agent-based simulation (ABS) to model microgrids and decentralized energy systems, providing granular insights into community-scale renewable integration. While effective for localized projects, its scalability to national grids remains constrained (Pochacker et al., 2014). A comparative evaluation reveals that PyPSA and pandapower are particularly synergistic: PyPSA excels in economic optimization and renewable integration, while pandapower addresses technical grid constraints.

Commercial and hybrid tools such as OpenDSS complement these open-source options by offering advanced distribution system simulations, including quasi-static time-series analysis for smart grids. Despite its robustness, OpenDSS's complexity and partial open-source availability pose barriers to widespread adoption (D. Montenegro et al., 2022). GridLAB-D, another open-source tool, focuses on demand-side modeling with sub-second resolution, incorporating behavioral and weather data to simulate residential and commercial energy use. While valuable for DSM studies, its limited spatial scope reduces its applicability to transmission-scale analyses (GridLAB-D, 2022).

Ringkjøb et al., (2018) reviewed different modeling tools encompassing a diverse array of approaches tailored to address the complexities of energy and electricity systems with high shares of variable renewable energy sources (VRES). These tools are broadly categorized into power system analysis tools, operation and investment decision-support models, and long-term scenario analysis frameworks. Power system analysis tools, such as CYME, DIgSILENT PowerFactory, and HYPERSIM, focus on granular temporal resolutions to simulate grid stability, power flows, and dynamic responses, making them indispensable for assessing short-term technical challenges like frequency regulation and fault management. In contrast, operation and investment-oriented models, including BALMOREL, EMPS, and PLEXOS, employ optimization techniques such as linear or mixed-integer programming to balance supply-demand dynamics, optimize unit commitment, and evaluate capacity expansion over decadal horizons, often incorporating stochastic methods to account for renewable variability.

The author adds that Long-term energy system models, such as TIMES, GCAM, and MESSAGE, adopt a broader perspective, integrating macroeconomic and policy-driven scenarios with technological pathways to explore decarbonization strategies. These models typically use time-slicing or representative periods to manage computational constraints, though this simplification risks underestimating the operational flexibility required for high VRES penetration. Hybrid tools like OSeMOSYS and Calliope bridge this gap by coupling high-resolution operational constraints with long-term planning, while agent-based models (e.g., EMLab-Generation) simulate market actor behavior to capture emergent dynamics in liberalized energy markets.

One of the most sophisticated tools for utility-scale energy planning is PLEXOS, a power system optimization model that employs mixed-integer linear programming (MILP) for generation dispatch and expansion planning. PLEXOS is widely used by utilities and market operators for simulating power generation, fuel dispatch, and energy market interactions. It allows for a comprehensive analysis of thermal and renewable energy systems while optimizing transmission and storage deployment. Its ability to integrate multiple time scales and policy constraints makes it suitable for long-term energy planning and operational forecasting (Energy Exemplar, 2021).

Another widely utilized utility-scale energy system model is the Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE). Developed by the International Atomic Energy Agency (IAEA), MESSAGE is a long-term optimization tool that enables planners to evaluate investment strategies for power generation infrastructure. It is particularly effective for multi-sectoral energy planning, as it incorporates detailed cost-benefit analyses for different expansion scenarios. The model also supports decision-making related to the integration of renewable energy and conventional power sources (Isik, 2016).

Similarly, the Wien Automatic System Planning Package (WASP) is an established tool used for least-cost generation expansion planning, particularly in developing countries. Developed by the IAEA, WASP utilizes dynamic programming to determine the most cost-effective expansion strategy while ensuring system reliability and adequacy. The model is particularly effective for hydro-thermal power planning, as it allows for the evaluation of different capacity expansion options under varying demand and resource constraints (IAEA, 2001).

The Integrated MARKAL-EFOM System (TIMES) is another widely applied optimization tool that extends the capabilities of the original MARKAL model. TIMES is based on a bottom-up approach and is used for national and regional energy system planning. The model integrates economic optimization techniques to assess energy technology evolution, policy impacts, and carbon pricing mechanisms. TIMES is particularly useful for assessing long-term energy transitions, given its ability to incorporate various technological pathways and demand-side measures (Ryder et al., 2023)

For researchers and policymakers seeking an open-source alternative, Balmorel provides a flexible modeling framework for electricity and district heating system analysis. This tool employs MILP optimization techniques to determine the least-cost expansion of generation, transmission, and storage infrastructure. Balmorel is particularly advantageous for cross-border power system studies, as it accounts for market interactions and regulatory constraints across multiple regions (Wiese et al., 2018).

Finally, the Long-range Energy Alternatives Planning System (LEAP) offers a scenario-based approach to energy system modeling. Unlike optimization-driven models, LEAP employs simulation techniques to project energy demand, supply, and emissions under different policy scenarios. It is mostly used in developing countries for national energy planning, particularly in assessing the long-term impacts of energy policies and sustainability measures. Its user-friendly interface and adaptability make it a preferred tool for government agencies and research institutions involved in low-carbon energy planning (Davis et al., 2020).

Among utility-scale energy planning and optimization tools, each presents strengths and applications depending on the specific needs of a power system. PLEXOS and WASP are particularly suited for detailed utility-scale expansion planning, while TIMES and MESSAGE offer broader economy-wide energy system modeling. Balmorel provides a valuable open-source option for electricity market analysis, whereas LEAP is best suited for scenario-based policy evaluation. The selection of an appropriate energy modeling tool depends on the scope, scale, and objectives of the analysis, as well as the level of technical expertise required for implementation.

## 2.3 Empirical Review

There has been great interest by scholars in developing sustainable energy plans for various countries. More recent studies focused on energy planning tools aiming towards more RE integration and CO2 mitigation.

Icaza et al., (2022) assessed the South American Electric Energy System, particularly focusing on integrating REs to transition away from fossil fuel-based systems. Their study emphasizes the Ecuadorian case, notable for its initial reliance on fossil fuels, particularly damaging in the Amazon region. Using an analysis in EnergyPlan, the research proposes realistic RE sources and their distribution to meet the projected 2050 demand, envisioning a 100% RE generation system in Ecuador. This transition is expected to have positive effects, including economic growth, increased production levels, and enhanced citizen well-being. By 2050, hydro, solar PV, and wind are expected to contribute considerably to the energy matrix, with 20 GW of installed electricity and 72.24 TWh of yearly production. The average production cost per MWh is anticipated to be approximately 18 US cents. This study highlights Ecuador's initial reliance on fossil fuels and proposes significant new technologies for a 100% renewable energy transition. However, the findings are limited to the technological dimension, excluding financial feasibility.

Simsek et al., (2020) compared energy scenarios for a low-carbon transition in Chile by 2030 using LEAP model to forecast the energy demand, supply, and emissions. The study offers insights into long-term energy planning, exploring alternatives and evaluating the impact of existing policies, NDCs, and SDGs. Results show that scenarios with considerable energy demand reductions lead to notable emission cuts, especially from the demand sector, with a need for energy efficiency and RE policies in transport, mining, and industries. Increased deployment of wind, solar, and hydropower could achieve over 80% RE generation by 2030, reducing emissions and diversifying the energy mix. While the paper focuses on demand reduction strategies, leading to significant CO2 emission decrease and increase of RE generation in Chile, it does not directly tackle the issue energy access.

Following the launch of a program called (REFIT) to facilitate the introduction of renewable energy (RE) generation into South Africa's power network, the National Energy Regulator of South Africa (NERSA) launches a RE program aimed at generating 17.8 GW of RE by 2030 through sources such as wind power, solar PV, concentrated solar power (CSP), landfill, and mini hydro. With an expected significant increase in generators to be connected to Eskom's transmission and distribution networks expected, Bello et al. (2013) examines the implications for South Africa's distribution networks, particularly under Eskom's (the national power utility) oversight in rural areas and smaller towns and municipal control in cities. It proposes a standardized approach, leveraging the SMART

Grid concept, to optimize the planning, design, and operation of distribution networks across the country while implementing initiatives like as distributed generation and enhanced demand management. This research is a great addition to this literature review, as it breaks down a program designed to increase RE generation and fight energy monoculture. It, however, is mainly a recollection and critique of the composition of the REFIT program and doesn't address electricity access issues.

In Kenya, Okomol et al. (2021) provide a detailed roadmap for both national and county governments on how to attain 100% energy access and prioritize sustainable energy transition, emphasizing the creation of green jobs and enterprises. Utilizing the LEAP energy modeling software, the article presents the Medium-Term Plan (MTP) and Long-Term Plan (LTP) updates from 2019 to 2030, focusing on expanding the country's power system while ensuring compliance with planning criteria and frameworks. The author analyzes 4 different scenarios, focusing on BAU, the need to reduce the wood fuel technologies in households, a transition to clean biogas fuels, LPG and solar, and finally, an ambitious goal to reach zero biomass use countrywide, with high adaptation of LPG, electricity and solar. Recommendations include sustaining broad-based development by ensuring stable and sufficient energy supply to meet growing demand, emphasizing the need for the Government of Kenya to prioritize sustainable energy initiatives.

This study serves as a foundational document for investors, particularly in energy generation and distribution, with recommendations regarding RE projects to invest in. The paper does not however quantify the level of investments or guide on the least cost of production for the recommended projects.



Ugwoke et al. (2021) underline the necessity for an integrated energy planning framework in low-income countries with rural populations and limited finances, aiming to utilize RE for economic development. They introduce a framework for integrated rural energy planning to enhance energy access in rural areas through renewable energy. Using case studies from rural Nigeria, they apply this framework to identify suitable sites, estimate energy demand, and assess renewable energy resources using GIS-based tools. The results provide insights into localized energy policies combining rural electrification with energy conservation measures, with potential relevance in similar contexts across the sub-Saharan Africa region and developing Asia. While the approach offers a unified roadmap for energy planning and RE integration to enhance rural energy access, it focuses solely on community-scale projects and does not address the complexities of urban areas with higher energy demands from industrial and commercial activities.

The Philippines has gradually demonstrated a strong commitment to RE sources, to combat climate change, surpassing many countries in their adoption and distribution of renewable energy in primary energy and electricity. Roxas & Santiago (2016) argue in their study on an alternative framework for renewable energy planning in the Philippines that the emphasis on aggressively increasing RE capacity, primarily through grid-connected applications, has neglected the potential benefits of off-grid RE solutions, which could replace costly diesel generation and improve community livelihoods.

This paper suggests a shift in focus from simply increasing megawatts to considering the broader impact of renewable energy (RE) on communities. It advocates for a planning approach that evaluates both the livelihood benefits and energy delivery effectiveness of different RE technologies in off-grid and on-grid connected regions. Additionally, it presents a real-life off-grid RE application addressing energy and economic poverty on a kW scale. The author stresses the importance of tailoring an Energy Reform Program (ERP) to the economic context and goals of the country, highlighting RE's potential to alleviate rural poverty. Key strategies include diversifying the energy mix for security and adopting a demand-driven approach to expand energy access, particularly on off-grid islands. It is important to note that these recommendations serve as suggestions rather than outlining a definitive energy plan for the Philippines.

Using the case study of Cambodia and Thailand, Chhay (2018) performed a Long-Term electricity planning, aiming at reducing the GHG emissions caused by an increasing reliance on fossil fuels to meet rising energy demands in Cambodia and Thailand. The study employs the LEAP model to analyze different scenarios from 2015 to 2050, including Business-as-Usual (BAU), Renewable Energy (RE), Carbon Capture Storage (CCS), Carbon Tax (CT), and Electric Vehicle (EV) scenarios. Results indicate that scenarios such as the CT500 (referring to a carbon tax increase from \$20/tCO2 in 2020 to \$500/tCO2 by 2050) show promise in significantly reducing CO2 emissions compared to BAU, with RE scenarios also demonstrating considerable potential. Notably, the costs of electricity production from RE sources remain lower than those of CCS and CT scenarios. Chhay, (2018) places a greater emphasis on CO2 emissions mitigation and does not relate the study's objectives to improving Burundi's electricity access rate.

### 2.4 Summary of Gaps

The analyzed studies highlight the importance of having energy plans adapted to countries. Depending on the researchers' objectives, some studies focus on transitioning from fossil fuels to renewable energy sources, others on enhancing rural energy access, or reducing carbon emissions. The identified gaps are:

i. Some studies have explored various scenarios that increase RE use, and reduce fossil fuels, but failed to contextualize the research to the energy access problem.
ii. While some tailored energy planning tools to improve energy access, they focused on community-based areas rather than at the country level.
iii. Although some studies developed extensive plans for underdeveloped countries, addressing energy access and RE exploration, they only considered the technological aspects, without quantifying investment needs or identifying the least-cost expansion scenarios.

This study addresses the identified gaps by developing an energy planning tool aimed at increasing energy access in Burundi. It focuses on utilizing renewable energy instead of fossil fuels and provides guidance on the least-cost expansion plan.

# CHAPTER 3 METHODOLOGY

## 3.1 Introduction

The research methodology comprised four distinct steps: first, an analysis of the current energy sector, existing power plants, and the power development plan created by the Ministry of Hydraulics, Energy, and Mines (MINHEM); second, an energy demand forecast for 2040; third, a description of investment scenarios modeled with the Wien Automatic System Planning (WASP-IV); and fourth, the presentation and comparison of results, as illustrated in the Flowchart of the methodological approach, Figure 3.1.

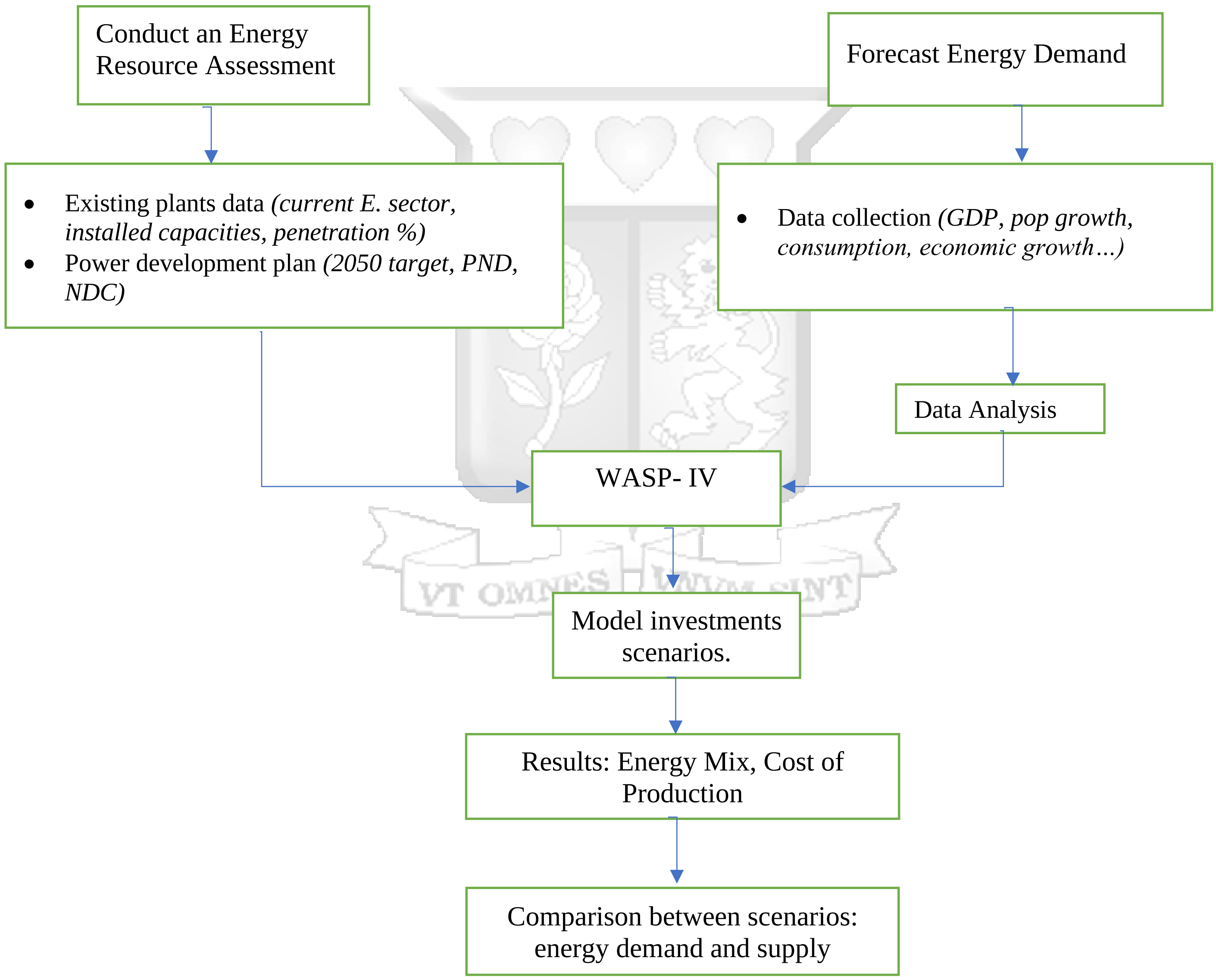


Figure 3.1 Flowchart of the methodological approach

### 3.2 Data Collection

The data for this study was acquired from Burundi's Ministry of Mines and Energy, as well as from the Water and Electricity Production and Distribution Authority (REGIDESO). Forecasting future energy generation requires Gross Domestic Product (GDP), growth rate, population size, historical data on electricity generation, and a power development strategy. Furthermore, any power generation technique must have maximum availability, fixed O&M costs, efficiency, and a long lifetime. The remaining data was obtained from publicly available online sources such as World Bank, IRENA, IEA reports on Energy Access, including African Development Bank Group, (2020), *Burundi Energy Access Project Phase1* (2024), among others.

### 3.3 Demand forecasting

Load forecasting was done using the econometric model, based on key economic and demographic indicators, as guided in Pegels, (2010). The methodology follows a step-by-step approach, incorporating population growth, GDP per capita trends, and elasticity factors to estimate future electricity demand. The electricity demand ($D_t$) was modeled as a function of population ($P_t$), GDP per capita ($Y_t$), and their respective elasticities. The general demand function is expressed using equation 1 as

$$\mathrm{D}_t = \mathrm{D}_0 * \left(\frac{\mathrm{P}_t}{\mathrm{P}_0}\right)^{ep} * \left(\frac{Y_t}{Y_0}\right)^{ey} \qquad 1$$

Where:

- $\mathrm{D}_t$ = Forecasted electricity demand in year t
- $\mathrm{D}_0$ = Base year electricity demand
- $\mathrm{P}_t$ = Population in year t
- $\mathrm{P}_0$ = Base year population
- $\mathrm{Y}_t$ = GDP per capita in year t
- $\mathrm{Y}_O$ = Base year GDP per capita
- *ey* = Population elasticity of electricity demand
- $ep$ = Income (GDP per capita) elasticity of electricity demand

The population elasticity ($ep$) is calculated as a function of change in population over the corresponding change in electricity demand over a period of time, whereas income elasticity (*ey*) is a function of the change in GDP Per Capita over the corresponding change in electricity demand over a period of time.

The future population was forecasted using an exponential growth model, based on the historical population growth rate ($r_p$ ), as per equation 2

$$P_t = P_0 * (1 + r_p)^t \qquad 2$$

Where:

- $r_p$ = Historical population growth rate (i.e observed steady 2% from 2010 to 2025)
- t = Years from the base year

The GDP per capita was forecasted using a similar exponential growth formula, incorporating the GDP growth rate ($r_y$), as indicated in equation 3.

$$Y_t = Y_0 * (1 + r_y)^t \qquad 3$$

Where:

- $r_y$ = GDP per capita growth rate (observed steady 2% from 2020 to 2025)
- t = Years from the base year

Finally, the peak load was derived using the peak load ratio ($PLR_o$), which represents the relationship between peak demand and total electricity demand. The formula for future PLR is presented in equation 4.

$$PLR_t = PLR_0 * \left(\frac{D_t}{D_0}\right)^e \qquad 4$$

Where:

- $PLR_0$ = Base year peak load ratio
- $D_t$ = Forecasted electricity demand
- $D_0$ = Base year electricity demand
- e = Elasticity factor

This method ensures that peak demand projections align with system planning needs, accounting for variability in demand growth. The projections, along with the peak load ratio, were input into the WASP software to model the optimal capacity of power plants needed annually. This process considers peak load capacity and the peak load ratio to determine the required dispatchable energy sources for meeting average load demand and assessing the necessary spinning reserves.

### 3.4 WASP Model

WASP-IV is the name given to the updated version of the model, which includes several additional features. Its goal is to ascertain, given a user-specified restriction, the economically viable generating growth policy for an electric utility system. WASP-IV assesses system characteristics such production costs, unseen energy requirements, and dependability using a probabilistic approximation. An optimal dispatch policy that satisfies external restrictions on fuel availability, environmental pollution, and power generation from particular plants is developed using linear programming. Additionally, it compares the costs of several system growth techniques using dynamic optimization.

The WASP-IV code allows one to identify the best expansion strategy for a power production system over a thirty-year period while staying within the planner's limits. The optimal is measured in terms of the lowest discounted total costs. Equation 5 represents a cost function/objective function that is used to evaluate each potential order of power units integrated into the system that meets the requirements.

$$B_j = \sum_{t=1}^{T} \left( I_{j,t} - S_{j,t} + F_{j,t} - L_{j,t} - M_{j,t} - O_{j,t} \right) \qquad 5$$

Where,

| | |
|---|---|
| $\boldsymbol{B_j}$ | is the objective function attached to the expansion plan j |
| t | is the time in years (1, 2, ..., T) |
| T | is the length of the study period (total number of years) |
| I | is the capital investment cost |
| S | is the salvage value of investment cost |
| F | is the fuel cost |
| L | is the fuel inventory cost |
| M | is the non-fuel operation and maintenance costs |
| O | is the cost of the unserved energy |

It is important to add that the I, S, F, L, M and O values are discounted to a reference date using a specific discount rate I. Finally, the least-cost expansion plan among all possible scenarios then determines the optimal expansion strategy. It is also important to note that the software operates under specific constraints. It assumes that the total installed capacity and generation must always meet or exceed peak demand. Furthermore, it allows users to define the available technologies and specify their expected commissioning years. As a result, expansion decisions are constrained only by predefined resource availability and technology limits. Lastly, power plants must operate within set fuel and efficiency parameters, meaning the model does not account for unexpected fuel supply disruptions. WASP-IV consists of several interdependent modules, each performing a specific function within the optimization process. Table 3.1 describes the 7 modules of WASP- IV, while Figure 3.2 represents a simplified flow chart of the model WASP-IV computer code.

Table 3.41 WASP Modules (adapted from WASP Manual)

| **Modules** | **Description** |
|---|---|
| **Module 1: LOADSY** (Load System Description) | This module processes information describing period peak loads and load duration curves for the power system over the study period. |
| **Module 2: FIXSYS** (Fixed System Description) | Information on the current generation system, any planned additions or retirements, and any user-imposed restrictions on fuel supply, environmental emissions, or the ability of certain plants to generate energy are all processed by FIXSYS. |
| **Module 3: VARSYS** (Variable System Description) | This last input module processes data describing the various generating plants which are to be considered as candidates for expanding the generation plan. Generator forced and unforced outrage, LOLP, reserve margin were studied. Key inputs include installed capacity, fuel characteristics, outage rates, emissions limits, and hydro reservoir constraints. |
| **Module 4: CONGEN (Configuration Generator)** | This module computes every feasible combination of expansion candidate additions from year to year that meet specific input criteria and that, when combined with the fixed system, can meet the loads. Additionally, it determines the combined list of FIXSYS and VARSYS plants' basic economic loading order. |
| **Module 5: MERSIM** | This module considers all configurations put forward by CONGEN and uses probabilistic simulation of system operation to calculate the associated |

| | |
|---|---|
| (Merge and Simulate) | production costs, energy not served and system reliability for each configuration. In the process, any limitations imposed on some groups of plants for their environmental emissions, fuel availability or electricity generation are also considered. The dispatching of plants is determined in such a way that plant availability, maintenance requirement, spinning reserve FIXSYS and VARSYS plants. |
| **Module 6: DYNPRO** (Dynamic Programming Optimization) | Based on previously calculated running expenses, input data on capital costs, energy not served costs, economic characteristics, and reliability standards, it determines the best growth strategy. |
| **Module 7: REPROBAT** (Report Writer of WASP in a Batched Environment) | For set expansion schedules and the optimal or nearly optimal power system expansion plan, it generates a report that summarizes the entire or partial outcomes. The file that can be utilized for a graphical representation of the WASP results also contains some of the outcomes of the computations carried out by REPROBAT. |

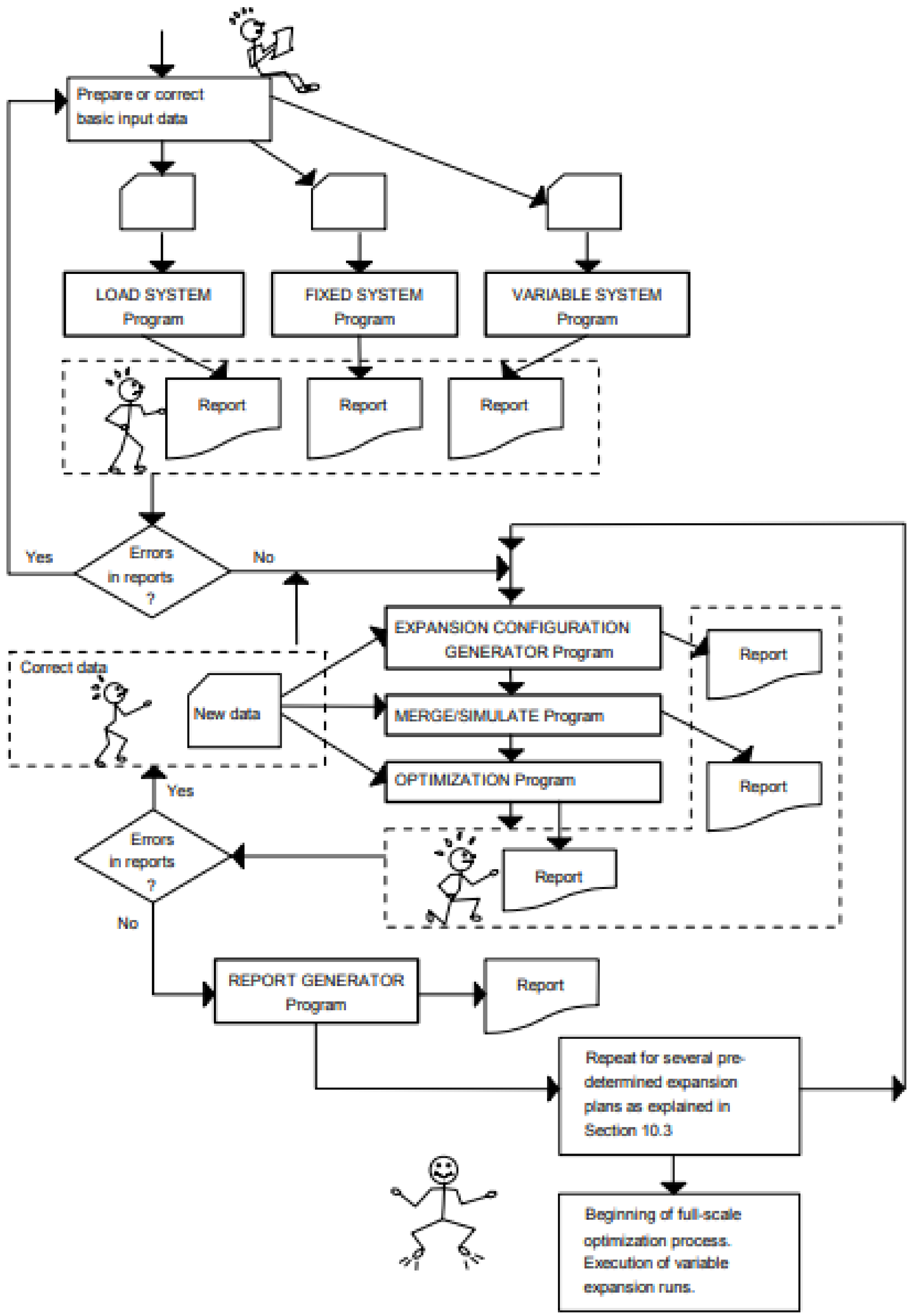


Figure 3.2 User interaction in running the WASP code (adapted from ORNL 73-7759 RI)

Since 2023 provided the most recent complete hourly load duration curve, it was selected as the base year. However, while 2023 serves as the reference point, this study assumes that the modeled planning begins in 2026 to develop a more practical and achievable expansion strategy. The data entered into Fixsys and Varsys was sourced from REGIDESO as part of the planning process for Burundi's integration into the Central African Power Pool (CAPP).

In the model, solar, peat-fired, and municipal waste power plants were classified as thermal plants since WASP-IV is designed to accommodate only hydro and thermal plant types. Additionally, the software enables generation and demand data to be divided into up to 12 periods within a year. For this study, three periods were considered, corresponding to Burundi’s three main seasonal weather variations. This approach is particularly relevant because the country's primary energy source is hydro, which is significantly affected by seasonal fluctuations in water availability.

### 3.5 Scenario Description

This section of the methodology involves modelling different scenarios, each sourced from the Ministry of Hydraulics, Energy and Mines. This includes examining current REGIDESO’s plan towards increasing Burundi’s electrification rate, existing and revised Nationally Determined Contributions (NDCs), and finally compute the optimal expansion plan. These strategies form the basis of the scenarios. In total, three distinct scenarios were established as outlined in Table 3.2.

Table 3.5 Scenarios Modeled

| Scenario | Description |
|---|---|
| Business As Usual (BAU) | This scenario consists of modelling the results of the forecasted energy when all variables and parameters of the Burundian energy system follow historical trends. |
| Nationally Determined Contributions (NDCs) | This scenario focuses on enhancing the production capacity of hydro and solar PV plants. |
| Optimal Expansion Plan | This scenario integrates the existing plants outlined in both the BAU and NDC scenarios and involved analyzing DYNPRO outputs before conducting new CONGEN iterations. Each new iteration was generated by increasing the minimum number of plants marked with (+) by one while reducing those marked with (-) by one in CONGEN, ultimately identifying the optimal expansion plan. |

### 3.6 Ethical Considerations

This work shall be conducted in accordance with the ethical research provisions of the University. This will include protecting the respondents, by observing anonymity and by giving them the option to opt out of the research whenever they feel like. Consent shall also be sought from the respondents. Full disclosure on the uses of the data will be useful in enhancing the ethicality of the process. The respondents will be informed that the data is useful for the research work and will be exposed to examiners and classmates during seminars.

Any requested documents will be submitted to the Strathmore University Institutional Scientific and Ethics Review Committee (SU-IERC). The committee holds the mandate of reviewing all proposed research projects, evaluating them, and deciding whether the research should be permitted to proceed based on the ethical and scientific merits of the project. Upon submission of requested documents, feedback on a proposal will take a minimum of 14 working days, and if successful, the research permit will be granted Ethical Approval.

# CHAPTER 4 RESULTS AND DISCUSSION

## 4.1 Introduction

This chapter presents the findings of the assessment on sustainable power generation scenarios in Burundi using a multi-criteria approach. It is structured into three main sections. The first section provides an overview of the country's energy resources, highlighting their availability and potential for electricity generation. The second section presents the results of the demand forecast over a 15-year period. Finally, the third section covers the simulation of various investment scenarios using the WASP model, evaluating their feasibility in terms of cost, sustainability, and energy security.

## 4.2 Energy resource assessment

Burundi possesses a diverse range of energy resources that have the potential to contribute to the country's electricity generation mix. Table 4.1 provides an assessment of the key energy resources available in Burundi, including hydropower, solar energy, biomass, wind energy, and fossil fuels.

Table 4.2 Energy Resources in Burundi

| Energy source | Potential | Location |
|---|---|---|
| **Hydro** | 300 MW | Ruzizi III & IV, Kagunuzi, Mulembwe, Kaburantwa, Kagera River |
| **Solar** | 4.5 - 5.5 kWh/m²/day | Northern and Eastern Burundi (Gitega, Muyinga, Kirundo) |
| **Biomass** | ~7.5 million tons of wood/year | Rural areas, coffee & sugarcane plantations (e.g., Ngozi, Kayanza, Ruyigi) |
| **Wind** | Wind speeds ~3-5 m/s | Highlands & Lake Tanganyika shores (e.g., Bururi, Rutana) |
| **Municipal waste** | | Bujumbura |
| **Peat** | 47-58M tons | |

Hydropower offers the greatest potential at approximately 300 MW economically viable. It is followed by solar energy which holds significant potential, as indicated by the Global Solar Atlas, which shows irradiation levels ranging from 4.5 to 5.5 kWh/m²/day, particularly in the northern and eastern regions. In addition, biomass remains a widely used energy source, primarily for cooking. The country's biomass potential was estimated at 8.5 tC/ha/yr, significantly higher than the global average Net Primary Production of 3-4 tC/ha/yr. This is primarily from agricultural residues and wood remains widely used for cooking but has potential for electricity generation through biogas and biomass power plants. Additionally, peat and municipal waste, concentrated in Bujumbura, represent further potential energy sources.

Meanwhile, wind energy assessments indicate moderate wind speeds (3-5 m/s) in highland and coastal areas, but further feasibility studies are needed to determine its viability for large-scale deployment. Finally, fossil fuels in Burundi are fully imported and primarily used for backup power. Given the high cost of imports and the country's commitment to sustainable development, fossil fuels are an increasingly less favorable option for future energy expansion.

### 4.3 Peak Load Demand Forecasting

This section presents the load forecasting results of the future peak load demand of Burundi over the study period (2025–2040). This was computed based on equations 1, 2, 3 and 4. The results are presented in table 4.2.

Table 4.3 Forecasted Peak Load Demand

| Year | Population Forecast (Million inhabitants), Pt | GDP Per Capita Forecast (US$), Yt | Demand Forecast (MW), Dt | Peak Load Ratio |
|---|---|---|---|---|
| 2023 | 13,689,450 | 193.01 | 82.67 | 0.61 |
| 2024 | 13,963,239 | 196.75 | 90.50 | 0.63 |
| 2025 | 14,242,504 | 200.57 | 99.08 | 0.67 |
| 2026 | 14,527,354 | 204.46 | 108.47 | 0.70 |
| 2027 | 14,817,901 | 208.43 | 118.75 | 0.73 |
| 2028 | 15,114,259 | 212.47 | 130.00 | 0.77 |
| 2029 | 15,416,544 | 216.59 | 142.32 | 0.81 |
| 2030 | 15,724,875 | 220.79 | 155.81 | 0.85 |
| 2031 | 16,039,373 | 225.08 | 170.57 | 0.89 |
| 2032 | 16,360,160 | 229.44 | 186.73 | 0.93 |
| 2033 | 16,687,363 | 233.89 | 204.43 | 0.98 |
| 2034 | 17,021,110 | 238.43 | 223.80 | 1.03 |
| 2035 | 17,361,533 | 243.06 | 245.01 | 1.08 |
| 2036 | 17,708,763 | 247.77 | 268.23 | 1.13 |
| 2037 | 18,062,939 | 252.58 | 293.65 | 1.18 |
| 2038 | 18,424,197 | 257.48 | 321.47 | 1.24 |
| 2039 | 18,792,681 | 262.47 | 351.94 | 1.30 |
| 2040 | 19,168,535 | 267.57 | 385.29 | 1.37 |

The load forecasting results indicate a significant percentage rise in electricity demand in Burundi, increasing by over 366% over the study period. This surge in demand is attributed to a confluence of factors, including a 40% growth in population and a 39% rise in GDP per capita. These figures reflect both demographic expansion and economic development, which are typically strong drivers of electricity consumption as industrialization, urbanization, and household energy access improve. Notably, the projected demand of 108.47 MW in 2026 closely aligns with the African Development Bank's (AfDB) forecast of 100 MW for the same year in the *Burundi Energy Access Project Phase1* (2021).

## 4.4 Optimal Expansion Plan Simulation on WASP

### 4.4.1 Input Modules

The demand projections over the study period were input into Loadsys. The first three modules were run one after the other as illustrated in Figure 3.2. The values in Table 4.3 and Table 4.4 summarize the existing, candidate and committed power plants used as inputs in the Fixsys and Varsys modules respectively. These represent the total currently installed capacities power plants, including the hydro power stations and thermal plants.

Table 4.4 Existing Power Plants

| Plant Name | Technology | Installed Capacity | Status | Commissioning Year |
|---|---|---|---|---|
| CHE Rwegura | Hydro | 18.00 | Existing | 1986 |
| CHE Ruzizi II | Hydro | 12.00 | Existing | 1958 |
| CHE Ruzizi I | Hydro | 3.50 | Existing | 1989 |
| CHE Ruzibazi | Hydro | 15.00 | Existing | - |
| Rusumo | Hydro | 26.67 | Existing | - |
| KABU | Hydro | 20.00 | Existing | - |
| CHE Mugere | Hydro | 8.00 | Existing | 1982 |
| CHE Nyemanga | Hydro | 2.80 | Existing | 1988 |
| CHE Ruvyironza | Hydro | 1.50 | Existing | 1984 |
| CHE Gikonge | Hydro | 1.00 | Existing | 1982 |
| CHE Kayenzi | Hydro | 0.80 | Existing | 1984 |
| CHE Marangara | Hydro | 0.28 | Existing | 1986 |
| CHE Buhiga | Hydro | 0.47 | Existing | 1984 |
| CHE Nyamyotsi | Hydro | 0.30 | Existing | - |
| CTH. en location (Interpetrol) | Diesel Plant | 30.00 | Existing | 2017 |
| CTH. de la REGIDESO | Diesel Plant | 5.00 | Existing | 1996 |
| Mubuga Solar Plant | Solar PV | 7.50 | Existing | 2021 |

| | |
|---|---|
| **TOTAL EXISTING INSTALLED CAPACITY, MW** | **152.82** |

Table 4.4 Candidate and Committed Power Plants

| Plant Name | Technology | Installed Capacity | Status | Commissioning Year |
|---|---|---|---|---|
| Kirasa-Karonke | Hydro | 16 | Committed | 2027 |
| Mpanda | Hydro | 10.4 | Committed | 2028 |
| Ruvyi Mule | Hydro | 10.65 | Committed | 2026 |
| Jiji | Hydro | 32.5 | Committed | 2025 |
| Mulembwe | Hydro | 17 | Committed | 2025 |
| Kabu 23 | Hydro | 15.5 | Committed | 2027 |
| Ruzizi III | Hydro | 49 | Candidate | 2027 |
| Siguvyaye | Hydro | 6.6 | Candidate | 2028 |
| Ruvubu | Hydro | 50 | Candidate | 2028 |
| Mini Hydropower | Hydro | 11 | Candidate | 2028 |
| Solar Project | Solar PV | 17 | Committed | 2027 |
| **TOTAL CANDIDATE INSTALLED CAPACITY, MW** | | **235.65** | | |

### 4.4.2 Output Modules Results

#### 4.4.2.1 Business as Usual Scenario (BAU)

CONGEN-MERSIM-DYNPRO sequential runs were undertaken without changing any input in the other modules. Based on predefined parameters in Loadsys, Fixsys and Varsys, WASP applied Equation 5 to execute the simulation. Figure 4.1 presents the number of units required for each year.

| YEAR | PRESENT WORTH COST OF THE YEAR ( K$ ) CONCST | SALVAL | OPCOST | ENSCST | TOTAL | OBJ.FUN. (CUMM.) | LOLP % | PEAT | SOL | MUN | FOIL | 0HYD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2037 | 13296 | 11603 | 13082 | 113583 | 128357 | 1487597 | 45.346 | 4+ | 4+ | 4+ | 3- | 4+ |
| 2036 | 43661 | 34065 | 14320 | 107669 | 131584 | 1359240 | 45.343 | 4+ | 2- | 4+ | 3- | 4+ |
| 2035 | 26717 | 17921 | 15567 | 104261 | 128624 | 1227656 | 45.337 | 4+ | 2- | 3 | 3- | 2+ |
| 2034 | 36802 | 21761 | 16817 | 117971 | 149829 | 1099032 | 45.347 | 2+ | 2- | 2- | 3 | 2+ |
| 2033 | 22485 | 11763 | 13935 | 135688 | 160345 | 949203 | 45.341 | 1- | 2- | 1- | 2- | 2+ |
| 2032 | 14027 | 6730 | 10501 | 122606 | 140404 | 788858 | 45.339 | 1- | 1- | 1- | 1- | 2+ |
| 2031 | 11777 | 4351 | 6164 | 108973 | 122563 | 648454 | 45.312 | 1- | 1- | 1- | 0 | 2+ |
| 2030 | 0 | 0 | 6766 | 93965 | 100731 | 525891 | 45.336 | 1- | 0 | 1- | 0 | 2+ |
| 2029 | 0 | 0 | 7403 | 78056 | 85459 | 425159 | 45.348 | 1- | 0 | 1- | 0 | 2+ |
| 2028 | 0 | 0 | 8098 | 61200 | 69298 | 339700 | 45.346 | 1- | 0 | 1- | 0 | 2+ |
| 2027 | 64265 | 17569 | 8874 | 43383 | 98952 | 270402 | 45.346 | 1- | 0 | 1- | 0 | 2+ |
| 2026 | 67497 | 12726 | 9546 | 45300 | 109616 | 171450 | 45.337 | 1- | 0 | 1- | 0 | 1 |
| 2025 | 0 | 0 | 10412 | 26705 | 37116 | 61834 | 30.716 | 0 | 0 | 0 | 0 | 0 |
| 2024 | 0 | 0 | 9975 | 9896 | 19871 | 24718 | 16.098 | 0 | 0 | 0 | 0 | 0 |
| 2023 | 0 | 0 | 4847 | 0 | 4847 | 4847 | 0.000 | 0 | 0 | 0 | 0 | 0 |

Figure 4.1 BAU DYNPRO Results on the Recommended Number of Units for an Optimal Expansion Strategy

The (+) and (-) signs signify that this expansion plan is not optimal and indicate the need for either adding or reducing a unit, as shown above. The model advises against incorporating peat-fired or municipal waste power plants before 2034, while recommending the expansion of hydropower capacity to meet growing demand.

#### 4.4.2.2 Nationally Determined Contributions

The NDC submitted scenario focused on an increase of the hydro power plants and integration of the solar plants, while reducing them by one, as suggested in the BAU scenario. Figure 4.2 presents the simulation results.

□SOLUTION # 1 VARIABLE ALTERNATIVES BY YEAR

| YEAR | CONCST | SALVAL | OPCOST | ENSCST | TOTAL | OBJ.FUN. (CUMM.) | LOLP % | PEAT | SOL | MUN | FOIL | 0HYD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | PRESENT WORTH COST OF THE YEAR ( K$ ) | | | | | | | | | | | |
| 2037 | 8710 | 7720 | 15934 | 125490 | 142413 | 1370725 | 45.340 | 3 | 3 | 3 | 4 | 4 |
| 2036 | 14625 | 11120 | 14201 | 120601 | 138307 | 1228312 | 45.341 | 3 | 3+ | 3- | 3- | 4 |
| 2035 | 48774 | 32604 | 15564 | 114752 | 146487 | 1090005 | 45.337 | 3- | 1 | 3+ | 3 | 4 |
| 2034 | 19952 | 12265 | 12943 | 125540 | 146170 | 943518 | 45.341 | 3- | 1 | 1 | 2 | 4 |
| 2033 | 0 | 0 | 9682 | 112096 | 121778 | 797348 | 45.329 | 1 | 1 | 1 | 1 | 4 |
| 2032 | 14027 | 6730 | 10609 | 97545 | 115451 | 675570 | 45.332 | 1 | 1 | 1 | 1 | 4 |
| 2031 | 33554 | 12697 | 6267 | 82476 | 109600 | 560119 | 45.228 | 1 | 1 | 1 | 0 | 4 |
| 2030 | 12955 | 4110 | 6730 | 65707 | 81282 | 450520 | 45.352 | 0 | 1 | 0 | 0 | 4 |
| 2029 | 0 | 0 | 7685 | 48295 | 55980 | 369238 | 45.338 | 0 | 0 | 0 | 0 | 4 |
| 2028 | 56335 | 17376 | 7704 | 35032 | 81696 | 313258 | 30.721 | 0 | 0 | 0 | 0 | 4 |
| 2027 | 76500 | 20914 | 8937 | 43359 | 107881 | 231562 | 45.345 | 0 | 0 | 0 | 0 | 2 |
| 2026 | 0 | 0 | 9913 | 51934 | 61847 | 123681 | 45.347 | 0 | 0 | 0 | 0 | 0 |
| 2025 | 0 | 0 | 10412 | 26705 | 37116 | 61834 | 30.716 | 0 | 0 | 0 | 0 | 0 |
| 2024 | 0 | 0 | 9975 | 9896 | 19871 | 24718 | 16.098 | 0 | 0 | 0 | 0 | 0 |
| 2023 | 0 | 0 | 4847 | 0 | 4847 | 4847 | 0.000 | 0 | 0 | 0 | 0 | 0 |

Figure 4.2 DYNPRO Results on the Recommended Number of Units for an Optimal Expansion Strategy

As shown in Figure 4.2, this combination also indicates that the expansion plan is not optimal. It recommends keeping all four hydropower units added in Varsys from 2028 while introducing the first solar unit in 2030, followed by at least three additional units in 2035. This is likely due to the absence of diesel power plants in the plan, making it difficult to ensure sufficient dispatchable capacity given Solar's intermittency. Furthermore, after 2034, more than two units of both peat-fired and municipal waste power plants are required to meet demand.

#### 4.4.2.3 Optimal Expansion Plan

After several iterations of combinations in CONGEN, the optimal expansion plan was determined. Figure 4.3 presents the required number of optimal units for each year.

Figure 2.1

SOLUTION # 1 VARIABLE ALTERNATIVES BY YEAR

| YEAR | PRESENT WORTH COST OF THE YEAR ( K$ ) CONCST | SALVAL | OPCOST | ENSCST | TOTAL | OBJ.FUN. (CUMM.) | LOLP % | PEAT | SOL | MUN | FOIL | OHYD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2040 | 4995 | 4359 | 14552 | 13723 | 28911 | 1735571 | 45.283 | 4 | 5 | 6 | 5 | 5 |
| 2039 | 33314 | 25508 | 15922 | 94418 | 118146 | 1706660 | 45.336 | 4 | 4 | 6 | 5 | 4 |
| 2038 | 23262 | 15476 | 14643 | 118212 | 140641 | 1588514 | 45.338 | 4 | 4 | 4 | 4 | 4 |
| 2037 | 53605 | 31112 | 15934 | 125490 | 163917 | 1447874 | 45.340 | 3 | 3 | 3 | 4 | 4 |
| 2036 | 0 | 0 | 14170 | 149720 | 163891 | 1283957 | 45.340 | 3 | 1 | 1 | 3 | 4 |
| 2035 | 14338 | 6880 | 15417 | 132306 | 155182 | 1120067 | 45.338 | 3 | 1 | 1 | 3 | 4 |
| 2034 | 15772 | 6677 | 12867 | 125564 | 147526 | 964884 | 45.342 | 2 | 1 | 1 | 2 | 4 |
| 2033 | 0 | 0 | 9682 | 112096 | 121778 | 817358 | 45.329 | 1 | 1 | 1 | 1 | 4 |
| 2032 | 14027 | 4610 | 10609 | 97545 | 117571 | 695580 | 45.332 | 1 | 1 | 1 | 1 | 4 |
| 2031 | 33554 | 8084 | 6267 | 82476 | 114213 | 578009 | 45.228 | 1 | 1 | 1 | 0 | 4 |
| 2030 | 12955 | 2543 | 6730 | 65707 | 82849 | 463796 | 45.352 | 0 | 1 | 0 | 0 | 4 |
| 2029 | 0 | 0 | 7685 | 48295 | 55980 | 380948 | 45.338 | 0 | 0 | 0 | 0 | 4 |
| 2028 | 56335 | 12076 | 7704 | 35032 | 86996 | 324968 | 30.721 | 0 | 0 | 0 | 0 | 4 |
| 2027 | 76500 | 14504 | 8937 | 43359 | 114291 | 237972 | 45.345 | 0 | 0 | 0 | 0 | 2 |
| 2026 | 0 | 0 | 9913 | 51934 | 61847 | 123681 | 45.347 | 0 | 0 | 0 | 0 | 0 |
| 2025 | 0 | 0 | 10412 | 26705 | 37116 | 61834 | 30.716 | 0 | 0 | 0 | 0 | 0 |
| 2024 | 0 | 0 | 9975 | 9896 | 19871 | 24718 | 16.098 | 0 | 0 | 0 | 0 | 0 |
| 2023 | 0 | 0 | 4847 | 0 | 4847 | 4847 | 0.000 | 0 | 0 | 0 | 0 | 0 |

Figure 4.3 Optimal Units Required for Each Year

Figure 4.3 indicates that no additions or reductions are suggested in the plan, confirming that this represents the optimal combination. Unlike the BAU and NDC scenarios, the plan proposes a significant increase in peat-fired, municipal waste, solar, and import/diesel power plant units starting in 2037.

Figure 4.4 illustrates the corresponding additional installed capacities, aligning with the optimal expansion strategy outlined in Figure 4.3.

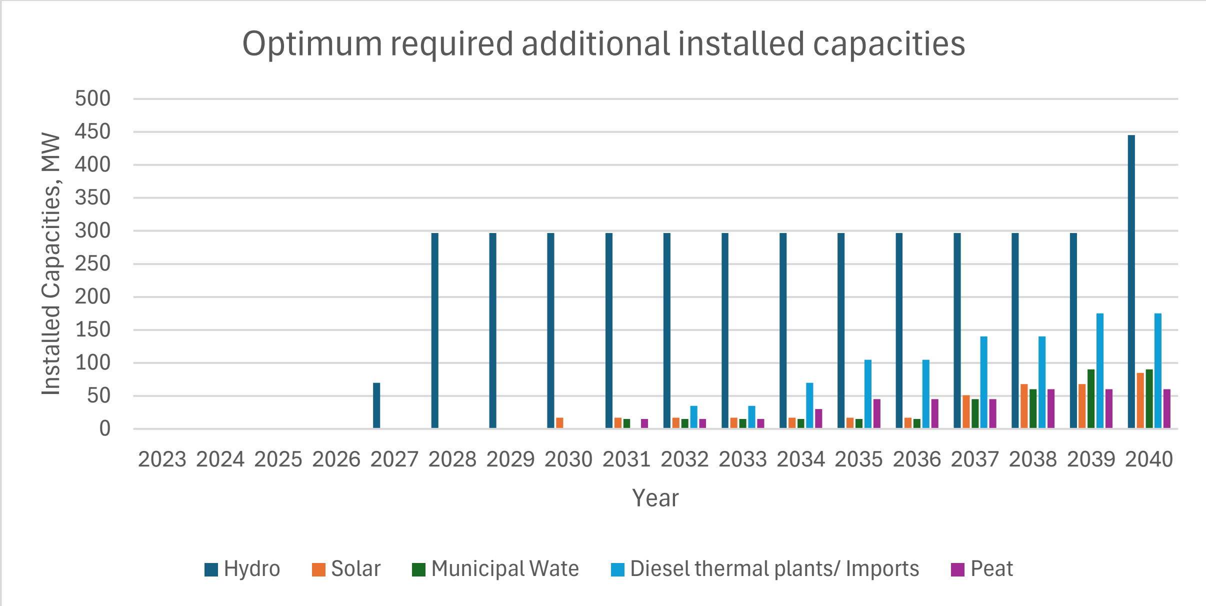


Figure 4.4 Optimum Required Additional Plants

The projected additional installed capacities. As illustrated in Figure 4.4 indicate a strong reliance on hydropower, with a major expansion in 2027 by 69.85 MW, increasing in 2028 by 296.65 MW and further to 445.25 MW by 2040, reinforcing its role as Burundi's primary energy source. Solar power is introduced in 2030 (17 MW) and steadily increases, reaching 85 MW by 2040. Municipal waste-to-energy (WTE) emerges in 2031 (15 MW) and expands to 90 MW by 2039, highlighting efforts to integrate waste management into energy production. Diesel thermal plants, which can also represent imports start contributing in 2032 (35 MW), rising to 175 MW by 2039, signaling ongoing reliance on fossil fuels for grid stability. Peat-based thermal power is introduced in 2031 (15 MW) and stabilizes at 60 MW by 2038, suggesting a strategy to utilize local resources.

Figure 4.5 represents the total amount of money to be invested each year.


Figure 4.5 Total Amount of Money to be Invested Each Year`

Figure 4.5 illustrates the annual investment trajectory required for Burundi's planned energy expansion from 2023 to 2040. From 2023 to 2026, there is a pattern of minimal spending characterized by operational costs of the existing plants only. From 2027, capital injections begin with the 69.75MW hydro plant addition. Early on, investments remain low as no new capacity is added until 2027, when a substantial increase is needed to support the initial hydropower projects. This trend continues with even larger investment peaks in subsequent years, particularly in 2028 and beyond, reflecting the accelerated expansion in hydropower, as well as the phased introduction of solar, municipal waste-to-energy, diesel thermal, and peat-based plants.

# CHAPTER 5 CONCLUSION AND RECOMMENDATIONS

## 5.1 Conclusion

This study aimed to assess sustainable electricity generation scenarios in Burundi using a multi-criteria approach. It involved assessing energy resources, forecasting electricity demand, and modeling various investment scenarios to identify the most optimal and cost-effective option for meeting demand over a 15-year period. The study considered three scenarios: business as Usual (BAU), Nationally Determined Contribution (NDC) and Optimal expansion plan.

In the BAU scenario, electricity generation followed historical trends with minimal intervention, leading to an increased reliance on existing hydropower resources without significant diversification. While this scenario maintained the current energy mix, it poses risks of supply shortages due to limited dispatchable capacity, especially during peak demand periods.

The NDC scenario aligned with Burundi's climate commitments, prioritizing renewable energy integration with increased solar and hydropower capacity additions. While this scenario contributed to sustainability goals, it does not fully address intermittency challenges due to the absence of sufficient backup generation, potentially compromising system reliability in the absence of flexible energy sources.

The optimized expansion scenario, determined through iterative modeling in CONGEN, provided the most balanced approach by incorporating diverse energy sources. It recommended maintaining all four hydropower units from 2028 while gradually introducing solar energy from 2030, followed by additional units in 2035. Unlike the BAU and NDC scenarios, this plan proposed significant additions of peat-fired, municipal waste, and diesel power plants from 2037 onward to enhance dispatchability and grid stability. The model also discourages early investments in municipal waste and peat-fired power plants before 2034, ensuring cost-effectiveness by phasing in these resources only when needed.

## 5.2 Recommendations

While this study provides valuable insights into Burundi's electricity generation expansion, the following areas require further research to enhance future planning and decision-making:

The study employed an econometric demand forecast model, based on the assumption that historical relationships between electricity demand and economic factors such as GDP, income, and industrial output remain unchanged over time. Given Burundi's commitment to industrial growth through the National Development Plan (NDP) 2018–2027, future research should incorporate more detailed socio-economic and industrial development projections to enhance demand forecasting and ensure alignment with national goals.

Additionally, this study primarily focused on the required capacity expansion without addressing funding constraints. Future research should conduct a comprehensive cost-benefit analysis, considering financing mechanisms, tariff impacts, and potential subsidies to support informed investment decisions.

Moreover, the modeling software used in this study does not account for power imports, instead prioritizing local generation. As Burundi strengthens its participation in Regional Power Trade, it is crucial to integrate cross-border electricity trade with neighboring countries to enhance supply reliability and reduce dependence on diesel power generation.

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# APPENDICES

**Appendix A: National Commission for Science, Technology and Innovation (NACOSTI) research certificate.**

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 835331

Date of Issue: 22/March/2025

**RESEARCH LICENSE**

**This is to Certify that Miss.. Leslie Igiraneza of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nairobi on the topic: Assessment Of Sustainable Electricity Generation Scenarios In Burundi Using Multi-Criteria Approaches for the period ending : 22/March/2026.**

License No: NACOSTI/P/25/417235

835331

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Director General

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

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**See overleaf for conditions**

## Appendix B: Ethical Review Approval

Strathmore UNIVERSITY

**15th November 2024**

Ms Leslie Nice Igiraneza,
leslie.igiraneza@strathmore.edu

Dear Ms Leslie,

**RE: Assessment of Sustainable Electricity Generation Scenarios in Burundi using Multi-Criteria Approaches**

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** proposal. Your application reference number is **SU-ISERC2335/24.** The approval period is from **15th November 2024 to 14th November 2025.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

**Mr Ambrose Rachier,**
**Chairperson; SU-ISERC**

Ole Sangale Rd, Madaraka Estate. PO Box 59857-00200, Nairobi, Kenya. Tel +254 (0)703 034000
Email admissions@strathmore.edu www.strathmore.edu

## Appendix C: Similarity Index



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## Appendix D: DYNPRO Final Simulation Results

```
            Demonstration Case (Fixed Expansion)
    0   27    0    3    4    1 0HYD HYD2     0.55     0.55 1.0000 0.0000 0.0000 0.0000 0.0000     0
 PEAT    0    8.   15.11000.12000.   35.    0.    6   10   1.0   30   15.    0.10    0.20
 SOL     0   10.   17.    0.    0.    0.    0.    4   10   0.5   12   17.    1.25    0.02
 MUN     0    8.   15.11000.12000.   35.    0.    7   10   1.0   30   15.    0.10    0.20
 FOIL    0   25.   37. 2616. 2525. 1414. 1542.    4   28   6.3   22   35.    2.30    7.50
    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.     6     0
     2     1     3     4
   0.02  4.21  4.21 83.97
  NAMH  NCH  JAV    CMWI    CMWB    CMWP    CMWC     CEM     CEP     CEA
  0HYD    1 2026    10.6     1.7     0.0     1.7     5.0     0.0     5.0
  0HYD    1 2026    10.6     1.7     0.0     1.7     5.0     0.0     5.0
  0HYD    1 2026    10.6     2.7     0.0     2.7     8.0     0.0     8.0
  0HYD    2 2027    59.2    10.6     0.0    10.6    31.0     0.0    31.0
  0HYD    2 2027    59.2    10.6     0.0    10.6    31.0     0.0    31.0
  0HYD    2 2027    59.2    14.7     0.0    14.7    43.0     0.0    43.0
  0HYD    3 2027   108.2    17.9     0.0    17.9    52.3     0.0    52.3
  0HYD    3 2027   108.2    17.9     0.0    17.9    52.3     0.0    52.3
  0HYD    3 2027   108.2    29.8     0.0    29.8    87.0     0.0    87.0
  0HYD    4 2028   118.6    19.6     0.0    19.6    57.3     0.0    57.3
  0HYD    4 2028   118.6    19.6     0.0    19.6    57.3     0.0    57.3
  0HYD    4 2028   118.6    32.5     0.0    32.5    95.0     0.0    95.0
  0HYD    5 2028   148.6    19.6    18.0    37.6    57.3    31.0    88.3
  0HYD    5 2028   148.6    19.6    18.0    37.6    57.3    31.0    88.3
  0HYD    5 2028   148.6    32.5    18.0    50.5    95.0    31.0   126.0
  0HYD    6 2038   168.6    26.8    18.0    44.8    78.3    31.0   109.3
  0HYD    6 2038   168.6    26.8    18.0    44.8    78.3    31.0   109.3
  0HYD    6 2038   168.6    39.7    18.0    57.7   116.0    31.0   147.0
    0
```

```
    WASP  COMPUTER  PROGRAM  PACKAGE
             DYNPRO  MODULE
              CASE  STUDY
  Demonstration Case (Fixed Expansion)


 *************************************
 *                                   *
 *   LIST OF VAR. EXPAN. CANDIDATES  *
 *                                   *
 *************************************
 *          THERMAL   PLANTS         *
 *                                   *
 *      SEQU.NUMBER        NAME      *
 *           1             PEAT      *
 *           2             SOL       *
 *           3             MUN       *
 *           4             FOIL      *
 *                                   *
 *************************************
 *        HYDROELECTRIC PLANTS       *
 *                                   *
 *      SEQU.NUMBER        NAME      *
 *           5             0HYD      *
 *                                   *
 *************************************
```

```
ALL COSTS WILL BE DISCOUNTED TO THE YEAR   2023
BASE YEAR FOR COST ESCALATION CALCULATION  2023
FIRST YEAR OF STUDY = 2023
DURATION  OF  STUDY =   18 YEARS
DISCOUNT RATE APPLIED TO ALL DOMESTIC COSTS - %/YR =  10.00
DISCOUNT RATE APPLIED TO ALL FOREIGN  COSTS - %/YR =  10.00

                                          *****  INPUT OF YEAR 2023  *****
INDEX =    2
        -- C A P I T A L   C O S T S  ($/KW) --     PLANT                CONSTR.
        (DEPRECIABLE PART)  (NON-DEPREC. PART)      LIFE      I.D.C.      TIME
PLANT    DOMESTIC FOREIGN     DOMESTIC FOREIGN     (YEARS)     (%)       (YEARS)
PEAT      318.0     477.0        0.0       0.0       40.      11.92        3.0
SOL       594.0     891.0        0.0       0.0       25.      19.20        5.0
MUN      3000.0    1000.0        0.0       0.0       25.      12.00        3.0
FOIL      300.0     600.0        0.0       0.0       40.      12.00        3.0
0HYD  HYDRO PROJECT(S) CAPITAL COSTS
ROR3      841.0     841.0                            50.      22.67        6.0
ROR1      970.0     970.0                            50.      22.67        6.0
VHY2      742.0     742.0                            50.      19.20        5.0
ROR2      866.0     866.0                            50.      19.20        5.0
 LMS        0.0       0.0                            50.       0.00        0.0
SECL        0.0       0.0                            50.       0.00        0.0
INDEX =   13
NUMBER OF BEST SOLUTIONS REQUESTED IS    1
INDEX =   16
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
          CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
USE LINEAR DEPRECIATION METHOD FOR SALVAGE VALUE CALCULATION
OBJECTIVE FUNCTION STATE    1 TO    1
       4847.
           1

                                          *****  INPUT OF YEAR 2024  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
          CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE    2 TO    2
      24718.
           1

                                          *****  INPUT OF YEAR 2025  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
          CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE    3 TO    3
      61834.
           2
```

```
                                                     *****  INPUT OF YEAR 2026  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
            CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE    4 TO    4
      123681.
             3

                                                     *****  INPUT OF YEAR 2027  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
            CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE    5 TO    5
      237972.
             4

                                                     *****  INPUT OF YEAR 2028  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
            CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE    6 TO    8
      319420.      324968.      294470.
             5            5            5

                                                     *****  INPUT OF YEAR 2029  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
            CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE    9 TO    9
      380948.
             7

                                                     *****  INPUT OF YEAR 2030  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
            CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE   10 TO   10
      463796.
             9
```

```
                                         *****  INPUT OF YEAR 2031  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
          CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE   11 TO   11
     578009.
          10

                                         *****  INPUT OF YEAR 2032  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
          CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE   12 TO   12
     695580.
          11

                                         *****  INPUT OF YEAR 2033  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
          CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE   13 TO   13
     817358.
          12

                                         *****  INPUT OF YEAR 2034  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
          CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE   14 TO   15
     964884.     932484.
          13          13

                                         *****  INPUT OF YEAR 2035  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
          CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE   16 TO   16
    1120067.
          14

                                         *****  INPUT OF YEAR 2036  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
          CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE   17 TO   17
    1283957.
          16
```

```
                                        *****  INPUT OF YEAR 2037  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
          CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE   18 TO   18
    1447874.
          17

                                        *****  INPUT OF YEAR 2038  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
          CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE   19 TO   21
    1600560.    1588514.    1577593.
          18          18          18

                                        *****  INPUT OF YEAR 2039  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
          CF1 =   1.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE   22 TO   22
    1706660.
          20

                                        *****  INPUT OF YEAR 2040  *****
INDEX =   11
COEFFICIENTS FOR CALCULATION OF COST OF ENERGY NOT SERVED - IN $/KWH :
          CF1 =   0.0000    CF2 =   1.0000    CF3 =   1.0000
INDEX =   12
CRITICAL LOSS-OF-LOAD PROBABILITY - IN (%) =   100.0000
INDEX =    1
OBJECTIVE FUNCTION STATE   23 TO   23
    1735571.
          22

OLUTION #  1 VARIABLE ALTERNATIVES BY YEAR
```

| YEAR------ | PRESENT WORTH COST OF THE YEAR ( K$ )------ CONCST | SALVAL | OPCOST | ENSCST | TOTAL | OBJ.FUN. (CUMM.) | LOLP % | PEAT | SOL | MUN | FOIL | 0HYD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2040 | 4995 | 4359 | 14552 | 13723 | 28911 | 1735571 | 45.283 | 4 | 5 | 6 | 5 | 5 |
| 2039 | 33314 | 25508 | 15922 | 94418 | 118146 | 1706660 | 45.336 | 4 | 4 | 6 | 5 | 4 |
| 2038 | 23262 | 15476 | 14643 | 118212 | 140641 | 1588514 | 45.338 | 4 | 4 | 4 | 4 | 4 |
| 2037 | 53605 | 31112 | 15934 | 125490 | 163917 | 1447874 | 45.340 | 3 | 3 | 3 | 4 | 4 |
| 2036 | 0 | 0 | 14170 | 149720 | 163891 | 1283957 | 45.340 | 3 | 1 | 1 | 3 | 4 |
| 2035 | 14338 | 6880 | 15417 | 132306 | 155182 | 1120067 | 45.338 | 3 | 1 | 1 | 3 | 4 |
| 2034 | 15772 | 6677 | 12867 | 125564 | 147526 | 964884 | 45.342 | 2 | 1 | 1 | 2 | 4 |
| 2033 | 0 | 0 | 9682 | 112096 | 121778 | 817358 | 45.329 | 1 | 1 | 1 | 1 | 4 |
| 2032 | 14027 | 4610 | 10609 | 97545 | 117571 | 695580 | 45.332 | 1 | 1 | 1 | 1 | 4 |
| 2031 | 33554 | 8084 | 6267 | 82476 | 114213 | 578009 | 45.228 | 1 | 1 | 1 | 0 | 4 |
| 2030 | 12955 | 2543 | 6730 | 65707 | 82849 | 463796 | 45.352 | 0 | 1 | 0 | 0 | 4 |
| 2029 | 0 | 0 | 7685 | 48295 | 55980 | 380948 | 45.338 | 0 | 0 | 0 | 0 | 4 |
| 2028 | 56335 | 12076 | 7704 | 35032 | 86996 | 324968 | 30.721 | 0 | 0 | 0 | 0 | 4 |
| 2027 | 76500 | 14504 | 8937 | 43359 | 114291 | 237972 | 45.345 | 0 | 0 | 0 | 0 | 2 |
| 2026 | 0 | 0 | 9913 | 51934 | 61847 | 123681 | 45.347 | 0 | 0 | 0 | 0 | 0 |
| 2025 | 0 | 0 | 10412 | 26705 | 37116 | 61834 | 30.716 | 0 | 0 | 0 | 0 | 0 |
| 2024 | 0 | 0 | 9975 | 9896 | 19871 | 24718 | 16.098 | 0 | 0 | 0 | 0 | 0 |
| 2023 | 0 | 0 | 4847 | 0 | 4847 | 4847 | 0.000 | 0 | 0 | 0 | 0 | 0 |