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Using Long-Term Energy System Analysis for Determining Land Value: The Case of the Lake Turkana Wind Power Project

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Abstract

Land values are typically derived in agricultural, property and social contexts, but rarely derived in the context of energy production. This thesis investigates the Lake Turkana Wind Project (LTWP) in Marsabit County, Kenya to derive land values for the areas most suitable for wind power production through a long-term energy system analysis. The Energy Transition and Investment Plan for 2023-2050 (ETIP), published by the Ministry of Energy and Petroluem, served as the basis for the model. The software of choice in this thesis is the Open Source Energy System Modelling Software (OSeMOSYS). Furthermore, data from the Kenya Power and Lighting Company (KPLC) was used to construct the framework of the mode. The land value of the potent areas in Marsabit were found to be 1.08 mill. USD per km^2, which is low when compared cases were larger wind turbines are used, and low when compared to other renewable energy technologies. This indicates that the land energy is under utilized, as it could potentially contribute more to the energy system while using less land area. By changing the turbine models, and thereby the energy potential in a plot of land, the land values for other renewable energy sources changes. Lastly, comparisons are done with the results of this model and the ETIP. It seems that the Net Zero pathway as outlined by the ETIP is either not strict enough, or Kenya is in a position where renewable energy technologies are so competitive and there is ample primary energy resources in Kenya such that there is little difference between the optimal solutions of a low cost and net zero pathways. Lastly, using land values to infer land rents is discussed. There could potentially be a difference in interest between the government and a company. Lands with higher land values are more beneficial to the energy system, which would increase the land rent. This, in turn, steers companies away as they seek to minimize land rents.

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Contents

Chapter 1 **8**
1.1 Introduction 8
1.2 Research Question 10
1.3 Literature Review 11

Chapter 2 **15**
2.1 Theoretical Background 15
2.1.1 Energy System Analysis 15
2.1.2 Linear Optimisation 16
2.2 Overview over the Kenyan Electrical Power System 17
2.2.1 Economic Profile and Governance of Energy Sector 17
2.2.2 Electricity Demand 18
2.2.3 Electricity Generation 18
2.2.4 Current and Future Challenges 20
2.3 The Lake Turkana Wind Project (LTWP) 21

Chapter 3 **23**
3.1 Methodology 23
3.2 Reference Energy System 24
3.3 Open Source Energy System Modelling Software (OSeMOSYS) 25
3.4 Input Variables 27
3.4.1 Sets 27
3.4.2 Parameters 30

Chapter 4 **45**
4.1 Results 45
4.1.1 Optimal Solution 45
4.1.2 Comparison with ETIP 47
4.1.3 Value of Land Area 48
4.2 Further Analysis 49
4.2.1 Investigating Different Turbine Models 49
4.2.2 Comparison of LTWP and Other Energy Sources 52
4.2.3 Changing the Reference Scenario 54

Chapter 5 **57**
5.1 Area As an Input Parameter . . . 57
5.2 Land Value for Indigenous Groups and the Local Populous . . . 58
5.3 The ETIP and the Net Zero pathway . . . 59

Chapter 6 **60**
6.1 Conclusions . . . 60
6.2 Limitations . . . 60
6.3 Further Research . . . 61

A Other Parameters **70**

B Example KPLC data **74**

List of Figures

1 Boxplot of the Load for 2020 (KPLC data) . . . 18
2 Montly average load curve (KPLC data) . . . 19
3 Shares of Generation Type per Month (KPLC data) . . . 20
4 Mean Power Density of Kenya (Badger et al., 2015). . . . 22
5 Reference Energy System of the Kenyan electrical energy system . . . 25
6 Seasonal average load curve . . . 28
7 Weekdays vs Weekends average load curve . . . 29
8 Electricity Demand by Sector from 2020 to 2050 (Ministry of Energy & Petroleum, 2023, p.49) . . . 31
9 Fuel Costs with actual data points and fits (EIA, 2010b, p.143) . . . 36
11 Mean Power Density Distribution of the 4 windiest areas in Marsabit Badger et al. (2015) . . . 41
12 The Cumulative Installed capacity per year for the 4 scenarios . . . 45
13 The New Installed capacity per year for the 4 scenarios . . . 46
14 Installed capacity in 2050 [GW] . . . 47
15 Comparison of the Net Zero from the ETIP and from this thesis . . . 48
16 Cumulative Installed Capacities per year for the 3 different wind turbine models . . . 50
17 New Installed Capacities per year for the 3 different wind turbine models . . . 51
18 Installed capacity in 2050 with V110 Scenario [GW] . . . 55

List of Tables

1 Summary of the 4 scenarios used for modelling . . . 23
2 Summary of sets used in the model . . . 30
3 Estimated demand per sector per year . . . 32
4 Fraction of total demand per time slice . . . 32
5 Capacity Factors per technology per timeslice for 2020 . . . 34
6 Residual Capacity [MW] . . . 34
7 Heating value for fossil fuels (EIA, 2010b, p.169) . . . 36
8 Capital, Fixed and Variable Costs . . . 37
9 Efficiencies for the technologies . . . 38
10 Amount of Maximum Theoretical Energy in Marsabit . . . 42
11 Amount of Maximum Theoretical Energy for the rest of Kenya . . . 42
12 Maximum motential Solar energy within Kenya . . . 42
13 Estimated Renewable Energy Sources in Kenya . . . 43
14 Emission Factors per Technology . . . 44
15 Allowed Emissions in the Net Zero scenarios . . . 44
16 Total costs of the 4 scenarios . . . 46
17 Opportunity cost of the 4 scenarios . . . 49
18 Energy available per wind turbine model . . . 50
19 Land Values of Marsabit Using Different Turbine Models . . . 51
20 Effect on total system cost by changing capital cost of the V136 model . . . 52
21 Land Values of Solar, Geothermal and Hydroelectric . . . 54
22 Land Values of Solar, Geothermal and Hydroelectric with V110 as a reference . . . 55
23 Fractions for parameter YearSplit . . . 71
24 Fractions for DaySplit . . . 71
25 Season Table . . . 72
26 Daytype Table . . . 72
27 Dailytimebracket . . . 72
28 Fraction of total demand per timeslice . . . 72

Nomenclature

ETIP Energy Transition and Investment Plan

GW Gigawatt

IMPx Imported “x”. E.g IMPGAS denotes imported gas

KETRACO Kenya Transmission Company

KPLC Kenya Power and Lighting Company

LTWP Lake Turkana Wind Project

MW Megawatt

MWh Megawatthours

OSeMOSYS Open Source Energy System Moddeling Software

PWRx Power plant “x”. E.g PWRHYDRO denotes a hydroelectric power plant

RES Reference Energy System

RESx Resource of “x”. E.g RESWATER denotes water as a primary energy resource

TWh Terrawatthour

USD U.S Dollars

Chapter 1

1.1 Introduction

As the countries around the world are trying to limit their carbon emissions in the energy sector in order to combat the climate crisis, global societies face challenges and conflicts on the path to net zero. However, most countries in the world realize the importance of decarbonizing, as is evident with the landmark agreement Paris Agreement (UNFCC, n.d.), which obligates nations lower their greenhouse emissions in order to prevent the global average temperature of exceeding 1.5 °C by 2050. Recently, the Intergovernmental Panel on Climate Change (IPCC) assessed the consequences of human-induced climate change in the 6th working report (IPCC 6, 2022). The consequences will not affect everyone equally, as marginal groups are more vulnerable to effects. Currently, generating electricity accounts for the vast majority of CO2-emissions (Ritchie, Rosado, & Roser, 2020), due to the lingering dependency on fossil fuels in the power sector. By moving towards renewable energy, like wind and solar, the power sector can decarbonize. The costs of renewable energy sources are rapidly falling, making the renewable energy technologies like wind turbines and solar PV panels competitive, often without subsidies (Roser, 2020). Especially wind power has become the cheapest form of energy available, which has made the installed capacity of wind energy surge in recent years (Ritchie, Roser, & Rosado, 2020).

However, moving away from fossil fuels towards renewable sources is not without challenges. Renewable energy technologies like wind and solar can only be constructed in areas with abundance of the resource. Wind turbines must be constructed in areas with consistently high wind speeds and solar energy technologies must be constructed in areas with high consistent solar irradiation. Incidentally, these areas are often in contention with nature and/or indigenous groups. One example is the Fosen case in Norway (Barstad, 2023), where the Supreme Court of Norway ruled that the indigenous rights of the Sámi people were infringed by the construction of a 801 MW wind park. A study by the Business & Human Rights Resource Centre recorded over 200 allegations linked to renewable energy projects between 2011 and 2021, where 44% of these allegations are from the wind and solar sectors (Richardson et al., 2022, p. 5). This underlines the challenges relating to decarbonizing the power sector. On the one hand, moving towards renewable energy sources is critical for avoiding the consequences of climate change, yet the marginalised groups that are the most vulnerable to the effects are often the ones that fall victim to land use conflicts. There seems to be a direct conflict between renewable energy and the rights of marginalized groups. However, the Business & Human Rights Resource Centre points out that it is possible to confiscate land area for renewable energy whilst maintaining human rights (Richardson et al., 2022, p. 5).

Another country currently in the midst of a land use conflict between indigenous groups and a wind power plant, is Kenya. This East-African country currently has Africa's largest wind park, namely the Lake Turkana Wind Project (LTWP) (Lake Turkana Wind Power Ltd., n.d.). This wind park is located in the north of Kenya, in the Marsabit County, where the highest wind power potential subsides (EPRA, n.d.). Since it's advent in 2014, LTWP has been plagued by legal troubles, where the local indigenous groups argue that the land area discriminates their rights (Republic of Kenya Supreme Court, 2014).

Kenya, being a low-income country, has had impressive economical growth in the past years (World Bank, 2024) and requires further economical growth to continue lifting it's population out of poverty and into middle-income status, as was planned by the Kenyan president in 2008 (Vision 2030, n.d.). As World Bank (2024) signify, the energy demands of Kenya are expected to increase drastically over the years, by several factors. One is the continued economical growth, which is energy intensive. Furthermore, as the population is lifted out of poverty, it becomes more hungry for energy as well. Balancing between higher energy demand while achieving the climate goals as per the Paris Agreement will prove to be a challenge for Kenya.

The Ministry of Energy and Petroleum recently published their plan on how the energy demands will be satisfied in the Energy Transition and Investment Plan (ETIP) for the years 2020-2050 (Ministry of Energy & Petroleum, 2023). In their report, they plan that onshore wind power accounts for a large portion of the electrictity generation mix. Since the vast majority of Kenya's wind power potential lies in Marsabit County, this means that this region is where the further consumption of land areas will take place. This is already in plans, as 5 companies have already stated their ambitions to construct wind farms (Mutua, 2024). However, with these massive confiscations of land area for wind power production, the conflicts between the power companies and the indigenous groups will arise, as is clear with LTWP. This brings up the question: How can wind power and indigenous groups coexist? What is the value of the land when used for power production when compared to the value which indigenous groups gives it? Can Kenya continue it's economic growth and fulfill it's future energy demand whilst developing wind energy in regions with indigenous groups?

This thesis seeks to investigate the land value that LTWP requires by means of a long-term energy system analysis. This will provide insight into it's necessity for future energy demands when compared to other energy sources. By comparing the land values of different renewable energy sources, policy makers can see which renewable energy sources that are the most valuable to the energy system per land area. This is valuable if the goal is to use the least amount of land for the energy system. Hopefully, choosing the energy sources with the highest land values will limit the amount of land use conflicts if the value of the land is well known. This is especially important wind energy power plants, like LTWP, and indigenous groups that utilize the same areas. The benefits of inferring land value from a long-term system analysis is that the land value will be gathered from the optimal solution, which includes all forms of energy, and not only by considering the costs and benefits of individual power plants in isolation.

The research will be done by analyzing 4 scenarios that have different power characteristics 30 years into the future. 2 of the scenarios will be Low Cost scenarios, one where the land area in Marsabit County is available for wind power extraction, and one where it is not. Likewise, the 2 other scenarios are the Net Zero pathways as outlined by the ETIP. One Net Zero scenario allows for the land area in Marsabit to be utilized, and the other does not. The results from this will be used to gauge a theoretical value of the land area when used for wind power production. With this, a monetary value can be given the land which policy makers can use to make better decisions when faced with the challenge of confiscating land areas.

1.2 Research Question

This thesis seeks to investigate the value of land areas when the land is used for electrical power production, in the context of reaching long-term climate goals, through means of long-term energy system analysis. The Lake Turkana Wind Project (LTWP) will be used as a case. This research aims to give policy makers a deeper understanding of how important certain land areas are for climate goals, and gain an understanding to the amount of potential compensation which must be payed if the land areas are exploited for power production. Policy makers can use the land values to quantify the effects of exploiting one land area for power production one can have on another. Thus, the research question of this thesis will be the following:

How can a long-term energy system analysis contribute to determining the value of an area used for wind power production in the context of reaching climate goals?

To answer this research question, the following sub questions will be investigated:

- What is the effect on land value when changing turbine models?
- How does the land value of LTWP compare to other renewable energy sources?
- How does changing the turbine model in LTWP affect land values for other renewable energy sources?

1.3 Literature Review

The term ”land value” is an already established concept in several different economical contexts, like agricultural, property and feasibility studies. The first economic theories of assessing land value were done by Ricardo (1817). He connected the land value with it’s fertility and determined that the more fertile a land area is, the higher it’s value becomes. In recent years, much research has been done on applying Ricardian methods to investigate how climate change affects land values (Nicita et al., 2020; Seo, 2016; Timmins, 2006). In all of these studies, the value itself is derived from the productivity of the land, and investigating how different effects of climate change (like increased precipitation, less solar irradidation etc.) affect productivity and therefore the land value. The field of spatial economics expands on determining land value (Gilles, 2018). Within this field, the location of the land must also be considered. Gilles (2018) refers to older economics theories derived von Thünen (1826), who argued that farmers should only pay land rent for a land which equals their profits from the land minus their transportation costs. In von Thünen’s theories, the land value to the farmer becomes higher the closer it is the to the central market place. In other words, in an agricultural context, land value is a function of it’s fertility and location.

Gilles (2018) continues to explain how Alonso (1964) developed an approach that advanced von Thünen’s theories into an urban context, which explains why city centres and properties adjacent efficient transportation networks have higher property values. The dynamic between transportation between the area where a good is produced and the transportation costs to the place where revenue is generated largely determines the land value. There are other methods to determine land value as well. Ustaoglu et al. (2016) uses the Net Present Value (NPV) to determine the land value for the EU countries (Ustaoglu et al., 2016). With this method, the all discounted revenues and costs are summed, and only positive NPVs are considered profitable. Again, the revenues stem from the output of agricultural products, which again determines the land value.

Land value also exists in the context of property evaluation in urban economics. This is not to be confused with housing prices. Bourassa and Hoesli (2022) compare 3 methods for appraisal of residential land values (Bourassa & Hoesli, 2022). Hedonic value pricing is a widely used method, which takes land characteristics (like lot size, type of street, amenities etc), neighbourhood and structure characteristics (like building size, number of bedroom, construction-quality etc.) as inputs to calculate property value. However, hedonic models also takes improvements into account, which do not necesarrily reflect the land value itself. Therefore, Bourassa and Hoesli (2022) compares hedonic models with so-called ”residual” and ”matching techniques”. The residual approach subtracts an appraised value of a structure from the total property value, which also includes depreciation of the structure. The third approach involves matching the sales of vacant land with the sale of a representative vacant land. This third approach is also used by other researchers (Albouy & Shin, 2022; Larson & Shui, 2022; Longhofer & Redfearn, 2022). In their research, land values are estimated by using transactions found in public records. The issue with this method, is that vacant land is rarely sold in urban areas. Still, Bourassa and Hoesli (2022) conclude that these matching techniques are the best method for determining land value. All of this research has the central assumption that the value is inferred by the market value. So, the price for which the specific land or a similar land was sold for becomes the value.

Thus far, land values has been looked at in agricultural and urban contexts. In the context of energy, a well researched subject is how energy installations affect land and property values. Most notably is the research on how wind power plants (Brunner et al., 2024; Heintzelman & Tuttle, 2012; Mei et al., 2024; S. Sampson et al., 2020; Vyn, 2018) and nuclear power plants (Gawande & Jenkins-Smith, 2001; Munro & Tolley, 2018; Zhu et al., 2016) influences property value. The impacts of installation of other power plants seem to not be as well researched. However, the impacts of opening coal or uranium mines do, but this is outside the scope of this review. S. Sampson et al. (2020) investigated the effects of installing wind turbine plants on agricultural lands in Kansas using hedonic pricing and found that wind turbines do not affect agricultural property values. Brunner et al. (2024), Heintzelman and Tuttle (2012), and Mei et al. (2024) did similar analyses and found the opposite to be true for residential property value, namely that wind turbines have a negative effect on property prices on properties close to the installation. However, Brunner et al., 2024 notes that the property prices recovers around 9 years in after the project announcement. Vyn (2018) expands on the literature by dividing municipalities into ”willing” and ”unwilling” and found that property values are only affected in ”unwilling” municipalities, also using a hedonic approach. For properties surrounding nuclear power plants Clark et al. (1997) and Munro and Tolley (2018) found no negative correlation between property values of homes next to nuclear power plants. Zhu et al. (2016) looked at land markets in China right after the 2011 accident in Fukushima, and found that the accident lowered land prices within 40 km of any nuclear power plant, but the impact became statistically insignificant in the long term. However, Gawande and Jenkins-Smith, 2001 did find a negative impact of property values in populous coastal urban areas close to shipment routes containing nuclear waste. The effects of solar power plants on land value does not seem to have been researched in large quantities. One researcher found that solar farms do not have any direct effect on agricultural land values (Abashidze & Taylor, 2023). These researchers investigates the effects of the construction of energy power plants has on already established land values.

Land values in an agricultural context is associated with the productivity, and property values are valuable for residents living in urban areas. However, land areas also contain a social value, which is more difficult to quantify. Especially indigenous groups attribute great social and cultural value to their lands. As Nysten-Haarala et al. (2021) pointed out, the value of land to and indigenous group is not possible to measure in a monetary value (Nysten-Haarala et al., 2021). There has been some research done on assessing the social values of land (Brown et al., 2014; Kline et al., 2004; Zahidi et al., 2024). However, since social value inherently cannot be measured in monetary terms, it is not an easy task to decide how land area should be best utilized. One existing method of considering social impacts when assessing for renewable energy projects is through a cost-benefit analysis (Misuraca, 2014). For energy projects, this type of analysis can be used to measure the feasibility of an investment option, by analyzing if the benefits outweigh the costs. Within these benefits, the social, ecological and cultural benefits are assessed. One example of this was done when assessing a wind power project in Latvia (Rozentale & Blumberga, 2021). Here, the researchers discuss the Kaldor-Hicks compensation test, which states that: ”social welfare of a project is positive in case the benefits of a project are so big that the project promoters would be able to compensate the costs for those who have loses due to the project”. For energy projects, this social value is of importance to consider. Since renewable energy like wind and solar must be installed in places that contain abundant primary wind speeds and solar irradiation, they are often in conflict with the social value given by local population and indigenous groups that already utilize the land area.

Conflicts regarding wind energy and indigenous groups and local populations are well documented, as documented by the Business & Human Rights Resource Centre (Business & Human Rights Resource Centre, 2020). As such, much research has been done on these land-use conflicts and how to best solve them. Nysten-Haarala et al. (2021) investigates the conflicts between reindeer herders in Northern Finland and wind power projects (Nysten-Haarala et al., 2021). In their view, areas used for reindeer herding should not be used for wind power projects due to the human rights issues. If they must, the herders should be compensated. Furthermore, Nysten-Haarala et al. (2021) discusses the issues with putting a monetary value on land used for traditional activities by indigenous groups, and that the compensations towards the reindeer herders are kept as a trade secret. One method of compensation is through implementing land rent that is payed to the owners of the land. Alonso Serna (2022) investigates the concept of ”land grabbing” in the context of wind energy projects and how land rent also can be contentious. For a compensation system like land rent to exist, there must be an owner or owners that collect the rent, which implies that someone must own the land. Furthering this notion, Martínez-Mendoza et al. (2020) researches the social impact of wind energy in the same location as Alonso Serna (2022) (Martínez-Mendoza et al., 2020). Martínez-Mendoza et al. (2020) conclude that the beneficiaries of a land rent are the farmers who own the land, and not necessarily the indigenous groups that also use the land area. All of this research focuses on the conflicts between renewable energy and the conflicts using quantitative analyses and see the conflicts from the perspective of the local populations and indigenous groups, but do not use arguments from an energy system analysis. Furthermore, land rent and other compensation methods are often kept secret and might not necessarily be fair. A producer might put a value on the lot it wants to construct a power plant on, given by the future benefits, costs and the current market value of the land, but this value will only be an isolated for that specific project. The local populous which rely on the land might not know how to properly value the land they posess.

The literature has several methods to determine land value in different contexts. However, there is a gap in how land value is determined when it is used for energy production. As mentioned, a cost-benefit analysis can be done to investigate if a power plant will be profitable in isolation, but it does not say anything about how valuable the plot of land is to the energy system. Without a more holistic way of thinking about land use, land use conflicts are bound to be prevalent, which is clear with the conflict regarding the LTWP. Therefore, other methods must be constructed such that the evaluation of land areas in an energy system context can be made more fair. This thesis seeks to determine the land value of the land in Marsabit in the context of energy system analysis. The derived values becomes the value of the land to the rest of the energy system, and is useful to quantify which areas provide the most benefits when used for power production.

Chapter 2

This chapter defines the context and the background behind of the research in this thesis. First, the theoretical background required will be discussed. Here, energy system analysis as a concept and linear optimization will be explained. Thereafter, the Kenyan electrical power system will be thoroughly investigated, by first explaining what kind of country that the electricity system serves, then by presenting the central actors that govern the system and lastly discuss the some challenges. Next, the Lake Turkana Wind Project will be presented, with a focus on it's potential and controversies.

2.1 Theoretical Background

2.1.1 Energy System Analysis

Energy system analysis is a field that analyses production, demand, limitations, markets, challenges and more associated with energy and energy use (Blok & Nieuwlaar, 2021). The field can be used to generate long-term strategies to meet expected energy demands at the lowest costs. Constructing energy models and scenarios is conventional (Blok & Nieuwlaar, 2021, p.298). According to Blok & Nieuwlaar, the two main methods of constructing models and scenarios are through optimisation and simulation. Policy makers and stakeholders can use the results to find make better choices for e.g which technologies to invest in, when to invest in them, and give insight into alternatives. These approaches are technological and economical in nature, and rarely directly take into account external variables that are not directly included in the model, like e.g land use change, ecological consequences and so on. Respected entities in the energy sector like the International Energy Agency (IEA), International Renewable Energy Agency (IRENA) and National Laboratory for Renewable Energy (NREL) all include long-term system analysis in their outlooks (Gagnon et al., 2024; International Renewable Energy Agency, 2023; IRENA, 2021b). Energy system analysis is also used by researchers to e.g investigate support schemes and incentives for wind energy in Spain (Ibanez-Lopez & Moratilla-Soria, 2017), investigate the long-term energy demands in Norway (Malka et al., 2023) and to analyze different strategies for implementing a sustainable electricity grid in Africa (Seck & Toba, 2019), to name a few examples. All of the mentioned reports use some energy system modelling framework and method to investigate the energy system in a long-term view.

For long-term energy analysis, several software tools exist on the market (Prina et al., 2022). Some examples include Balmorel (citation), EnergyPLAN (Lund et al., 2021) and TIMES (successor to MARKAL) (Nijs & Ruiz Castello, 2019). These models are freely available to download, but are written in the code language known as GAMS, which requires a license to run. This thesis will use a free and open source software, which anyone can use. For the long-term energy system modelling, this thesis will employ the modelling software known as OSeMOSYS. The reasoning behind this will be explained in chapter 3.3.

2.1.2 Linear Optimisation

As previously described, energy system analysis often uses a method known as linear optimization. At its core, linear optimization seeks to maximize or minimize a linear objective function subject to a set of linear constraints (Bosch & Trick, 2005). A linear optimization problem has the general form:

$$\begin{aligned} & minZ = \sum a_i x_i \\ s.t: \quad & b_{ij} x_{ij} \leq \text{or} \geq c_i \end{aligned}$$

where Z is the total cost of the system, which is to be minimized, x_i is the variable which is optimized, a_i is the cost of one unit of variable x_i and c_i is the constraint that variable x_i is subject to. b_{ij} is a coefficient that is related to the constraint. Variables can have several constraints and there may be several constraint functions, all depending on the system that is optimized. Therefore, all linear optimization models are different.

Blok and Nieuwlaar (2021) explains the benefits of linear optimisation: One of the key strengths of linear optimization in energy system modeling lies in its ability to handle large-scale, interconnected systems with numerous decision variables and constraints. Energy systems are inherently complex, often including a diverse set of energy sources, conversion technologies, storage options, and demand types, to name a few. Linear optimization provides a systematic method of representing these intricacies mathematically. As Bosch and Trick (2005) explains, by formulating the cost function strategically, linear optimisation can be used to minimize the cost in several different contexts. In energy system analysis, would the input variables (x_i) are typically the amount of energy which should be produced and a_i would be the cost per energy unit. If a researcher seeks to e.g minimize emissions from the power sector, the researcher could define the coefficient variables (a_i) to be factors expressed as emissions per energy unit. Thus, linear optimization can be used to make decision-makers informed choices regarding optimizing the societal welfare in the energy system.

2.2 Overview over the Kenyan Electrical Power System

In this section, the demand and production profile of the Kenyan electrical system is investigated, along with a brief economic overview that the electrical system serves and a discussion regarding current and future challenges Kenya faces. In order to investigate the characteristics of the demands and production of electricity, a dataset from the Kenya Power and Lighting Company (KPLC), was made available for this thesis. This dataset contains the electricity production of every power plant connected to the electricity grid for the year 2020, with a resolution of half an hour. A screenshot from the 1^{st} of January is provided in appendix B.

2.2.1 Economic Profile and Governance of Energy Sector

Kenya is an East-African, lower-income country with a population of of around 52 million (World Bank, 2024). According to the World Bank, Kenya's economic growth has been strong for the past 2 decades, averaging a growth in GDP of 4.8% from 2015 to 2019. The years after the pandemic, Kenyas economy grew by 4.8% in 2022 and 5.4% in 2023, which is the expected level of growth for the next 2 years. Furthermore, the poverty rates in the country declined from 35.8% in 2022 to 35.1% in 2023.

In 2019, the way which the energy sector is governed was changed through the Energy Act (Government of Kenya, 2019). In this Act, the goal was to further liberalize the energy sector, and allow for more entities to invest in electricity production. Prior to 2019, the distribution network and retail market was controlled by one government-controlled entity, namely the aforementioned KPLC. The Energy Act of 2019 gives room for the retail space to be opened up by private actors, while responsibility of the distribution network is still that of Kenya Power. The top Authority of the Energy Sector is the Energy & Petroleum Regulatory Authority (EPRA), which will oversee and regulate the energy sector. The transmission network is controlled, maintained and expanded to by Kenya Electricity Transmission Company (KETRACO). Other entities in the space include Kenya Electriciy Generating Company (KenGen), which is a majority state-owned company with a broad portfolio of hydroelectric, geothermal, wind and coal power plants and stands for most of the country's electricity generation (KenGen, n.d.) and the Geothermal Development Company (GDC), which oversees the development of geothermal sites (Geothermal Development Company, n.d.).

2.2.2 Electricity Demand

Figure 1 illustrates the typical load curve in Kenya. This boxplot shows the median load at the given times as the line in the middle of the boxes. The boxes and of the lines show the corresponding 50th and 75th percentile. The white dotes are outliers in the dataset. The clear outlier in the figure, happened on May 9th, where there was a nationwide blackout due to the collapse of a transmission line (Mwende, 2020). As Figure 1 shows, there are three distinct periods of the day: One at night with low load, one during the day with intermediate load and the evening with the highest peak. These are denoted by the vertical stripped lines.

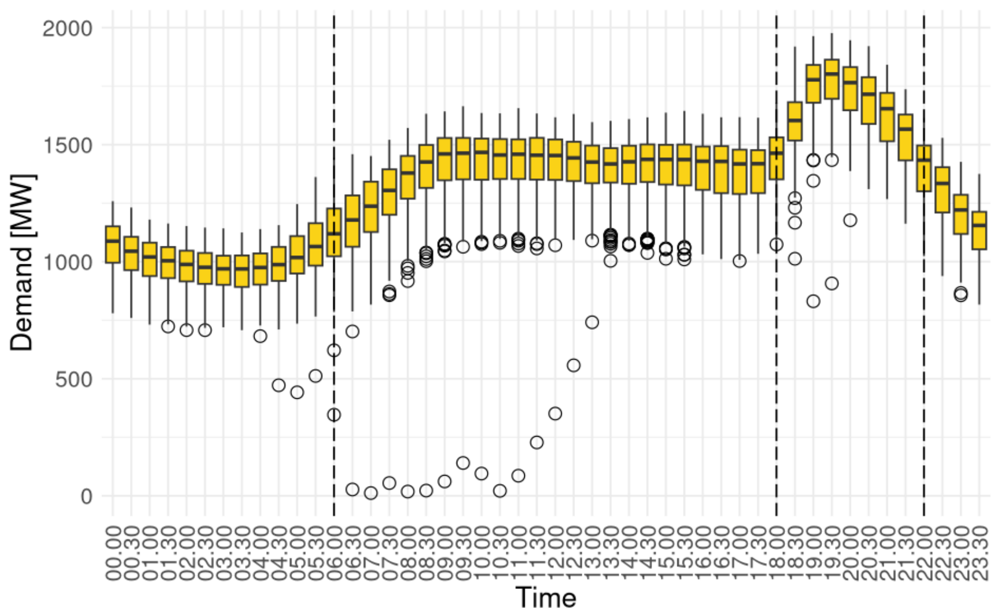


Figure 1: Boxplot of the Load for 2020 (KPLC data)

There is also some difference between the loads during different months, as is clear from figure 2. Here, it is clear to see that April and May have a lower demand than the other months. One explanation for this, is that Kenya experiences the rain season during these two months. November and December also experience heavier rainfaills, albeit not as large as in April and May. Indeed, as Figure 6 shows, there is a considerable difference in average demand during the two different seasons.

2.2.3 Electricity Generation

Kenya can boast a high share of renewable energy in it's energy mix. In 2022, the EPRA estimated that 86.96% of the country's energy production came from renewable sources, where most of the

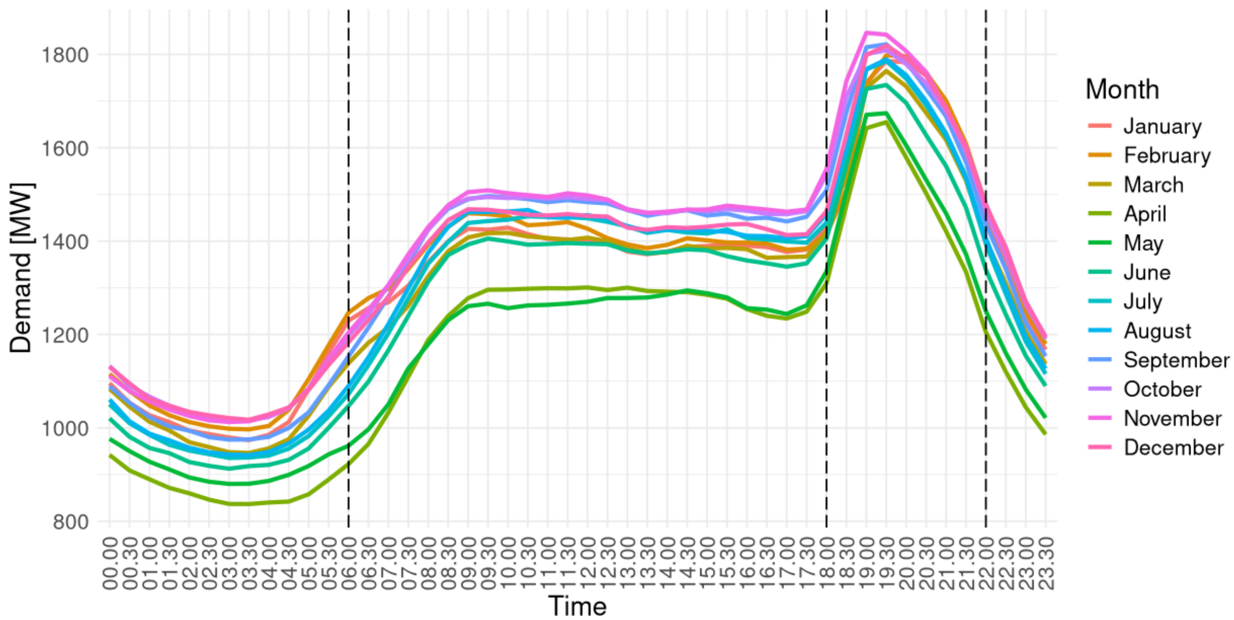


Figure 2: Montly average load curve (KPLC data)

energy came from hydroelectric and geothermal (EPRA, 2022, p. 25). From the KPLC dataset, the share of renewables is even higher. From Figure 3, the share of each generation type for every month in 2020 is shows. The figure clearly shows that the largest part of the electricity generation comes from the geothermal and hydroelectric plants. LTWP also provides a large part of the generation. Together, these 3 generation types generated an average of 92% of the electricity demand in 2020. The fossil fuel plants are mainly generating during high peak hours, namely during the evening.

It must be noted that the used data does not contain the actual demand of customers of KPLC, but merely the generation. From correspondence with a former employee at KPLC, the demand is not measured directly but based on forecasts. The generators must also compensate for losses during transmission and distribution. From the available dataset, a total of 11.50 TWh was generated throughout 2020. When reading through the annual report of KPLC, the total sales of the periods 2019/2020 and 2020/2021 were 8154 and 8553 GWh respectively (KPLC, 2022, p.194). KPLC register their periods lasting from June of the current year to June of the next, which means that the electricity sales of 2020 can be estimated by summing the halves of the total sales of each period. This brings the sales of 2020 to 8353.3 GWh, or 8.35 TWh. This is substantially less than the produced electricity in 2020. This means that the efficiency of the whole system is 72.61%. In other word, the overall losses in the system is 27.39 &. This inefficiency can be caused by two main factors: technical inefficiency and economical inefficiency. This is discussed in greater detail

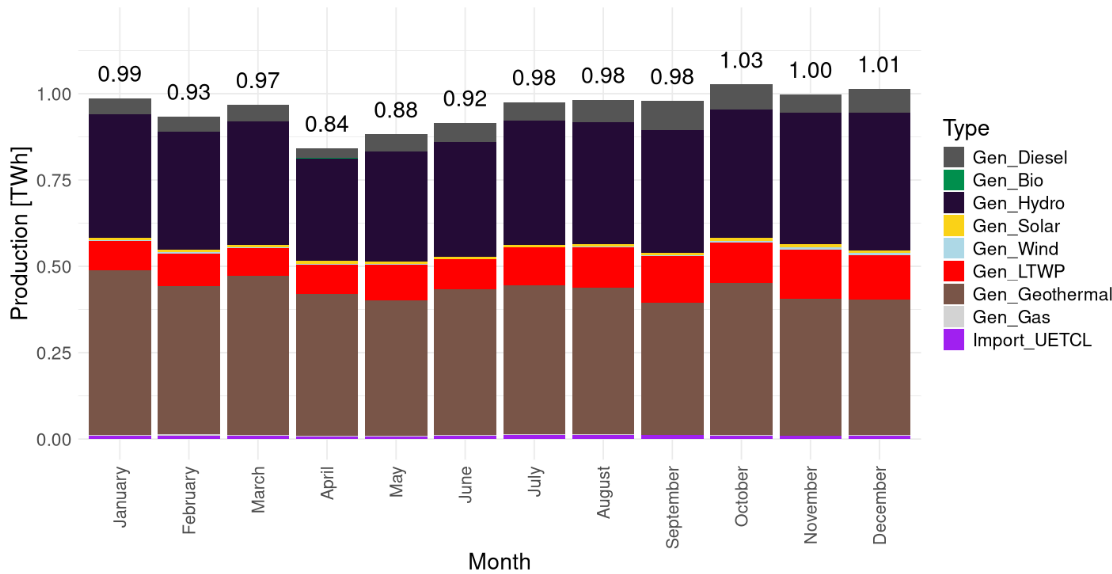


Figure 3: Shares of Generation Type per Month (KPLC data)

in section 2.2.4.

2.2.4 Current and Future Challenges

As explained in section 2.2.1, Kenya is a country experiencing high economical growth, something which will increase the demand for energy demand as the population is lifted out of poverty and the economy becomes more energy intensive. The national government has its pledge to turn Kenya into a middle income-country by 2030. As the economy grows, and more people are lifted out of poverty, the energy demands will also rise. Furthermore, the remaining people who do not have access to electricity will probably connect to the grid or gain electricity access with off-grid technology.

In Kenya, as in many other African countries, traditional cooking methods such as the use of firewood are prevalent. The national government incentivizes a transition to electric cooking methods for health reasons (Ministry of Energy & Petroleum, 2023, p. 47). This shift would leads to an increase in energy demand and necessitates additional infrastructural and resource considerations.

As previously discussed, the efficiency when looking at generation and sales is not high. One factor is the technical one, which entails that a loss of power over the line. This is probably around like 5%, but might be further increased by other technical limitations. Another reason for the inefficiency is of a more economical factor. According to correspondence with a former employee of KPLC and current professors at Moi University, it is well-known that people illegally connect to the grid to access electricity without paying for it. This is especially the case in the slums of Nairobi.

There are currently at least 1000 electrical cars in the country (KPLC, 2022). Kenya is very reliant on mini busses (matatus), cars and motorbikes (boda boda) for public transport and have limited options in terms of alternative means of transportation. The major exception is the train line between Nairobi and Mombasa, which is an electric train. However, achieving carbon neutrality requires electrification of all these processes, which represents a significant shift.

2.3 The Lake Turkana Wind Project (LTWP)

LTWP is located in the north of Kenya, in the region called Marsabit, just west of Lake Turkana in Loyangalani County (Lake Turkana Wind Power Ltd., n.d.). According to the Kenyan National Bureau of Statistics, the region had a population of 459785 people (KNBS, 2019, p.7) and a population density of 6 people per km^2, which is the lowest in the country. Marsabit is inhabited by 14 distinct tribes, each with their own language and culture (Interpeace, 2023). The county has experienced an increasing amount of conflicts which are often related to contention of resources like water, land and pasture. Rather unfortunately, it is in this county that the definitive best areas for wind energy are located, as illustrated by figure 4. This figure maps the mean power density of the whole country. Marsabit is outlined by white.

The wind park is comprised of 365 turbines of the type Vestas V52-0.850 Power Technology, 2014. In total, LTWP a capacity of 310 MW. By itself, it supplies 16% of the country's electricity demand. As part of the construction, a power line from the region that connects the wind park to the central grid, along with substations were built and is maintained by KETRACO (Lake Turkana Wind Power Ltd., n.d.). Construction started in 2014 and was commisioned in 2016. LTWP is an independent power producer (IPP), which means that it is privately owned and has a long-term power purchase agreement with KPLC which includes a fixed prive over a 20-year period. The total land area used by LTWP is 162 km^2, where the turbines are mostly configured in strings.

Currently, the LTWP is fighting a legal battle to continue ownership of the land deeds (Republic of Kenya Supreme Court, 2014). The case started in 2014, when the local community brought forth the case. Since then, the court ruled that the deeds were acquired unjust, and has sinced dismissed an application by LTWP to set aside the judgement (Gerald Andae, 2023). This has now put the power plant in a limbo state, where ownership of the land will be reverted back to the local community, and the future of LTWP is uncertain. Andae writes that the local community argue that the land area is "central to their survival and livelihood as it is their cultural, ancestral and grazing land held under an intergenerational trust for future generations". What will happen to the wind park is unclear, but the land deeds will be given back to the local community in the near future. Andae writes that this process could take between 5 and 7 years. Coincidentally, Vestas sold off its shares in LTWP as recently as 19th of February 2024 to BlackRock (Vestas Wind Systems, 2024). The company states in it press release that this "follows Vestas strategy of developing wind farms without being a long term owner". According to the analyses of Business & Human Rights Resource Centre (2020), Blackrock is one the worst-performing companies in terms of human rights policies and practices.

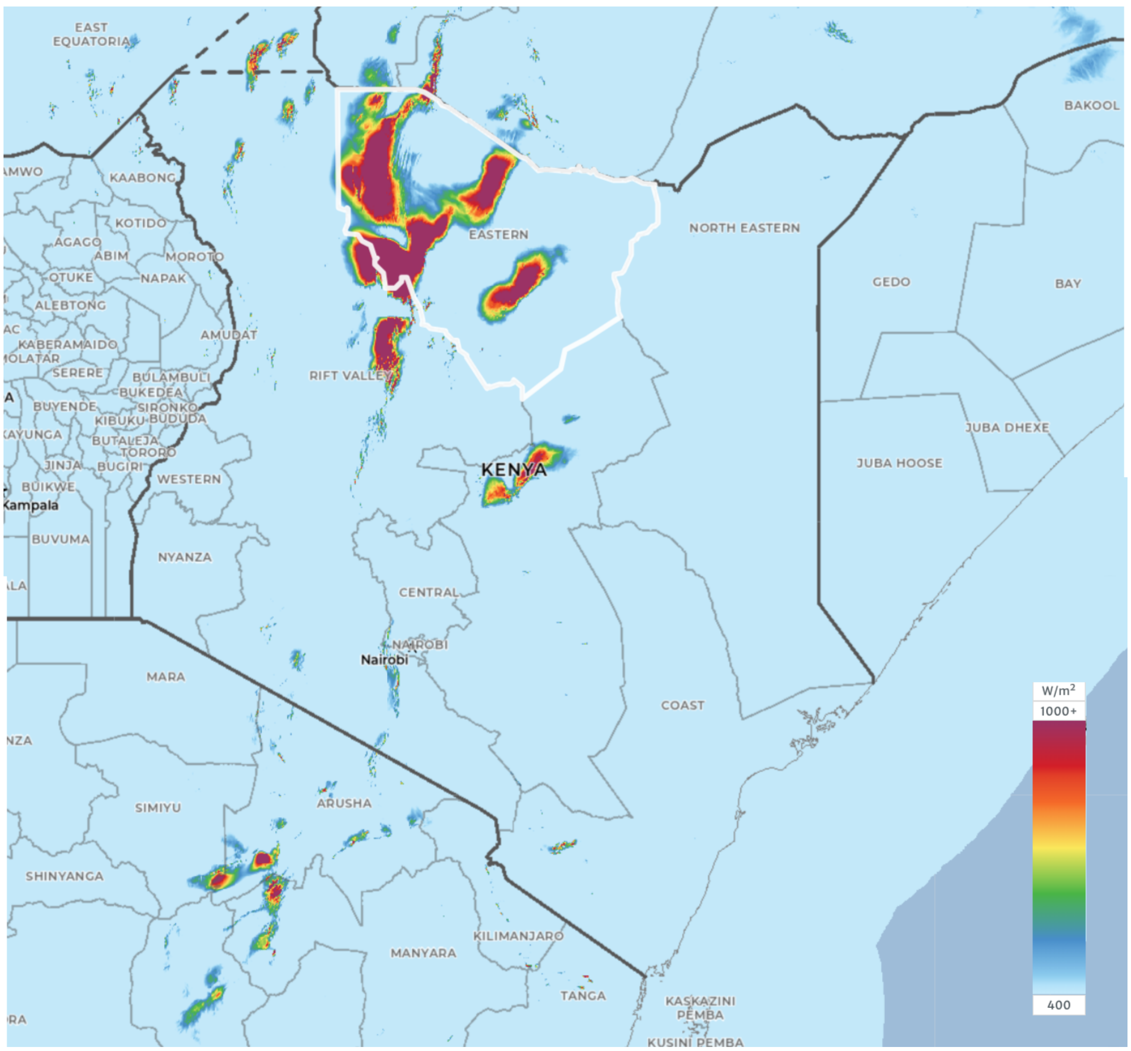


Figure 4: Mean Power Density of Kenya (Badger et al., 2015).

Chapter 3

3.1 Methodology

As discussed in section 2.2, this thesis uses real-world data from KPLC. There are 4 scenarios which will be compared, which are based on the demand projections from the ETIP (Ministry of Energy & Petroleum, 2023, p.49). The 4 scenarios will be 2 Low Cost scenarios and 2 Net Zero scenarios, one of each where the land areas in Marsabit are available for wind power production and without these land areas. The low cost scenario is defined as the scenario where there are no limits to emissions, and OSeMOSYS can freely choose the most optimal power generation mix based on the maximum constraints and costs. In the net zero scenario, an annual emission limit is enforced. The emission limits is also taken from the ETIP (Ministry of Energy & Petroleum, 2023, p.9). The low cost scenario where the wind resources in Marsabit is allowed serves as the reference scenario. The 4 scenarios are described in Table 1.

Table 1: Summary of the 4 scenarios used for modelling

Scenario Name	Description
LTWP_LowCost (ref. scenario)	No limits to LTWP resources, no emission limits
NoLTWP_LowCost	LTWP resources are 0, no emission limits
LTWP_NetZero	No limits to LTWP resources, annual emissions limits in place
NoLTWP_NetZero	LTWP resources are 0, annual emissions limits in place

First, the reference energy system (RES) is constructed. This will serve as the basis for input variables which go into OSeMOSYS. OSeMOSYS is explained in section 3.3. As will be explained in section 3.4.1 and 3.4.2, the input variables are divided into sets and parameters. The sets regarding technologies and fuels are directly taken from the RES, whereas the sets regarding time resolution is conceived from the KPLC data. The resulting energy system model which is constructed using OSeMOSYS is, from this point on referred to as ”the model”. The units regarding capacity will be in MW. For ”Activity”, the unit will be in TWh, meaning energy production. The monetary unit will be Million 2020 USD and units regarding CO2 emissions will be in MtCO2.

The simulations are done on a computer system running Fedora Linux 40 with an Intel Core i5-8350U 8-core processor and 16 GB of memory. As previously stated, OSeMOSYS_PuLP is used due to the relative easier method of data input. This is not expected to make a difference in the solutions, as both OSeMOSYS written in GNU MathProg and Python both use the same solvers. The simulations use the standard solver included in the PuLP package, namely CBC_CMD.

The results from the model are compared to ETIP. The land value is derived from the opportunity cost divided by the amount of land area that is used in the reference scenario in the end of the model period in the year 2050. So, the installed capacity in 2050 determines the used land area. Opportunity cost is the potential benefit that an investor can realize when choosing one opportunity instead of another (Fernando, 2024). In this analysis, the opportunity cost is the difference between the total cost of the reference scenario and the scenario without LTWP. The opportunity cost will then be divided by the amount of land area that LTWP requires, based on the installed capacity in the year 2050.

$$\text{Land Value} = \frac{\text{Opportunity Cost [mill. USD]}}{\text{Land Used [km}^2\text{]}} \tag{1}$$

After the land value for the land in the Marsabit region is determined, the effect of different turbine models on the land value will be investigated. Thereafter, the land value of the Marsabit region is compared with other renewable technologies. From this point on, the term LTWP will now generally refer to the areas in Marsabit suitable for wind power production, as illustrated in figure 10a.

3.2 Reference Energy System

The RES is illustrated in Figure 5. Boxes denotes ”Technologies”, where lines are ”Fuels”, as is necessary for OSeMOSYS. Import of primary energy resources and the primary resources available within Kenya are denoted with ”IMPx” and ”RESx” respectively, where ”x” is the primary energy resource. For example, ”IMPGAS” denotes imported natural gas, where ”RESGAS” the gas resources which can be extracted within Kenya. ”PWR” denotes power production, where the primary energy resource is converted into electricity. For example, a natural gas power plant is denoted as ”PWRGAS”. The white boxes are technologies which are found in the dataset given by KPLC. The red technologies are not in the Kenyan energy mix as of now, but are left in so that OSeMOSYS can decide to invest if it is part of the optimal energy production mix. LTWP is denoted by blue.

In this model, only the electricity which is connected to the grid will be considered. Kenya might have a high potential for off-grid power generation, but it will be omitted in this model, due to a lack of data and time constraints. Adding the off-grid technologies will make the modelling

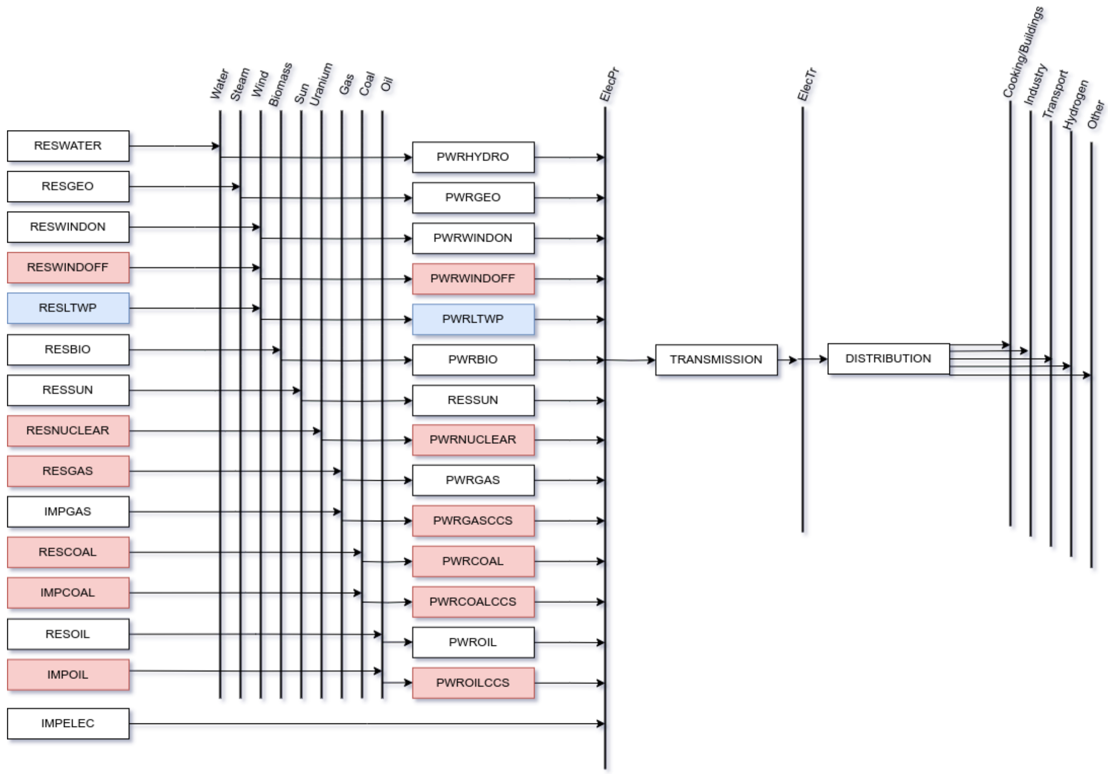


Figure 5: Reference Energy System of the Kenyan electrical energy system

process more difficult, since the model will them assume that the demand in urban areas can be fulfilled with off-grid technologies, which is not realistic. Off-grid technologies only satisfy ”off-grid demands”. This means that we assume that all electricity demand can be satisfied by the grid and the technologies hooked up to the grid. This is a simplification of the power system within Kenya today, as many off-grid technologies are currently present in Kenya, and may play a role in the future (International Renewable Energy Agency, 2021). Furthermore, for simplification, no storage is included in he model. Kenya possesses plentiful hydroelectric resources, with a total dam capacity of 24.79 km^2 (“Kenya - Total dam capacity”, n.d.). The electricity system does have opportunity for energy storage.

3.3 Open Source Energy System Modelling Software (OSeMOSYS)

As explained in chapter 2.1.1, the modelling software of choice for this thesis is the so-called ”Open Source Energy System Modelling Software” (OSeMOSYS). Howells et al. describes OS-eMOSYS as a ”full-fledged system optimization model for long-term energy planning” (Howells et al., 2011). Furthermore, they claim that OSeMOSYS ”potentially requires a less significant learning curve and time commitment to build and operate", when compared to other energy system models like MARKAL/TIMES, MESSAGE, PRIME EFOM and POLES. They further explain how OSeMOSYS can provide broader understanding to e.g. developing countries who might not have as much research resources as industrialized countries. In technical terms, OSeMOSYS is a deterministic linear optimization model, which means that it seeks to minimize the total system cost by optimizing the input variable given the pre-determined constraints (Howells et al., 2011). It has been translated into several programming languages and has gained extensions. The model was initially written in GNU Mathprog, but has been translated into GAMS and Python. Additionally, Dreier and Howells have extended the functionality of OSeMOSYS by adding Monte Carlo simulations to their version of the model, using the linear programming package "PuLP" in Python (Dreier & Howells, 2019). This version of OSeMOSYS has the added benefit of more user-friendly data input methods. The original structure of OSeMOSYS required each variable to be input through .csv-files in a matrix-like structure. OSeMOSYS_PuLP addresses this by allowing the user to input data in spreadsheets, which arguably are easier for the user.

Gardumi et al., 2019 gives an explanation on how OSeMOSYS functions. The structure consists of seven "blocks", which are: (1) the objective function, (2) costs, (3) storage, (4) capacity adequacy, (5) energy balance, (6) emissions and (7) constraints. These blocks are represented by a total of 11 sets, and 52 parameters. The "sets" define the physical structure of the model, like the technologies which the model contains, the years of the modelling period, the fuels which are included, which emissions are included and so on. The sets are usually derived from a reference energy system (RES). The parameters are the inputs to the model. Each parameter is a function of one or more sets. For example, the parameter "CapitalCost" is a function of the sets "region", "technology" and "year". This means that to define capital costs, OSeMOSYS needs an input value per region (r), technology (t) and year (y).

OSeMOSYS has been used to model several different regions and countries in the world. Olsson & Gardumi modelled the on-grid electricity system in Bangladesh (Olsson & Gardumi, 2021) using 6 different scenarios. Tchandao et al has made a similar analysis on Togo (Tchandao et al., 2023), but with 3 scenarios. Gebremeskel et al also conducted similar research on Ethiopia, using 4 scenarios (Gebremeskel et al., 2023). They also coupled OSeMOSYS with the modelling framework LEAP (Long-range Energy Alternatives Planning System). Pinto de Moura et al modelled Bolivias energy system using 4 different scenarios (Pinto de Moura et al., 2017). They also researched the potential of potential trade between South American countries using SAMBA (South America Model Base). These 4 papers show that OSeMOSYS can be used for conventional energy system model analysis on different regions in the world. All these papers use data and assumptions which are relevant for their respective countries and analyze how different policy scenarios have different long-term outcomes.

As with all models and their results, the results are only valid if the quality of input data is sufficient. This fact also applies to OSeMOSYS. A central assumption which is made is that of ”perfect foresight”, which means that all trends regarding future demands, cost projections and so on are assumed to be correct. Naturally, on cannot foresee the future. This means that there is a lot of uncertainty which might not be addressed. Dreier & Howells have added Monte Carlo simulations as an extension tot eh OSeMOSYS framework to include this (Dreier & Howells, 2019). The explain this with a clear example, namely with wind power. Generation from this power source rarely matches with the prognoses and this stochastic behaviour is not captured in the usual model. Interest rates, demands, fuel costs etc. also follow trend which cannot be accurately predicted. Therefore, these limitations must be carefully considered when constructing the model.

3.4 Input Variables

3.4.1 Sets

As described in section 3.3, the sets define the physical structure of the model, and is taken from the RES. A list of the 11 sets and a short description, as per Gardumi et al. (2019), is provided:

- YEAR: The time frame of the model
- TECHNOLOGY: A system component, like a power plant, a demand, or a resource. All technologies have some associated cost, capacity constraint, emission etc.
- TIMESLICE: The time split of modelled year, for example ”Summer Night”, ”Summer Day”, ”Winter Night” and ”Winter Day”
- FUEL: An energy vector, energy service or proxy which is an input and/or output of a technology.
- EMISSION: Emission deriving from the operation of a technology. An example is CO2.
- MODE_OF_OPERATION: The number of modes of operation a technology can have. For example, a Combined Heat and Power plant produces both heat and power, in two separate modes.
- REGION: The region(s) of interest, for example a country.

- SEASON: Successive numerical value(s) indicating the number of seasons (e.g Winter and Summer) in the model, and the order in which the seasons appear.

- DAYTYPE: Successive numerical value(s) indicating the number of day types (e.g Weekday and Weekend) in the model, and the order in which the day types appear.

- DAILYTIMEBRACKET: Successive numerical value(s) indicating how many parts the day is split into (e.g night, morning, evening), and the order in which they appear.

- STORAGE: Denotes the technologies which have storage.

In figure 5, the fuels and technologies are visible. The modelling period will be from the year that LTWP was fully operational, namely the year 2020, to the end of the period shown by the ETIP, which will then be 2020-2050. The next important aspect which must be decided is that of the time resolutions. Figure 2 show that there is a visible difference between the average load curve in April and May, which might be explained by the fact that these two months are in the rain season in Kenya. Analyzing the average between the months within the rain season and dry season shows a marginal difference in power demand, as illustrated by figure 6. Therefore, the model will contain two seasons, namely ”Rain” and ”Dry”.

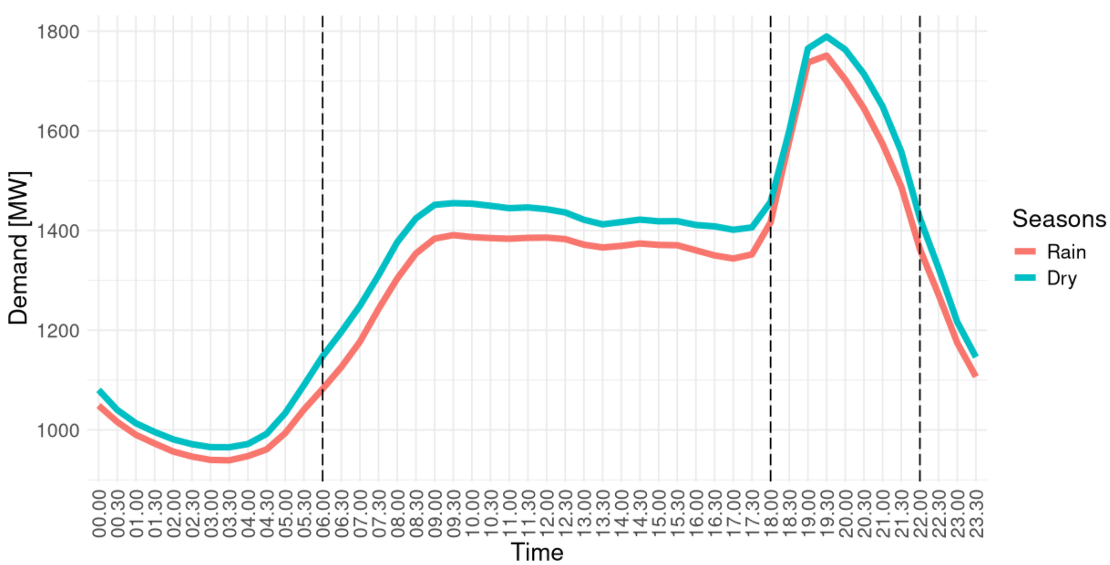


Figure 6: Seasonal average load curve

Weekdays and weekends have a considerable difference in terms of load, as can be seen in Figure 7. This is to be expected, because the weekends are typically used for leisure, which does not require as much energy as the weekdays. Interestingly, the energy demand on the typical

Sunday is much lower than on Saturday. This could indicate that plenty of Kenyans still work on Saturdays, and is not taking the entire weekend of for leisure. Therefore, daytypes will be divided into weekdays (WND) and weekends (END).

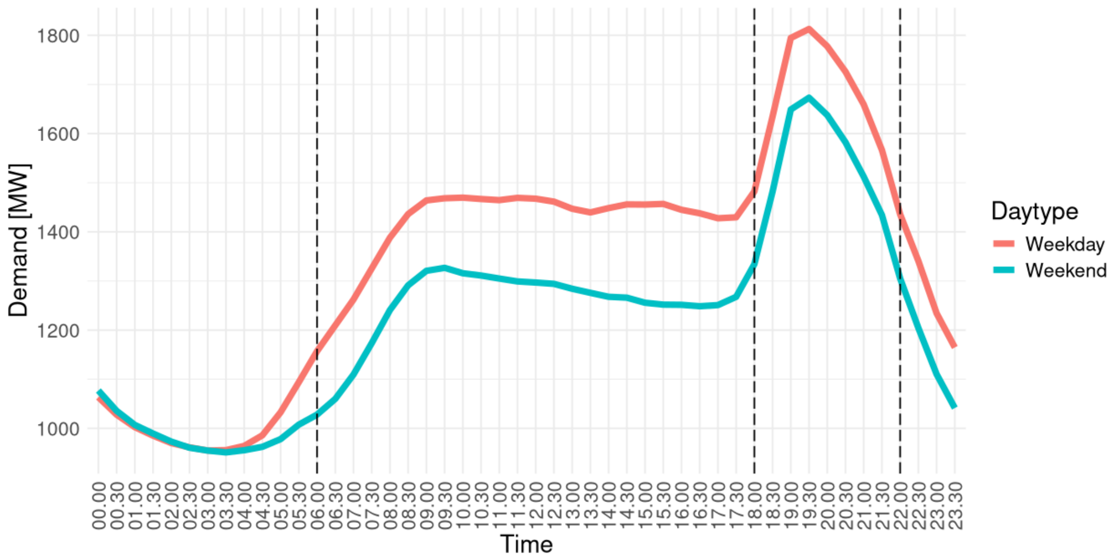


Figure 7: Weekdays vs Weekends average load curve

Furthermore, all load curves, illustrated by figures , 2, 6 and 7 show 3 distinct load levels during the day, namely the night (N), day (D) and evening (E). These will serve as the ”Dailytimebrackets”. This means that we will have 12 time slices in total. In this model, only electricity is of interest, which means that all technologies will only have 1 mode of operation, which is electricity generation. CO2 will be the only emission of interest. Lastly, the model will not include any form of storage. This is a strong implication, which is discussed further in section 6.2. A summary of the sets for the is shown in table 2.

Table 2: Summary of sets used in the model

Sets	Value
REGION	Kenya (but it is possible to import electricity, using the techonology IMPELEC)
DAYTYPE	2 - Denoted by WKD (weekday) and WND (weekend)
EMISSION	CO2
FUEL	16 fuels (see figure 5)
DAILYTIMEBRACKET	3 - Denoted by D (day) and N (night) and E (Evening)
SEASON	2 - Denoted by WET and DRY
TIMESLICE	2 Daytypes (WKD, END), 3 Dailytimebrackets (N, D, E) and 2 Seasons (RAIN, DRY), equals 12 timeslices: WKD_D_RAIN, WKD_D_DRY, WKD_N_RAIN, WKD_N_DRY, END_D_RAIN, END_D_DRY, END_D_RAIN, END_D_DRY, END_D_RAIN and END_D_DRY.
MODE_OF_OPERATION	1
STORAGE	None
TECHNOLOGY	31 technologies (see figure 5)
YEAR	2020, 2021, 2022 ... 2050

3.4.2 Parameters

As previously discussed, each parameter is a function of one or more sets. In this section, the input parameters are explained. These entail the demands, the capacity factors of the technologies, the residual capacities, the costs (capital, variable and fixed), efficiencies of technologies, max capacities and energy limits and emissions and emissions limits. Most of the parameters are derived from the KPLC data set, or from the data set provided by NREL (2022) and EIA (2010a). It must be noted that this data set collects data which has been gathered from the US energy system. However, the costs are assumed to be representative for Kenya. In an analysis like this, it is the difference in costs between the technologies which is important, and not the costs themselves. If neither of these sources contain the required data, it will be extracted from OSeMOSYS Starter Kits Allington et al. (2021). A contains the remaining parameters which are required as inputs to OSeMOSYS.

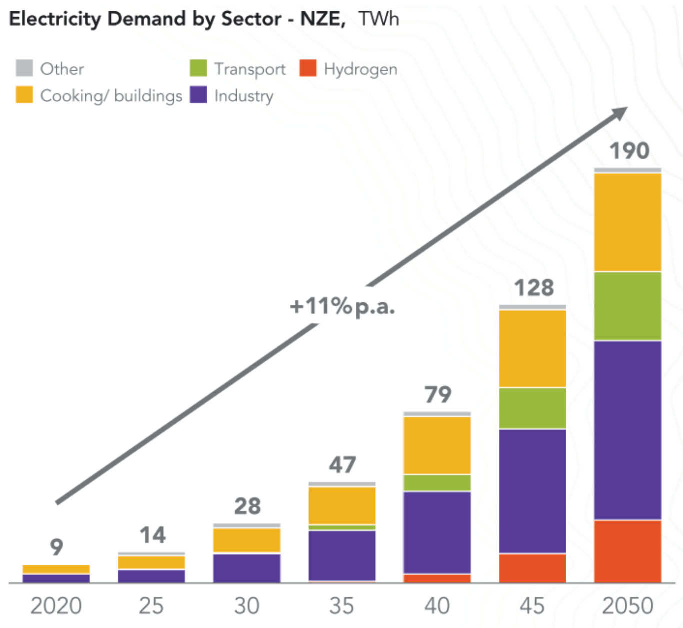


Figure 8: Electricity Demand by Sector from 2020 to 2050 (Ministry of Energy & Petroleum, 2023, p.49)

Demands

The demands are taken from the ETIP (Ministry of Energy & Petroleum, 2023, p.49). The Ministry has divided electricity demand into 5 sectors: (1) Cooking/Buildings, (2) Industrial, (3) Transportation, (4) Hydrogen and (5) Other. The same sectors are chosen for this model. As stated in section 3.2, the whole demand is assumed be met by the electric power grid, and does not contain on off-grid technologies. The Ministry foresees that the growth in demand for the transport and hydrogen sector is driven by the country's net zero pathways. It projects that the transport sector will not have any electricity demand until the years between 2030-2035, which is also true for the hydrogen sector. Furthermore, the large increase in electricity demand for cooking is a shift away from traditional, biomass-based cooking techniques to electric cooking Ministry of Energy & Petroleum, 2023, p.47. This shift is already incentivized through policy due to health reasons.

As seen in Figure 8, only the total demand per year is stated, and not the demands of the individual sectors. Despite prolonged correspondence with the Ministry in an effort to get the data behind the report, it was not possible to get the actual value of the demand per sector. Therefore, this was to be estimated. The estimations per sector is tabulated in Table 3. These demands will be input to the parameter called "SpecificAnnualDemand".

Since the model uses every year from 2020 to 2050 in the simulation, the demands between the years must be found. This is achieved by means of regression analysis, and fitting a function that

Table 3: Estimated demand per sector per year

Sector	2020	2025	2030	2035	2040	2045	2050
Cooking/buildings	4.70	6.26	12.06	18.19	26.82	35.96	45.19
Industry	4.30	6.26	14.39	24.64	38.78	57.89	82.55
Transport	0.00	0.00	0.00	2.27	7.61	18.70	31.31
Hydrogen	0.00	0.00	0.00	0.38	3.99	13.30	28.82
Other	0.00	1.47	1.56	1.52	1.81	2.16	2.13
Total	9.00	14.00	28.00	47.00	79.00	128.00	190.00

can be used to find the demands per year. Since the demands are data points with a exponential growth, the fitted function is assumed to be a 2^{nd} degree polynomial.

Table 4: Fraction of total demand per time slice

Time Slice	Fraction	Time Slice	Fraction
END_E_RAIN	0.02	WKD_E_DRY	0.08
END_E_DRY	0.03	WKD_N_RAIN	0.08
END_N_RAIN	0.03	END_D_DRY	0.09
END_N_DRY	0.04	WKD_N_DRY	0.12
WKD_E_RAIN	0.06	WKD_D_RAIN	0.16
END_D_RAIN	0.06	WKD_D_DRY	0.24

In addition to the demands per year, OSeMOSYS requires the parameter "SpecificDemand-Profile". The value of this parameter is the annual fraction of demand that the time slice requires. In other words, this parameter differentiates between the demands per time slice. The values are gathered from the KPLC data. The days are sorted into separate lists corresponding to which time slice that day belongs to. For example, day 128 (7^{th} of May) was a weekday in the rain season, and thus belongs to the time slice "WKD_RAIN". The fractions are summarized in table 4.

Capacity Factors

The KPLC data is used to determine the capacity factors. OSeMOSYS requires a capacity factor per technology, per time slice. This means that every technology will have 12 capacity factors. The capacity factors where calculated using equation 2.

$$CF_{i,j} = \frac{G_{i,j}}{C_i * H_j} \tag{2}$$

Here, *CF* is the capacity factor of plant *i* at time slice *j*. *G* is the energy plant *i* generated at time slice *j*. *C* is the installed capacity of plant *i* and *H* is the amount of hours in time slice *j*. The capacity factors which are calculated from the data are tabulated in Table 5. As expected with fossil fuels, the capacity factors are very low during non-peak hours and high during peak hours. The fossil fuels with high fuel costs only turn on during high peak hours. Solar has expected capacity factors, 0 during hours where there is no sun, and above zero during the day, when there is abundance of sun. Based on this year alone, it would seem that solar power has somewhat higher capacity during the rain season, but this is not conclusive. Wind (excluding LTWP) has very different capacity factors depending on the season. This is only the wind park Ngong, located on top of Ngong Hills south of Nairobi, which seemingly has very different weather patterns during the rain and dry season. LTWP is rather stable throughout the year which underlines the valuable wind power potential of Marsabit. Unsurprisingly, the two baseload technologies, hydro and geothermal are rather stable throughout the year. Still, geothermal can be somewhat regulated as it produces less during the night when demand is low and more during high peak hours. The expectation regarding hydroelectric is that it would produce more during the rain seasons, as there is more precipitation, but this seems to not be the case. This means that the hydroelectric power plants have ample storage capacity between the seasons. For the rest of the technologies which are included in the model, but are currently not present in the power generation mix (e.g. nuclear and coal), some capacity factors must also be assumed. For off-shore wind, the capacity factor is assumed to be be same as LTWP. In reality, this could be somewhat higher, as offshore winds in principle have higher speeds and blow at a more stable rate. However, the wind speeds offshore in Kenya are not particularly higher than the wind speeds in Marsabit Potential, 2020. Coal, being a non will have a capacity factor of 1, and nuclear is assumed to be 0.95.

These capacity factors are only what has been actually used, and not necessarily what will be inputted into OSeMOSYS. For OSeMOSYS, capacity factor which is available per time slice is of interest. This means that for the non-intermittent power technologies, the capacity factor will be 1, as these technologies are assumed to be dispatchable at all times. This is not reflected in Table 5.

Table 5: Capacity Factors per technology per timeslice for 2020

	Diesel	Bio	Hydro	Solar	Wind	LTWP	Geothermal	Gas
WKD_N_RAIN	0.02	0.00	0.45	0.00	0.21	0.45	0.61	0.00
WKD_N_DRY	0.02	0.00	0.45	0.00	0.12	0.53	0.64	0.00
WKD_D_RAIN	0.12	0.02	0.66	0.39	0.21	0.51	0.69	0.01
WKD_D_DRY	0.14	0.01	0.68	0.38	0.11	0.49	0.72	0.01
WKD_E_RAIN	0.40	0.01	0.75	0.00	0.22	0.43	0.72	0.32
WKD_E_DRY	0.46	0.00	0.74	0.00	0.09	0.41	0.76	0.34
END_N_RAIN	0.01	0.03	0.43	0.00	0.19	0.50	0.59	0.00
END_N_DRY	0.01	0.00	0.42	0.01	0.10	0.51	0.62	0.00
END_D_RAIN	0.05	0.03	0.58	0.41	0.19	0.54	0.62	0.01
END_D_DRY	0.07	0.01	0.60	0.36	0.11	0.47	0.68	0.01
END_E_RAIN	0.18	0.01	0.77	0.00	0.20	0.46	0.73	0.24
END_E_DRY	0.25	0.00	0.74	0.00	0.12	0.39	0.75	0.26

Residual Capacity

"Residual Capacity" contains the amount of capacity that is available from before the modelling period. Throughout the modelling period, it should decrease as power plants become older and degrade. The residual capacity will be the capacity that is installed in the year 2020, which is gathered from the KPLC dataset and crossed checked with the annual report from KPLC from 2020 (Cozier, 2014). The technologies degrade with exponential decay. All technologies are assumed to degrade at a rate of 1% each year, except for wind and solar, which degrade at a rate of 1.6& (Staffell & Green, 2014). However, it must be noted that a flat rate of 1& is a simplification. The residual capacities are tabulated in table 6. All technologies not shown here have a residual capacity of 0, except for the transmission grid (TRANS) and the distribution grid (DISTR).

Table 6: Residual Capacity [MW]

Technology	2020	2025	2030	...	2050
PWRHYDRO	808.78	769.14	731.45	...	598.25
PWRGEO	841.80	800.54	761.31	...	622.68
PWRWINDON	25.00	23.09	21.36	...	15.57
PWRLTWP	300.00	275.91	255.83	...	184.35
PWRBIO	2.00	1.90	1.81	...	1.48
PWRSUN	50.00	46.36	42.99	...	31.77
PWRGAS	56.00	52.83	49.83	...	39.46
PWROIL	640.42	609.03	579.18	...	473.72

Costs

As previously described, OSeMOSYS has 3 different parameters for the technologies, namely capital costs, variable costs and fixed costs. The chosen dataset containing the economical data is gathered from NREL (2022). As mentioned in section 3.1, this data base has costs for the American market. For this analysis, all costs are in million 2020 USD. This means that the costs will either be in mill. USD per TWh or mill. USD per MW. Transmission and distribution is also assumed to not have any costs of any kind attached to it, for simplification. All costs are tabulated in table 8.

First, the capital costs are discussed. In this model, all natural resource reserves (like RESWATER, RESNUCLEAR etc.) and energy imports (IMPGAS, IMPCOAL etc.) are expected to be sunken costs and are therefore set to 0. Naturally, this is not exactly accurate, as there are capital costs connected to extraction of energy source, through mining and infrastructure. In other words, e.g a coal mine must be invested into so that the coal can be extracted. The same applies for import infrastructure. This means that only the power generation technologies have a non-zero capital cost. The intermediate values were found using interpolation using a 2nd degree polynomial. For the table, it is clear to see that all technologies become cheaper in the long-term, but that the most mature generation technologies have the least decrease in prices. It is also clear to see that wind power, gas and oil are the cheapest technologies in terms of overnight costs.

Secondly, the fixed costs are the operation and maintenance costs (O&M) associated with each technology. Here, the same assumptions applies as before, meaning that all imports and reserves do not have any fixed costs attached to them. This means that only power generating technologies have a fixed costs above 0.

Lastly, the variable costs are discussed. NREL (2022) separates fuel costs from variable costs, so the fuel costs must be taken from another source,. The costs of fossil fuels, especially gas, has historically been to be highly volatile. This is proven by Russia's invasion of Ukraine and the instability that has brought to the fossil fuel market (Energy & Climate Intelligence Unit, 2023; Zhang et al., 2024). Predicting the future fuel prices is difficult, which brings a certain uncertainty to long-term energy modelling. For this thesis, the fuel costs are gathered using historical prices in the US market from 2012 to 2022 (EIA, 2010b, p.143). The prices were converted from USD per MMBtu as they appear in the report to mill.USD per TWh, using the heating values found in the same report. The heating values are tabulated in Table 7.

The fuel costs undergo a similar regression analysis as described in section 3.4.2. In this model, it is assumed that the prices for fossil fuels is expected to rise a steady rate for the modelling period. This is due to the assumption that the demands for fossil fuels will decrease due to countries moving towards renewable energy source. To achieve this effect, a linear regression is assumed

Table 7: Heating value for fossil fuels (EIA, 2010b, p.169)

Fuel	Heating Value [MMBtu/TWh]
Coal	9.997
Petroleum	10.334
Natural Gas	11.069

for natural gas and petroleum. For the prices of coal, a 2^{nd} degree polynomial was assumed. This gives the prices as illustrated in Figure 9. Here, the data from EIA (2010a) is plotted as points, and the fitted line is shown extending until the year 2050. It is assumed that coal as a power source increases the most in price, as it is assumed that the demand for coal will fall the most due to it being the most carbon intensive of the fuel sources.

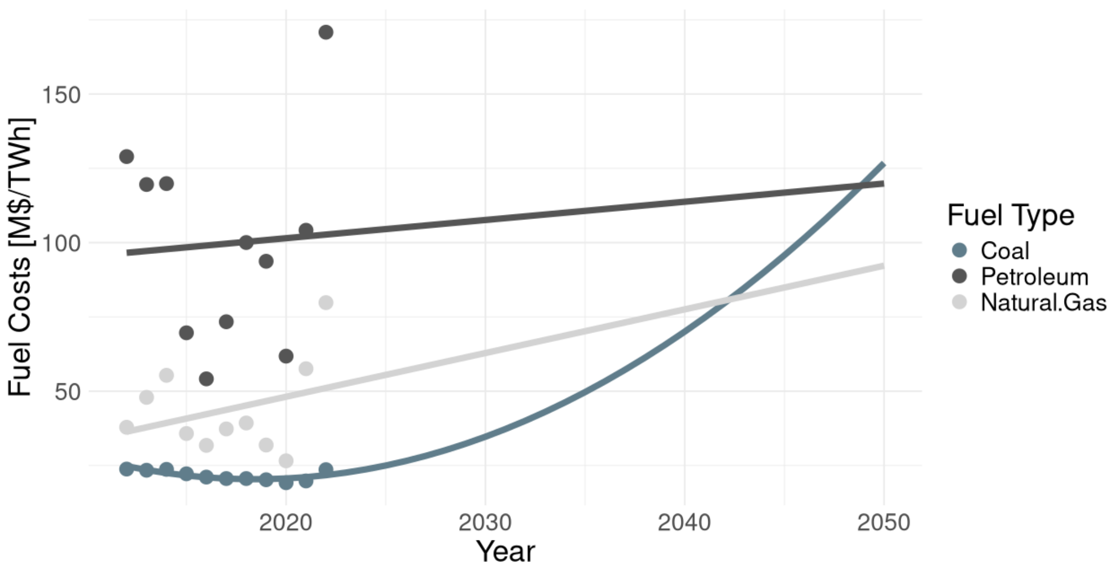


Figure 9: Fuel Costs with actual data points and fits (EIA, 2010b, p.143)

Electricity price is assumed to be 33.32 KSH/kWh, which corresponds to 249.225 M$/TWh. This is the median price for small-scale industries and is also highly speculative. It is not assumed that it will change much anyways, since the capacity of imported electricity is low, and is set to not increase. This price is also highly speculative, as it is very difficult to predict the electricity prices which is imported from neighbouring countries. The electricity price is not determined endogenously, but depends on the demand, supply, transmission capacity and other factors. However, this model assumes that the transmission capacity of imported electricity is 4800 MW, and will not grow.

Table 8: Capital, Fixed and Variable Costs

	Capital Costs [mill USD / TWh]				Fixed Costs [mill USD / TWh]				Variable Costs [mill USD / MW]			
Tech	2020	2025	...	2050	2020	2025	...	2050	2020	2025	...	2050
PWRHYDRO	5.28	5.28	...	2.67	0.08	0.08	...	0.07	0.00	0.00	...	0.00
PWRGEO	6.05	4.51	...	2.85	0.21	0.19	...	0.16	0.00	0.00	...	0.00
PWRWINDON	0.06	0.05	...	0.03	0.04	0.04	...	0.03	0.00	0.00	...	0.00
PWRLTWP	0.06	0.05	...	0.03	0.04	0.04	...	0.03	0.00	0.00	...	0.00
PWRWINDOFF	2.66	2.11	...	1.65	0.11	0.1	...	0.07	0.00	0.00	...	0.00
PWRBIO	4.08	3.95	...	3.31	0.15	0.15	...	0.15	5.80	5.80	...	5.80
PWRSUN	1.3	0.96	...	0.6	0.02	0.02	...	0.01	0.00	0.00	...	0.00
PWRNUCLEAR	6.34	6	...	5.02	0.15	0.15	...	0.15	2.84	2.84	...	2.84
PWRGAS	0.95	0.86	...	0.76	0.03	0.03	...	0.03	5.00	5.00	...	5.00
PWRGASCCS	2.4	1.97	...	1.44	0.07	0.06	...	0.06	6.00	6.00	...	6.00
PWRCOAL	2.57	2.34	...	1.87	0.07	0.07	...	0.07	8.00	8.00	...	8.00
PWRCOALCCS	4.63	4.17	...	2.85	0.12	0.12	...	0.11	15.00	15.00	...	13.00
PWROIL	0.95	0.86	...	0.76	0.03	0.03	...	0.03	5.00	5.00	...	5.00
PWROILCCS	2.4	1.97	...	1.44	0.07	0.06	...	0.06	6.00	6.00	...	6.00
IMPNUCLEAR	-	-	-	-	-	-	-	-	7.15	7.21	...	7.68
IMPGAS	-	-	-	-	-	-	-	-	26.57	26.57	...	26.57
IMPCOAL	-	-	-	-	-	-	-	-	19.19	19.19	...	19.19
IMPOIL	-	-	-	-	-	-	-	-	61.80	61.80	...	61.80
IMPELEC	-	-	-	-	-	-	-	-	249.22	249.22	...	249.22

Efficiencies

OSeMOSYS represents the efficiencies of the technologies within the parameters "InputActivityRatio" and "OutputActivityRatio". For a power generating technology, the value of the former parameter should be the reciprocal of the efficiency. For example, a technology with efficiency of 35% (0.35) would have the value $0.35^{-1} = 2.857$ as the value for "InputActivityRatio". In addition, these parameters are used to link the input and output fuels of the technologies. NREL (2022) does not include the efficiencies of the the technologies, neither does EIA (2010a). Therefore, the efficiencies are gathered from the Starter Kits (Allington et al., 2021). The efficiencies are tabulated in Table 9. All resource and imports have an efficiency of 1.

Table 9: Efficiencies for the technologies

Technology	Efficiency	Technology	Efficiency
PWRHYDRO	0.95	PWRGAS	0.30
PWRGEO	0.80	PRWGASCCS	0.48
PWRWINDON	0.20	PWRCOAL	0.37
PWRLTWP	0.20	PWRCOALCCS	0.37
PWRWINDOFF	0.50	PWROIL	0.35
PWRBIO	0.35	PWROILCCS	0.35
PWRSUN	0.20	TRANSMISSION	0.95
PWRNUCLEAR	0.35	DISTRIBUTION	0.90

Max Capacities and Production

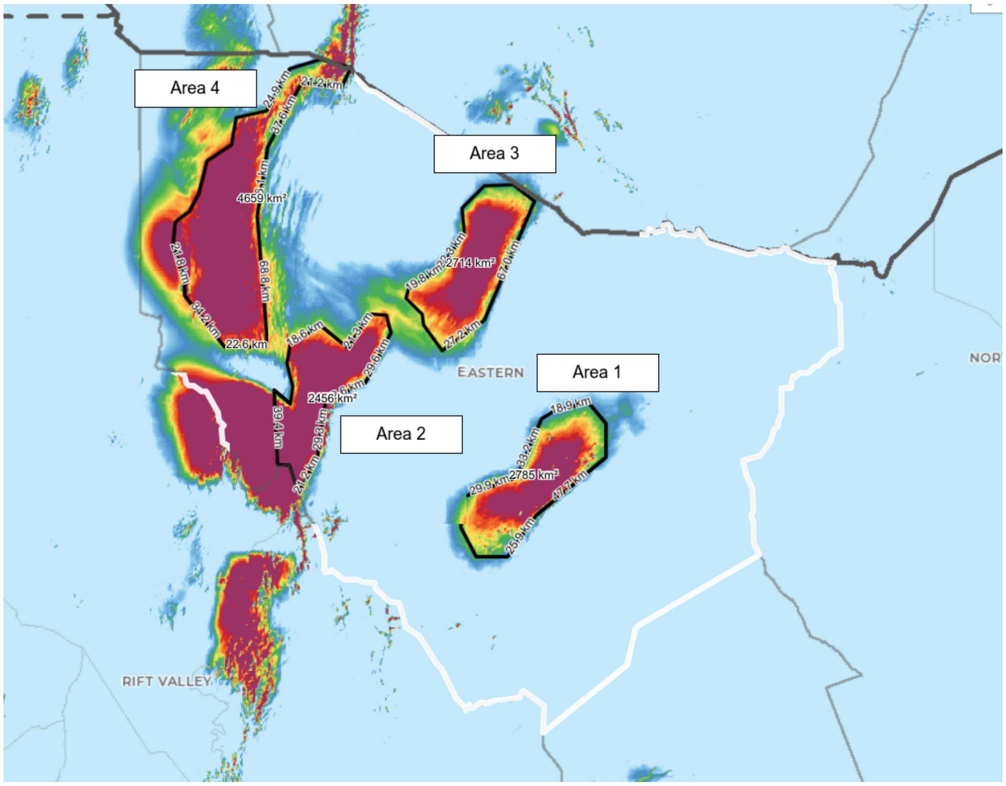
This section will look at the max capacities and the upper limits to energy production levels for the different technologies. The maximum amount of energy that can be produced throughout the modelling period is stored within the parameter "TotalTechnologyModelPeriodActivityUpperLimit". This is particularly interesting for the renewable technologies, as they have limited primary energy resources. This means that the technologies beginning with "RES" must have some limit to their maximum energy potentials. A summary of the potential renewable energy resource for all the renewable technologies are tabulated in Table 13.

Both the capacities and the imports of fuels are assumed to be limitless. The imports of electricity (IMPELEC) has a total capacity of 4800 MW (KETRACO, n.d.). This includes the line between Uganda-Kenya, Ethiopia-Kenya and Tanzania-Kenya. For this model, it is assumed that there are no additional transmission lines built in the modelling period, as there are no current plans to build any more. The power generating technologies are also assumed to be limitless, but limited by the amount of the corresponding input resource. So, the model has an unlimited amount of e.g.

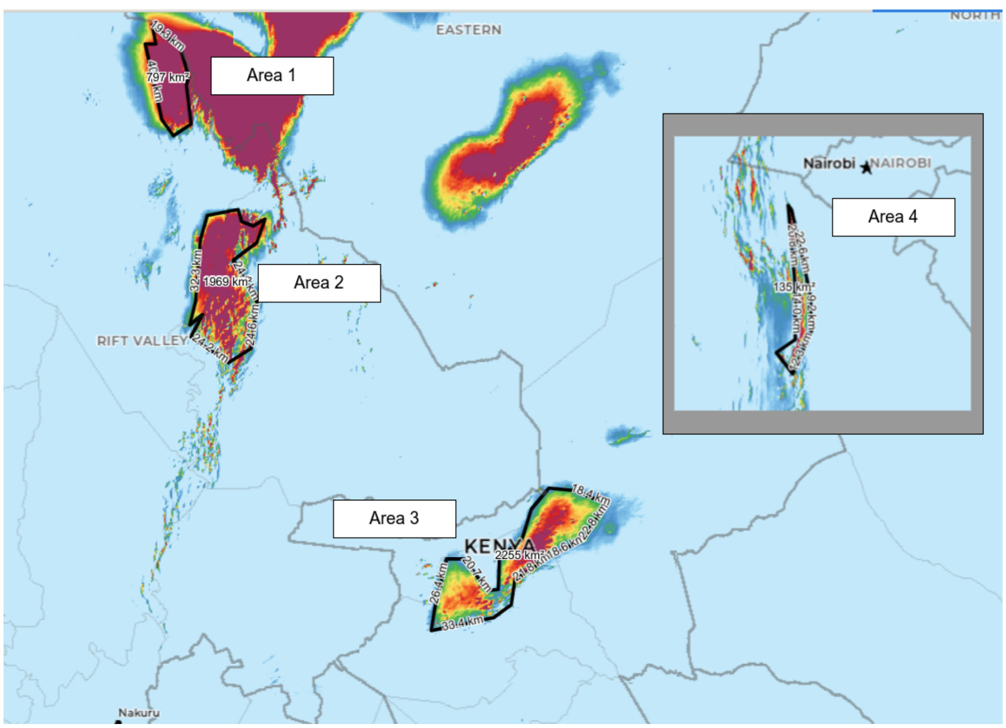
hydroelectric plants it can build, but a limited amount of water. According to the researchers from the OSeMOSYS Starter Kit Allington et al. (2021), Kenya does not have any oil, coal, natural gas or uranium reserves. Because of this, all of these resources must be imported. This eliminates the complication that would have arisen if the resources had a capital cost above 0. If there would have been reserves in Kenya, then the model would have had to have a capital cost attached to the reserve, to simulate investing in some extraction infrastructure, like e.g. a coal mine.

The most important resource limit that must be considered in this thesis, is the amount of land area available in Marsabit. Since the inputs must be in terms of energy, the available land area must be expressed in terms of energy. For this purpose, Global Wind Atlas is used (Badger et al., 2015). Using this tool, it is possible to see the wind speeds and the mean power density (MPD) of any region of the world. The MPD is a measure of how much power per swept area is in a land area (Kalmikov & Dykes, 2010). So, a turbine with a larger swept area will produce more power than a turbine with less swept area. As is clear from Figure 4, the highest amount of wind resources are found in Marsabit. For this analysis, the 4 areas illustrated in Figure 10a are of interest.

The MPD of the 4 areas is illustrated in Figure 11. The total wind power is found by multiplying each point along the curve with 2% of the area to find the MPD in each 2% of area. So, for area 1 with a size of 2785 km^2, 2% of the area will have a MPD of 1610 W per m^2, the next 2% will have an MPD of 1506 W per m^2 and so on. The next step is making an assumption as to how many turbines fit into 1 km^2. The amount of space that a wind turbine requires is greatly influenced by a multitude of factors like the turbine arrangement, the geographical characteristics, land marks in the area, wake effects etc. Some areas within a given wind park might have a higher density and/or different arrangement than other parts of wind park. For the current configuration of LTWP with 365 turbines and a total land area of 162 km^2 (Peikko, n.d.), the density of LTWP becomes $365/162 = 2.25$. However, these turbines currently in LTWP are set up largely in a string, and does not seem to utilize the space in the most efficient manner. Since it is the maximum theoretical energy which is calculated, a higher density is needed. For this thesis, the space required for each turbine is 4 MW per km^2 (Denholm Paul et al., 2009, p.22). This means that in every km^2, 4 turbines with a capacity of 1 MW will fit. For the V52-0.850, the assumed density of turbines is equal to $4/0.085 = 4.71$ turbines per km^2. turbines per km^2. This means that the model will assume that the density of turbines is almost double of what the wind turbines currently have.Thereafter, the amount of power which can extracted from the wind is calculated by multiplying the swept area of the turbine with the MPD. The swept area is assumed to be that of the turbine models which are already installed at LTWP, namely the Vestas V52-0.850 Power Technology (2014). These turbines have a rotor diameter of 52 meters, which equals a swept diameter of $A = \pi(52/2)^2 = 2122.64$



(a) Land areas with the highest MPD in Marsabit



(b) Land areas with the highest MPD in the rest of Kenya m^2. Lastly, to convert from power to energy, it is assumed an operating hour of $24 * 365 = 8760h$. This must not be confused with the capacity factor of LTWP, which is inserted into the model. This is done because the data from Global Wind Atlas is the mean over the whole year. Still, this is unrealistic and highly speculative. With these parameters, the total amount of theoretical energy found in Marsabit, using the V52-0.850 can be calculated. The method of estimating the maximum energy potential from one area in LTWP can be summarized as:

$$E_i = \sum 0.02 * A_i * \mathbf{MPD_i} * A_s \tag{3}$$

Where E_i is the energy in area i, A_i is the area, $\mathbf{MPD_i}$ is the vector containing the MPDs in at every 2% of the area and A_s is the swept area of the turbine.

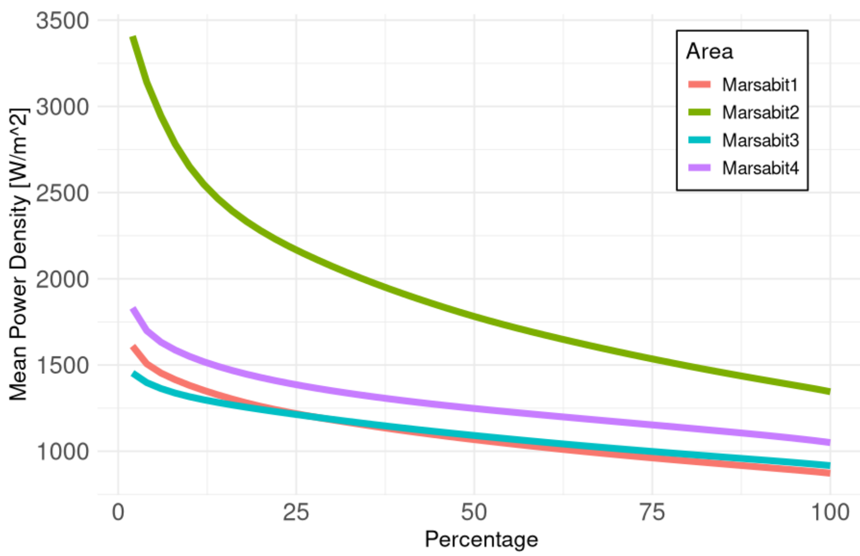


Figure 11: Mean Power Density Distribution of the 4 windiest areas in Marsabit Badger et al. (2015)

The results are tabulated in Table 10. It must be noted that the efficiency and capacity factor of the wind turbines is added to the model as described in section 3.4.2 and 3.4.2.

A similar approach is done to find the wind potential in the rest of Kenya. There are 4 other areas which are of interest, as illustrated in 10b. As is expected, the potential for wind energy in the rest of the country is vastly lower in comparison with Marsabit. The exact same assumptions are made for both LTWP and wind energy for the rest of the country. The results are tabulated in Table 11. Here, it is immediately clear the difference between LTWP and the rest of the country. Marsabit as a region has almost 3 times the wind energy potential as the rest of the country.

The solar resources are found from an estimation of the renewable energy potential of African

Table 10: Amount of Maximum Theoretical Energy in Marsabit

	Size [km^2]	Power (with V52) [MW/turbine]	Max. Amount of Turbines [# turbines]	Theoretical Energy [TWh]
Area 1	2785	117.00	13105	194.01
Area 2	2456	201.93	11558	295.42
Area 3	2714	117.78	12772	190.43
Area 4	4659	136.18	21925	377.93
Total	12614	572.90	59360	1057.88

Table 11: Amount of Maximum Theoretical Energy for the rest of Kenya

	Size [km^2]	Power (with V52) [MW/turbine]	Max. Amount of Turbines [# turbines]	Theoretical Energy [TWh]
Area 1	796.66	142.83	3748	67.78
Area 2	1969	156.08	9265	183.07
Area 3	2266	95.87	10663	128.78
Area 4	135	82.28	635	6.67
Total	5155	478.06	24311	386.32

countries (IRENA, 2021a, p.42). Here, IRENA (2021a) has tabulated the potential of solar energy within three categories, each category separated the Global Horizontal Irradiation (GHI). The three categories each have their associated range of GHI. Then, IRENA (2021a) has divided the amount of area which receives the different ranges of GHI. This data is tabulated in Table 12. For this thesis, the highest value is chosen. As previously mentioned, it must be noted that the efficiencies and capacity factors that are used within the model. Since the solar irradiation is measured in kWh/m^2/year, it must be multiplied by the amount of years in the modelling period, namely 30. In this way, the total amount of energy is calculated which will be inserted into the model.

Table 12: Maximum motential Solar energy within Kenya

Range [kWh/m^2/year]	Area [km^2]	Energy [TWh]
1500-2000	66369	3086.16 - 4114.88
2000-2500	451266	27978.49 - 34973.12
2500-3000	7565	586.29 - 703.54
Total	525200	31650.94 - 39791.54

The amount of available biomass is also gathered from (IRENA, 2021a, p.56). Here, the potential amounts of ethanol which can be made from sugarcane per hectar of land area is estimated.

Sugarcane is the most important crop used to produce biofuel (IRENA, 2021a, p.23). For electricity generation, biofuel is just one of the options as a source for electricity generation (U.S Energy Information Administration, n.d.). Another widely used source is wood and wood pulp, which is omitted from the report. IRENA (2021a) estimates the amount of land area that can be used to produce soybeans and Jatropha, which can also be used for bioethanol production. Kenya is reliant on biomass uses for cooking. As is outlined in the ETIP (Ministry of Energy & Petroleum, 2023) and previously described in section 2.2.4, cooking is still done using traditional cooking methods which rely on biomass as an energy source. Therefore, biomass as a source of electricity will be contended, as there will be demand for biomass as an energy source in cooking. These aspects make estimating a total amount of biomass resources available for electricity generation difficult and highly speculative. In this thesis, the foundation for the theoretical maximum for biomass will only be using bioethanol as the primary energy source. IRENA (2021a) estimates a total of 33100 million litres of ethanol can be made from harvested sugarcane in Kenya. Using a heating value of 21 MJ/litre (IEA-AMF, n.d.), this translates to 2502.36 TWh. However, the actual energy is likely much larger.

The amount of energy which can be extracted from hydroelectric and geothermal resources are gathered from the Starter Kit (Allington et al., 2021). The theoretical potential of offshore wind is gathered from an estimate done by the World Bank (Potential, 2020). Since these values are all measured in terms of power (MW), they are all multiplied by the amount of hours in a year for 31 years. As previously stated, the efficiencies and capacity factors are added to the corresponding power technologies which utilize the resource.

Table 13: Estimated Renewable Energy Sources in Kenya

Renewable Resource	Energy Available [TWh]
RESWATER	2444.04
RESGEO	2715.6
RESWINDON	386.32
RESWINDOFF	376.68
RESLTWP	1057.882
RESBIO	2502.36
RESSUN	39791

Emissions and Emission Limits

The technologies that emit CO2 are biomass (PWRBIO), coal (PWRCOAL), oil (PWROIL) and gas (PWRGAS). The emission factors are gathered from Allington et al. (2021). Biomass is an interesting case, as there is a direct emission from burning biomass, but can still be considered renewable. This is because the CO2 which is emitted is assumed to be taken up again when the biomass grows back, thus the net carbon emitted is 0 (U.S Energy Information Administration, n.d.). For simplification, the direct emissions from biomass is be used as the emission factor . Furthermore, the carbon capture technologies are assumed to be able to capture 95% of the carbon emissions. The emission factors are tabulated in table 14.

Table 14: Emission Factors per Technology

Technology	CO2 Emission Factor [kg.CO2/GJ]	CO2 Emission Factor [Mton CO2/Twh]	With CCS 95 %
PWRBIO	100.00	0.36	0.02
PWRCOAL	94.60	0.34	0.02
PWROIL	77.40	0.28	0.01
PWRGAS	56.10	0.20	0.01

For the Net Zero scenarios, there must be a limit to emissions. For this thesis, the emissions limits are taken from the ETIP (Ministry of Energy & Petroleum, 2023, p.9). The ministry describes this pathway as an ”orderly transition”, which will focus to decarbonizing the sectors with lowest abatement costs first and optimize for long-term economic gain and lower environmental impact. This pathway is compared with two alternatives, one which assumes a delayed transition, and one with a quicker transition. The Ministry has chosen a path which they claim is more ”balanced” and will prove a larger economical gain. They claim further that in 2050, the carbon emissions that come from the different energy sectors will be offset by afforestation and reduction in deforestation. The specific allowable carbon emissions that will be used in the model are tabulated in Table 15.

Table 15: Allowed Emissions in the Net Zero scenarios

Year	2020	2025	2030	2035	2040	2045	2050
Total C02 emissions [MtCO2e]	19	26	33	37	36	30	20

Chapter 4

In this section, the results are presented. First, the optimal solution of the energy mix and the total costs per scenario are presented. This results are then compared with the ETIP. The land value of Marsabit is presented. After the results are presented, further analyses are done. The first analysis investigates the effect of changing wind turbine models on the land value. The second analysis will compare the land values of different energy technologies. The third analysis will investigate the effects on land values of the different technologies if the reference scenario changes. The new reference scenario is a scenario where LTWP utilizes an alternative wind turbine model.

4.1 Results

4.1.1 Optimal Solution

The results of the 4 scenarios can be seen in figure 12. Here, the cumulative installed capacities per year are shown as per the optimal solution is shown. The new installed capacities are shown in Figure 13. The technologies in these figures are only the power production technologies connected to the grid, which is denoted by ”PWR”. Here, ”PWRLTWP” is the technology that uses the areas in Marsabit for power production.

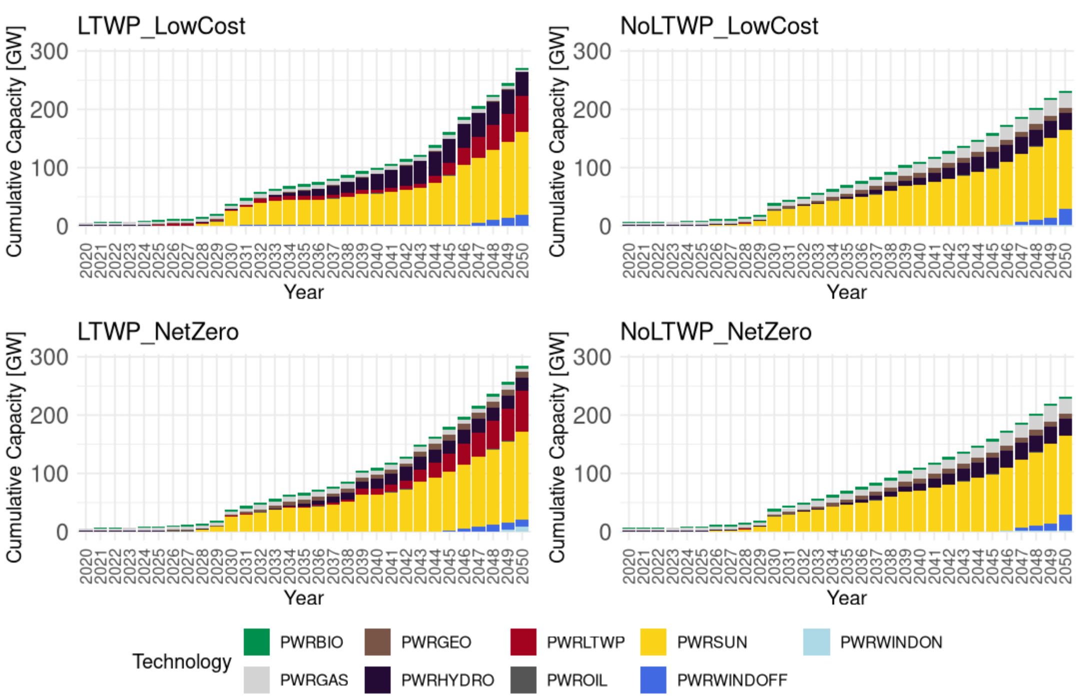


Figure 12: The Cumulative Installed capacity per year for the 4 scenarios

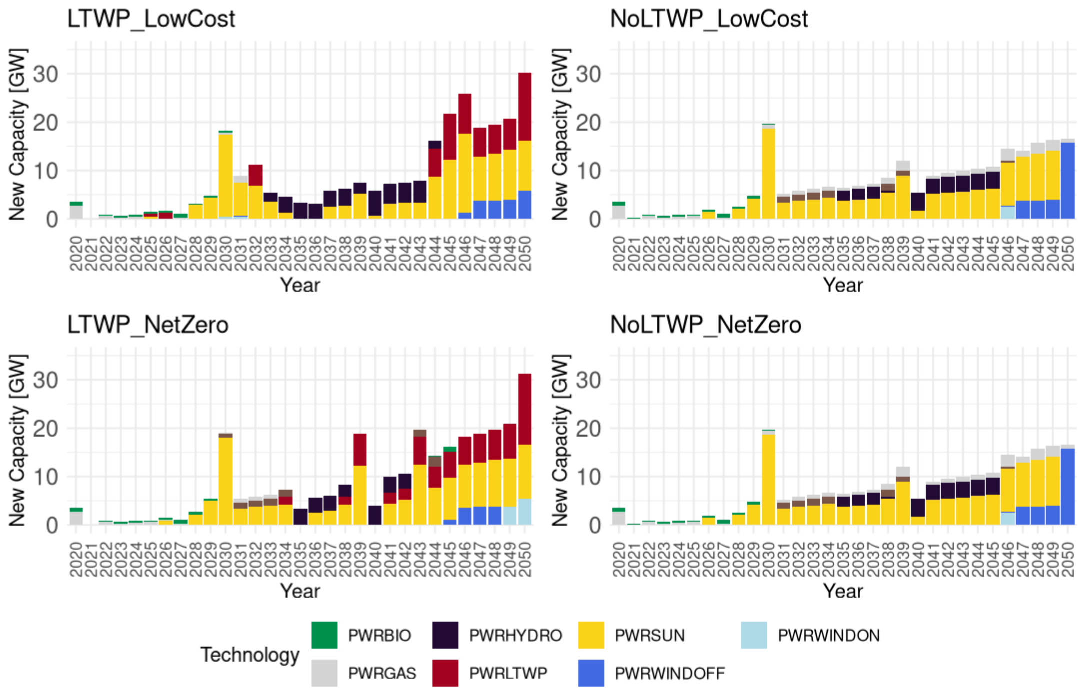


Figure 13: The New Installed capacity per year for the 4 scenarios

Table 16: Total costs of the 4 scenarios

Scenario	Total Cost [Mill. $]
LTWP_LowCost (reference)	245035
NoLTWP_LowCost	258680
LTWP_NetZero	245035
NoLTWP_NetZero	258680

The total system costs of the scenarios are tabulated 16, which shows that there is minimal difference in the 4 scenarios. It is clear that there is no difference in the total costs between Low Cost and Net Zero for two cases where we do and do not have the Marsabit wind potential available. The figures illustrate the same conclusion, there is little difference in the built capacity between the Low Cost and Net Zero scenarios. The optimal solution determines that the renewable energy sources are cheap enough to invest in and that the investment in natural gas is small enough so that the CO2 emissions are still within the given limits. Naturally, one can discuss if it is possible to have CO2 emissions from the power sector in order to reach net zero targets, but it is assumed that this is possible, as described in section 3.4.2. Because renewable energy technologies are so cheap in all forms, the optimal energy mix is the exact same. The total installed capacity of the capacities in the year 2050 is shown in Figure 14.

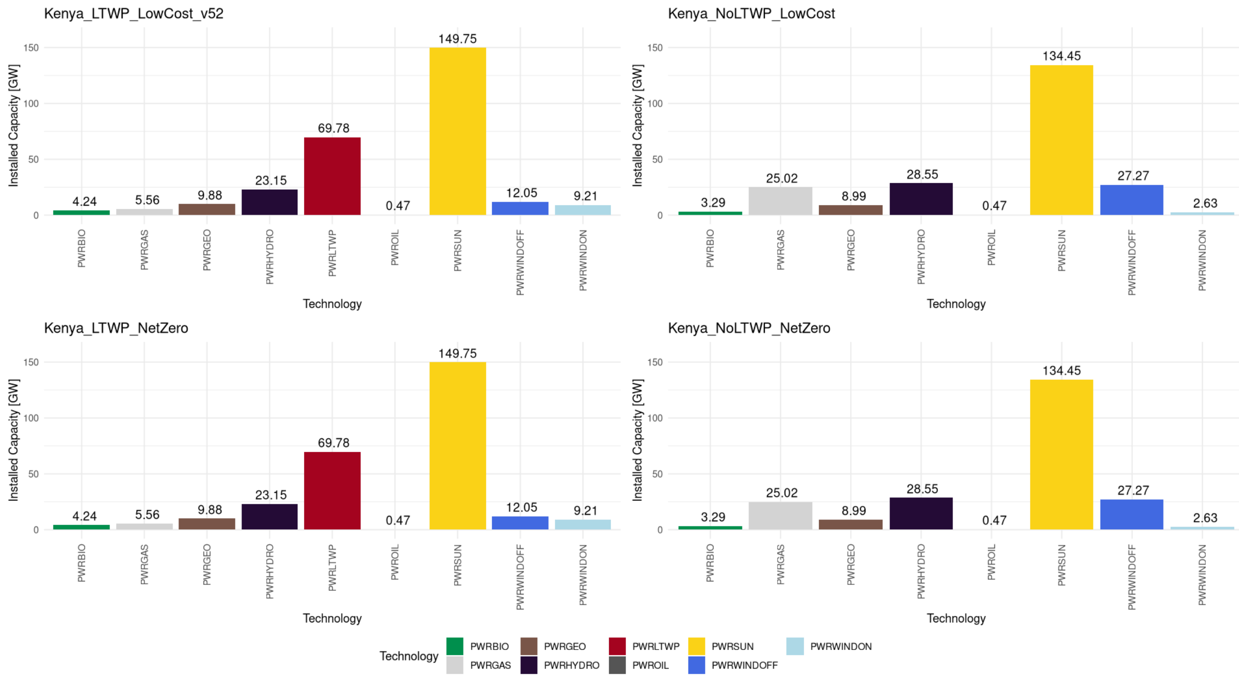
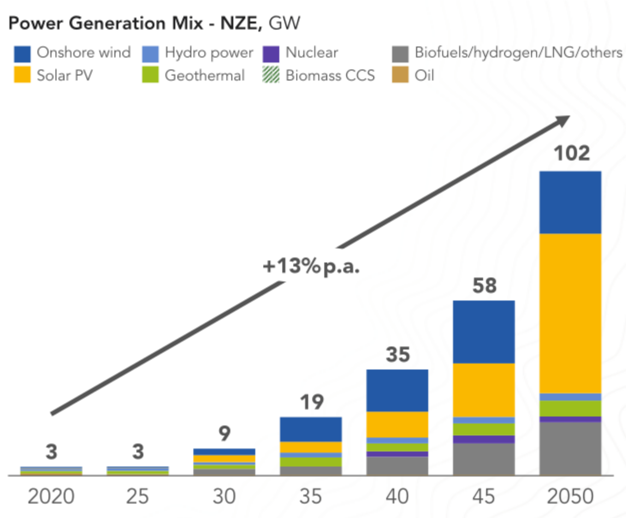


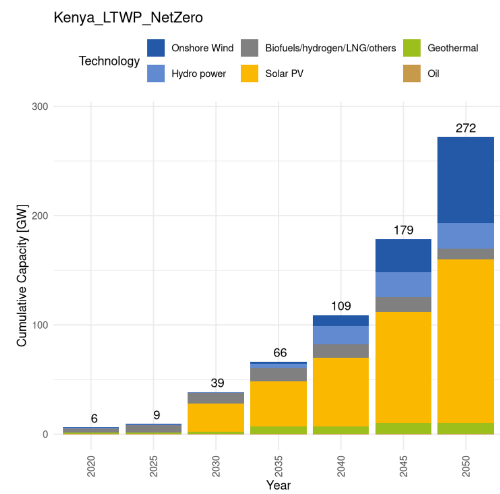
Figure 14: Installed capacity in 2050 [GW]

4.1.2 Comparison with ETIP

Figure 15 illustrates the differences between the Ministry's planned generation mix (Ministry of Energy & Petroleum, 2023, p.51) and the results from the Net Zero scenario. Here, a large difference in total installed capacity is clear. The ministry claims that in 2050, solar PV should have a capacity of 50 GW and onshore wind around 18 GW. How does this compare with the assumed demand of 190 TWh in 2050? Assuming a capacity factor of 0.2 for Solar PV and 0.5 for onshore wind, this would mean yearly energy production of $50 * 0.2 * 8760 + 18 * 0.5 * 8760 = 182.20$ TWh, something that is very close to the country's total electricity demand by 2050. For almost every year, the total installed capacity Net Zero scenario is much larger than the ETIPs total installed capacity. The differences might have several explanations. Naturally, it is impossible to verify due to the lack of transparency from the Ministry, as obtaining the data used for the ETIP is not possible. One explanation is that the ETIP scenario includes a form of storage, something that could reduce the amount of necessary capacity needed, as the system could choose when to produce and not to produce to a higher degree. The Ministry does not disclose any assumption regarding some form of energy storage in the ETIP. Another explanation is perhaps that the Ministry will rely more on using biofuels, hydrogen, LNG and the like, something that is not included in the model and that there is a difference in the modelling software used. Another reason is that



(a) Power Generation Mix from ETIP (Ministry of Energy & Petroleum, 2023)



(b) Power Generation Mix in Net Zero scenario

Figure 15: Comparison of the Net Zero from the ETIP and from this thesis

the installed capacities the ETIP perhaps do not take efficiencies into account, something that the results from OSeMOSYS does! This explains the majority of the difference. If the capacities are multiplied by their respective efficiencies, then the results become much more equal. So, the ETIP looks at the generation mix, meaning how much is generated by each power technology, the results from the Net Zero considers the installed capacity.

4.1.3 Value of Land Area

As discussed in section 3.1, the value of the land area will be calculated by first calculating the opportunity cost, which is the difference between the reference scenario and the other scenarios. The land value is calculated by dividing the opportunity cost by the estimated land area that LTWP requires. In the scenarios where LTWP is allowed, the opportunity costs become 13645 mill. USD, both for low cost and net zero. In 2050, two scenarios where LTWP is included, they both calculate an installed capacity of 69783 MW in the year 2050, which is equal to $69783/0.850 = 82097$ turbines. However, this exceeds the the estimated maximum turbines that fit within the land area, as tabulated in table 10. This is strange, as the the maximum allowed energy is 100% utilized and not exceeded in the model. In other words, in the optimal solution, LTWP generates 1057.88 TWh over the modelling period. The result of this discrepancy is that optimal solution uses a larger land area than what be allowed. Going forward, the maximum amount of land area in Marsabit will be used, namely 12614 km^2. Since the costs are in terms of mill. USD per capacity, the optimal solution has more capacity than what should be allowed. This means that opportunity cost should be somewhat lower than what the model calculates. The land value becomes $13645/12614 = 1.08$ mill. USD per km^2. The opportunity costs are tabulated in Table 17. Keep in mind that the values in the column denoting the land area used, it is the land area of LTWP in the parallel scenarios where LTWP was allowed.

Table 17: Opportunity cost of the 4 scenarios

Scenario	Opportunity Cost [Mill. $]	area used [km^2] (in)	Land Value [Mill. USD / km^2]
NoLTWP_ LowCost	13645	12614	1.08
NoLTWP_ NetZero	13645	12614	1.08

Thus, the land value of the most potent areas for wind power in Marsabit is 1.08 mill. USD per km^2 for the whole modelling period. One can then ask, what this value actually implies. This value is the value of the land to the long-term energy system. Since it is derived from the total system cost of the energy system, it can only be compared in the context of energy system analysis. Since the total system cost does not include any electricity sales, benefits to the Kenyan GDP and other economic activities, it cannot be used directly to compare the land value of Marsabit if it is used for e.g agriculture or tourism, since these two sectors have completely different economical contexts. In order to get a better understanding what the land values are useful for, the next part of this thesis will be to compare the land value of wind power in Marsabit with other land values of other energy sources. From this point forward, the Net Zero scenario will be used as a reference. This is

4.2 Further Analysis

4.2.1 Investigating Different Turbine Models

The amount of energy which is assumed to be theoretically obtainable from Marsabit is based on the assumption that the wind turbine that will be used is the V52-0.850 which is the one which actually is there, in LTWP, as described in section 3.4.2. Per industry standards, this is a very small turbine model. By increasing size of the model turbine, more energy would be exploitable. Naturally, bigger turbines require more land area. So what are the consequences of increasing the wind turbines?

For further analysis, 3 different turbine models were used, as tabulated in Table 18. Despite the fact that larger models require more area, the larger models get a much larger increase in capacity

Table 18: Energy available per wind turbine model

Model Name	Rotor Diameter [m]	Capacity [MW]	# per km^2	Efficiency	Max Energy [TWh]
V52-0.85 (current)	52	0.85	4.7	0.2	1057.9
V110-2.0	110	2.0	2	0.3	11138.5
V136-4.2	136	4.2	0.87	0.4	35755.2

and therefore energy output. Note that the amount of energy per wind turbine is calculated without the efficiency nor the capacity factor. These two parameters are included in the actual simulation within the parameters "InputActivityRatio", which contains the ratio of energy the turbine is able to harvest from the wind, and "CapacityFactor" which is assumed to be the same for all models, namely 0.7. The amount in Table 18 is supposed to the theoretical maximum from the windiest areas in Marsabit. By running the model with the net zero scenario as a reference, using the 3 different turbine models, the effect of the increase is visible.

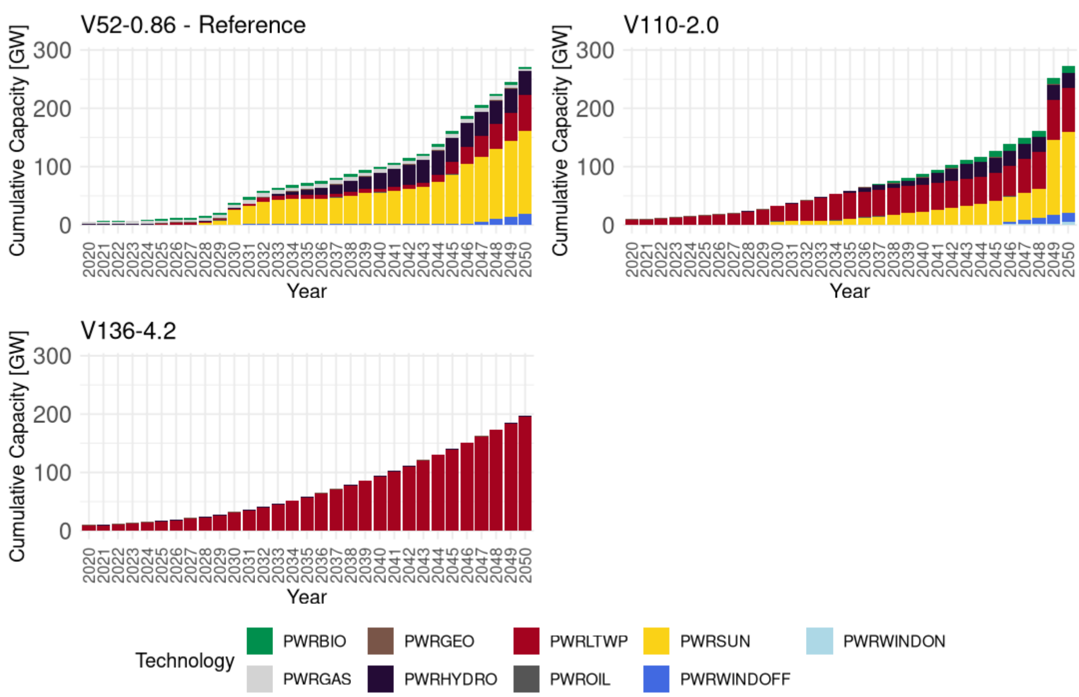


Figure 16: Cumulative Installed Capacities per year for the 3 different wind turbine models

The results are illustrated in Figure 16 and 17. The figures show that by changing the models of the wind turbines, the model prefers investing fully in the LTWP turbines. This could indicate

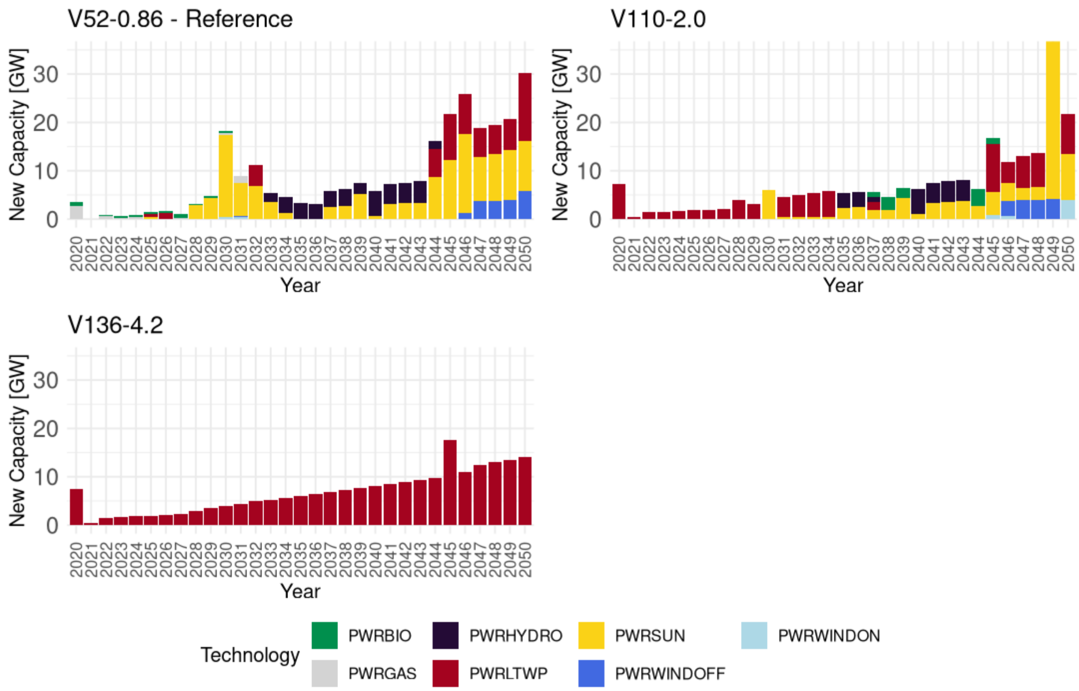


Figure 17: New Installed Capacities per year for the 3 different wind turbine models

that the area is rather under utilized, and that the choice of the current wind turbines are a poor choice in terms of utilizing the area efficiently. In the scenario that the larger turbine models are used, almost the entire electricity demand is generated by LTWP, with a utilization of 75.6 %. The land values of these scenarios are tabulated in Table 19. Naturally, these wind turbines face the same weakness as described in section 4.1.3, so the land values should be somewhat lower.

Table 19: Land Values of Marsabit Using Different Turbine Models

Scenario	Opportunity Cost [Mill. USD]	Area used [km^2]	Land Value [Mill. USD / km^2]
No LTWP	13645	12614	1.08
Using V110-2.0	85577	12614	6.78
Using V136-4.2	155013	9656	16.26

The land values becomes very different with the larger wind turbine models. In the scenario with the V110 model, 100% of the land area was used for production, but the limit was not reached for the scenario using the V136 model. As Table 19 shows, the value of the land when compared to the scenario where LTWP is not allowed is increased by roughly 1600 %. This is a massive increase in value by just changing the turbine model. This further makes the argument that with the current turbine models, the wind power resources in Marsabit are heavily under utilized. If the park were to change the turbine model to the V110 or V136, and keep the same capacity (310 MW), then it would need a land area of 77.5 km^2 and 84.8 km^2 respectively, given the assumptions from Table 18. Compared to the current land area (162 km^2), the change in turbine models could reduce the amount of required land area by nearly half.

Naturally, the comparison is not a completely fair one, as the assumed costs are the same for each scenario. Finding the specific capital costs for each turbine is difficult. The costs now, which are gathered from NREL, are made with a reference turbine of 2 MW. Assuming that the larger turbines have higher capital costs, due to more material demand, the V52 is made more expensive than what it is, and that the V136 is cheaper than what it realistically is. So how can this be accounted for, to make the comparison more fair? By ways of sensitivity analysis, capital costs of PWRLTWP were increased by 20%, 40% and 60% in 3 different scenarios. The results are tabulated in table 20. The optimal solutions did not change for any of the scenarios, except that the total cost increased slightly. This means that despite the higher capital cost increase associated with the V136, it is still the preferred generation technology, according to OSeMOSYS. In fact, even if the capital costs were multiplied by 10, the optimal solution does not change. This means that the costs of the turbines can increase by tenfold and still not have any effect on the optimal solution, which indicates that the most important parameter for the wind turbines is the capacity.

Table 20: Effect on total system cost by changing capital cost of the V136 model

V136 Capital Cost Increase	Total System Cost [Mill. USD]
20%	90781
40%	91540
60%	92678
100%	93817
200%	97612
1000%	124123

4.2.2 Comparison of LTWP and Other Energy Sources

This thesis has derived a land value for the areas in Marsabit with high wind power potential. The next step is to compare the value of LTWP with other energy sources. This will be done with the same method as described in 3.1, except that the Net Zero pathway will be chosen as the reference scenario. The other energy sources in question will be solar, geothermal and hydroelectric, as they are consistently part of the optimal solution to the scenarios. The results are tabulated in Table 21

To start, solar will be investigated. As figure 14 shows, the installed capacity of solar energy (PWRSUN) in the reference scenario (LTWP_NetZero), capacity becomes 149.75 GW in 2050. By taking another solar power plant in Kenya as a reference, a land area footprint can be determined. The Garissa solar power plant has a rated capacity of 55 MW and a land use of 85 ha (Igadwah, 2018). This is equal to 0.85 km^2, which equals a footprint of $55/0.85 = 64.71$ MW/km^2. An installed capacity of 149.75 GW would equal a total land area of $149.75 * 10^3/64.71 = 2314.171$ km^2. Next, by running the model with the Net Zero scenario without solar energy, the total cost becomes 301305 mill. USD. The opportunity cost becomes $301305 - 245035 = 56270$ mill. USD. Thus, the land value of solar power becomes $56270/2314.171 = 24.32$ mill. USD per km^2.

Next, geothermal is considered. Geothermal as an energy source utilizes areas in a different manner than wind and solar. As with all renewable energy sources, geothermal power plants must be located at exact locations where the primary energy source is abundant, in this case where steam can be extracted. The difference between geothermal and wind & solar, wind and solar power plants are built in larger areas and are surrounded by the primary energy source, geothermal must be built on top of steam geysers. One could make the distinction that wind and solar power plants are build inside their primary energy source, while geothermal is built around it's primary energy source. The land area itself is not a limiting factor, rather the availability of steam is. This means that the land use of geothermal power plants has a different interpretation. According to U.S. Department of Energy Geothermal Technologies Office, 2019, geothermal is one of the most space efficient power sources per unit of energy, requiring a land footprint of 404 m^2 per GWh (U.S. Department of Energy Geothermal Technologies Office, 2019, p. 42). In the reference scenario, the installed capacity of the power plants. Figure 14 shows that the installed capacity of geothermal energy (PWRGEO) is 9.88 GW. From Table 5, the average capacity factor of geothermal energy is calculated, which equates to 0.68. Thus, in 2050, the geothermal will generate $9.88*8760h*0.68 = 58853$ GWh. This means that geothermal has a footprint of $58853*404*10^-6 = 23.77$ km^2. When the reference scenario is simulated without geothermal, the total cost becomes 253231 mill. USD, which leads to an opportunity cost of $253231 - 245035 = 8199$ mill. USD. Finally, the land value becomes $8199/23.77 = 344.93$ mill. USD per km^2.

Hydroelectric power also utilizes area differently from wind and solar. As with geothermal, hydroelectric power plants must be built around their primary energy resource, namely water. For large hydro plants, dams are built around large lakes which then become part of the utilized area of the power plant. This means that the area used must be interpreted differently from wind and solar, as it is not as easy to scale up and down as wind and solar. Like geothermal power plants, hydroelectric power plants are limited by the availability of the water, and not by the area that is available. (PWRHYDRO) has an installed capacity of 23.149 GW, as shown in figure 14. According to Ritchie, 2022, the median land footprint of hydroelectric power plants are 33 m^2 per

MWh and 14 m^2 per MWh for small-to-medium plants (smaller than 360 MW) and large plants (above 660 MW) respectively. According to the data given by KPLC, none of the power plants are larger 360 MW. By using the average capacity factor for hydroelectric of 0.61, as provided by table 5 the energy output of hydroelectric in 2050 becomes $23.149*10^3*0.61*8760 = 123700706$ MWh. This equals a land footprint of $123700706 * 33 * 10^{-6} = 4082.12$ km^2. Running the model without hydroelectric power gives a total cost of 285872 mill. USD, which leads to an opportunity cost of $285872 - 245035 = 40877$ mill. USD. The land value becomes $40877/4082.12 = 10.01$ mill USD per km^2.

Table 21: Land Values of Solar, Geothermal and Hydroelectric

Scenario	Opportunity Cost [Mill. $]	Area used [km^2]	Land Value [Mill. USD / km^2]
No LTWP	13645	12614	1.08
No Solar	56270	2314	24.32
No Geothermal	8199	23	344.93
No Hydro	40877	4082	10.01

As table 21 shows, geothermal has the highest and value, despite having the lowest opportunity cost. From a land use perspective, geothermal energy has a very small land footprint when compared to the other renewable energy sources. However, as previously discussed, the land value must be interpreted differently than from the other sources, as the plant cannot be scaled up in the same that solar, wind and to some extent, hydro can. The land value for LTWP is low compared to the other energy technologies, and also low when compared the cases where other turbine models were used (table 19). This indicates that the current configuration of LTWP is poorly utilized.

4.2.3 Changing the Reference Scenario

Thus far, the land values are derived using the opportunity costs with the reference scenario, which only uses the V52 turbine model. This section will investigate the effects of changing the reference scenario, so that it uses the V110. The installed capacities of the different power producing technologies in 2050 per the optimal solution is illustrated in figure 18.

The method of calculating the used land areas per the different energy sources will be the same is in section 4.2.2. In the scenario where the V110 is used (see 19), the installed capacities in 2050 for solar, geothermal and hydro are 138.87 GW, 0.62 GW and 25.59 GW respectively. The footprints of the technologies are 64.71 MW per km^2, 404 m^2 per GWh and 33 m^2 per MWh. For hydro and geothermal, the capacity factors are the same is section 4.2.2. The used land for

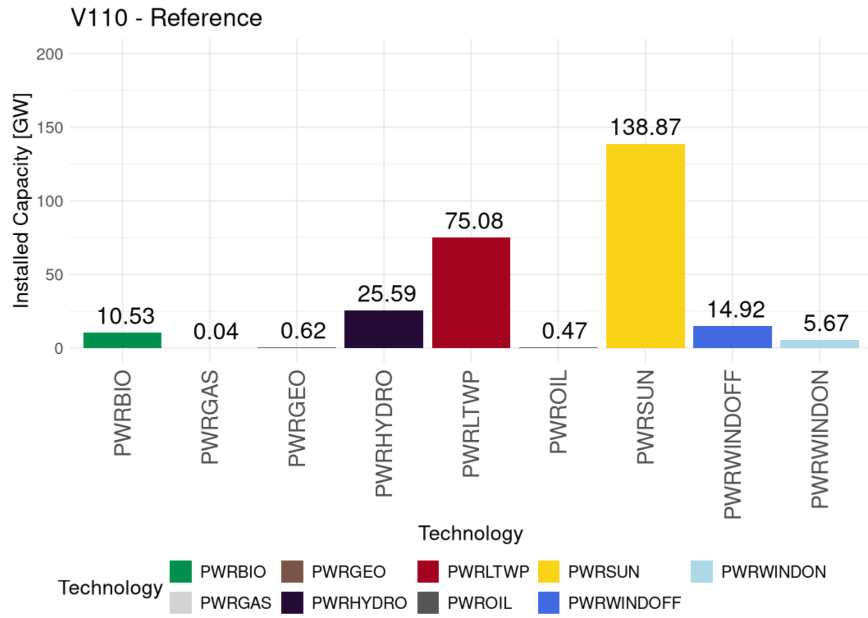


Figure 18: Installed capacity in 2050 with V110 Scenario [GW]

solar is $138.87 * 10^3/64.71 = 2146.03$ km^2. After the simulation, the opportunity cost became $176269 - 159458 = 16811$ mill. USD. Finally, the land value for solar becomes $16811/2146.03 = 7.83$ mill. USD per km^2. For geothermal, the energy produced becomes $0.62 * 8760h * 0.68 = 3693$ GWh which leads to the used area land becoming $3693 * 404 * 10^-6 = 1.49$ km^2. The opportunity cost of geothermal is $161811 - 159458 = 2353$ mill. USD, which leads to a land value of $2353/1.49 = 1579.20$ mill. USD per km^2. For hydro, the produced energy in 2050 becomes $25.59 * 10^3 * 0.61 * 8760 = 136742724$ MWh, which leads to the used land area becoming $136742724 * 33 * 10^{-6} = 4512.5$ km^2. The opportunity cost of hydro is $195448 - 159458 = 35990$ mill. USD, which leads to a land value of $35990/4512.5 = 7.98$ mill. USD per km^2. The results are tabulated in table 22.

Table 22: Land Values of Solar, Geothermal and Hydroelectric with V110 as a reference

Scenario	Opportunity Cost [Mill. $]	Area used [km^2]	Land Value [Mill. USD / km^2]
No LTWP	85577	12614	6.78
No Solar	16811	2145	7.83
No Geothermal	2353	1.49	1579.2
No Hydro	35990	4512.5	7.98

Comparing table 21 with table 22 shows a sharp decrease in the land value of solar, a small decrease for hydro but a vast increase in the land value for geothermal. This last results is due to that geothermal saw no further investment in the reference scenario. The installed capacity for geothermal in this scenario equals it's residual capacity with the degradation the geothermal plants endure over the 30 years. The other results are the results that would be expected. As the land value for wind power rises, the land values for the other energy sources decreases. This illustrates the dynamic that investing in different technologies creates in the long-term. If one technology is invested in more than others, the demand for other technologies become smaller, which decreases the value of the land which that technology would be constructed on.

Chapter 5

In this chapter, key aspects of the thesis are discussed. First, the role of solar power in the electricity generation mix is investigated. Thereafter, an attempt is made to relate the value of the land area to an applicable monetary value. Lastly, the Net Zero pathway which is defined by the ETIP is discussed.

5.1 Area As an Input Parameter

As discussed in section 4.1.3, there is a discrepancy between the amount of land area that the model is supposed to be constrained by and what it actually uses. Since all input parameters into OSeMOSYS had units of either capacity, energy or monetary values, the land area of Marsabit had to be represented by an energy term, which was derived in section 3.4.2. This derivation proved to be inaccurate. Naturally, this brings into question, the accuracy of method andwhat other ways the theoretical energy maximum could be derived. One potential method could converting the land are, in km^2, into energy by using a conversion factor inputted into the parameter ”CapacityToActivityUnit”. Then, the resource technologies (RESWATER, RESSUN, RESLTWP etc.) would be constrained by the amount of allowable area. As was discussed in 4.2.2, renewable energy sources are limited by the amount of area were the primary energy source is located. However, one issue with this method, is that it the conversion from km^2 to energy could be difficult to accurately measure per technology. Energy system models do not contain a way of directly inputting area as the input, only energy.

A method that is used to get around this issue is by employing a so-called ”Modeling to Generate Alternatives” (MGA) (Chen et al., 2022; DeCarolis, 2011; Patankar et al., 2023). As DeCarolis (2011) explains: ”MGA uses the optimal model solution (the total cost) as an anchor to explore the surrounding feasible region.” This method could be used to first find the total cost, and thereafter find the minimum optimal land use. This method is beyond the scope of this thesis, but does provide a robust method for taking both system costs and land use into account when optimizing.

5.2 Land Value for Indigenous Groups and the Local Populous

The land values derived in this thesis are only comparable to other land values in the energy system. The next step is using the land value as a means to increase social welfare. As discussed in section 1.3, a method of reducing land use conflicts is through a land rent. Nysten-Haarala et al. (2021) illustrates the difficulty of putting a monetary value on indigenous land, and Martínez-Mendoza et al. (2020) discusses that farmers who have clear land ownership benefits more from land rents, but not necessarily indigenous groups. If the original reference scenario is taken into account, the land value of the areas illustrated in figure 10a became 1.08 mill. USD per km^2. By taking the current area of LTWP as a case (162 km^2), the total value of that land becomes $162 * 1.08 = 174.96$ mill. USD. By dividing this value by the 30 years used in the model period, the annual value becomes $174.97/30 = 5.832$ mill.USD per year. In for 10 months in 2020, LTWP generated 11.05 billion KSH in sales, equals 84.35 mill. USD with an exchange rate of 131 KSH/USD, equalling 6.9$\%$ of the revenues generated from electricity sales. If LTWP decides to use larger turbines, the land value would increase and with it the proposed land rent. However, with larger turbines, less area would be needed, as discussed in section 4.2.1. For example, if the V110 was chosen with a required demand of 310 MW, then it would need a land area of 77.5 km^2. From table 19, the land value when using the V110 is 6.78 mill. USD per km^2. This would result in a yearly land rent of $6.78 * 77.5/30 = 17.75$ mill. USD per year.

An interesting dilemma arises from this method of determining land value. A company that seeks to minimize costs would choose the cheapest alternative. As is tabulated in table 19, the project with the lowest land value is the V52 model, which is the model with the least amount of energy output per km^2. Logically, this would mean that in order to minimize costs, companies are incentivized to choose the projects with the lowest energy output, which uses the most amount of space per energy output. This seems counter-intuitive, as in order to minimize land use conflicts, it should the goal of a company to use as little area as necessary. However, this is where the role of the government plays a large role. Only a government or entity that seeks to maximize social welfare would be interested in reducing the total costs. The government can recognize that a project with the least land value is the one which is most easily replaceable by another project. For example, if a government anticipates that a project that chooses the lowest land values will cause conflict, it can argue that the energy output could more easily come from another energy source. For a concrete example: LTWP in it's current configuration has a land value of 1.08 mill. USD per km^2, and solar power has a land value of 24.32 mill. USD per km^2. A company would choose LTWP, as it would need to pay the least amount of land rent, but the government would argue that solar should be chosen instead, as this would mean less land used and likely less conflict.

5.3 The ETIP and the Net Zero pathway

As was discovered in section 4.1.1, the optimal solutions and total costs for the low cost and net zero scenarios were exactly the same. This brings some questions into fruition. For one, how realistic are the fuel prices for gas, oil and coal in the model? The results could indicate that the prices are too high. Since fuel prices are highly speculative and volatile, it is impossible to predict the prices accurately. A sensitivity analysis on fuel prices can be made to investigate different levels of fuel prices, but this was left out due to time constraints. Still, one could wonder why the optimal solution still allows for sizeable investment into natural gas plants. Figure 14 shows that even in the scenarios with LTWP, there is still 5.56 GW of installed capacity for natural gas (PWRGAS). This might imply 3 things. First, that the net zero pathway provided outlined by the ETIP is not strict enough. The Ministry relies on carbon sinks from forestry, but the effectiveness of forests as a carbon sink is debated (Luhtaniemi, 2023; Roebroek et al., 2023). The second implication is that the model recognizes that there must be some non-intermittent power generation in the mix for the high peak hours, since this model does not contain any direct form of storage in the model. If sufficient energy storage was added in the model, perhaps natural gas would not be invested in. The third implication of the similarity between the low cost and net zero scenarios is that renewable energies simply are cheaper than fossil fuel technologies. As Roser (2020) illustrates, is that renewable energy is now competitive without government subsidies, something that OSeMOSYS recognizes. Kenya as a country is still under heavy economic growth, and lacks much energy infrastructure. However, one ”benefit” of the late industrialization of Kenya and developing countries is that their industrialization has the opportunity to not be based on fossil fuels, falling victim to the phenomena of ”Carbon Lock-in” (Sato et al., 2021). This is a phenomena where past commitments into carbon intensive power plants result in a certain amount of greenhouse gases for the lifetime of the power plants.

Chapter 6

6.1 Conclusions

This thesis derived the land values of the areas with high wind power density in Marsabit. In the reference scenario, the land value became 1.08 mill. USD per km^2. This is rather low when compared to the land values of solar, geothermal and hydro, which were found to be 24.32, 344,93 and 10.01 mill. USD per km^2 respectively. The land value would increase if LTWP used larger wind turbine models, achieving land values of 6.78 mill. USD per km^2 and 16.26 mill. USD per km^2 for the turbine models V110-2.0 and V136-4.2 respectively. When changing the wind turbine model to a larger turbine model, the land value of the other technologies decreases. This illustrates the complex dynamics that investing in one technology can have on another.

Using land value as a method of gauging a fair land rent can be done, as the value is tied to the benefits to the energy system. If a government allows for a land area to be exploited for energy production, it can use the land value to infer a land rent. This method of infering land rent will hopefully provide a more fair method than letting a company decide how to compensate for the exploitation of land area for projects in isolation. When power companies do so, they will want to pay the least amount of land rent.

The results from the optimal solutions of the 4 scenarios showed no large difference between the results of the scenarios. This indicates two things. One, seen from a long-term energy analysis, is that LTWP in it's current configuration is not crucial for Kenya's Net Zero ambitions, as long as there is enough solar power available. The second is that the net zero pathway outlined by the ETIP either is not strict enough, or renewable energy technologies have become so competitive that they will always be part of the optimal solution.

6.2 Limitations

As discussed, the method of calculating the theoretical maximum of wind energy present in Marsabit was flawed. The maximum energy was based on the turbine model, the area available and the MPD of the area, but estimating the used land area from the resulting installed capacity was inaccurate.

No storage functionality was added to the model, which might have an impact on the optimal solution. Intermittent power sources like wind and solar can only produce during periods of high wind speeds or during the day, and cannot store that energy. Kenya has a lot of hydroelectric power capacity, which can be interpreted as a form of storage in the model. However, OSeMOSYS does allow for storage functionality, and this was not used.

Another limitation of this thesis is the lack of sensitivity analyses to test the robustness of the model. Especially for the prices with high volatility, like fuel prices, a sensitivity analysis investigates the impact of fluctations in prices on the optimal solution. At no point did the optimal solution invest in carbon capture technology for carbon intensive power generation (COALCCS, OILCCS, GASCCS). If the fuel prices were lower, the model would presumably do so. Another sensitivity analysis which was omitted was the discount rate. For the whole period, the default discount rate of 0.05 was chosen. The discount rate might also have some impacts.

6.3 Further Research

Recommended further research is to see how the land value calculated in this way can be compared with other land values in other contexts. For example, how can the land value in an energy system context compare with land values when the land is used for tourism, agriculture or housing? This is especially interesting for solar power, as solar power often competes more directly with agricultural land than other energy sources.

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A Other Parameters

This appendix includes the rest of the the parameters which the model requires to work. The models which are not explicitly described either here in chapter 3.4.2 use the default value.

Default Values

	VALUE	PARAM	VALUE
AccumulatedAnnualDemand	0.00	REMinProductionTarget	0.00
AnnualEmissionLimit	Inf	ReserveMargin	1.00
AnnualExogenousEmission	0.00	ReserveMarginTagFuel	0.00
AvailabilityFactor	1.00	ReserveMarginTagTechnology	0.00
CapacityFactor	1.00	ResidualCapacity	Inf
CapacityOfOneTechnologyUnit	0.00	ResidualStorageCapacity	999.00
CapacityToActivityUnit	1.00	RETagFuel	0.00
CapitalCost	0.00	RETagTechnology	0.00
CapitalCostStorage	0.00	SpecifiedAnnualDemand	0.00
Conversionld	0.00	SpecifiedDemandProfile	0.00
Conversionlh	0.00	StorageLevelStart	999.00
Conversionls	0.00	StorageMaxChargeRate	99.00
DaysInDayType	7.00	StorageMaxDischargeRate	99.00
DaySplit	0.00	TechnologyFromStorage	0.00
DepreciationMethod	1.00	TechnologyToStorage	0.00
DiscountRate	0.00	TechWithCapacityNeededToMeetPeakTS	0.00
EmissionActivityRatio	0.00	TotalAnnualMaxCapacity	Inf
EmissionsPenalty	0.00	TotalAnnualMaxCapacity Investment	Inf
FixedCost	0.00	TotalAnnualMinCapacity	0.00
InputActivityRatio	0.00	TotalAnnualMinCapacity Investment	0.00
MinStorageCharge	0.00	TotalTechnAnnualActivityLowerLimit	0.00
ModelPeriodEmissionLimit	Inf	TotalTechAnnualActivityUpperLimit	Inf
ModelPeriodExogenousEmission	0.00	TotalTechModelPeriodActivityLowerLimit	0.00
OperationalLife	1.00	TotalTechModelPeriodActivityUpperLimit	Inf
OperationalLifeStorage	99.00	TradeRoute	0.00
OutputActivityRatio	0.00	VariableCost	0.00

YearSplit [l,y]

TIMESLICE	Fraction	TIMESLICE	Fraction
WKD_N_RAIN	0.16	END_N_RAIN	0.06
WKD_N_DRY	0.22	END_N_DRY	0.09
WKD_D_RAIN	0.10	END_D_RAIN	0.04
WKD_D_DRY	0.14	END_D_DRY	0.06
WKD_E_RAIN	0.04	END_E_RAIN	0.02
WKD_E_DRY	0.06	END_E_DRY	0.02

Table 23: Fractions for parameter YearSplit

DaySplit[lh,y]

1	Dailytimebracket	Value (constant through all years)
2	1	0.000913242009132
3	2	0.00142694063927
4	3	0.000399543378995

Table 24: Fractions for DaySplit

Conversionls[l,ls], Conversionld [ld,l], Conversionlh[lh,l]

TIMESLICE	Season	
	1	2
WKD_N_RAIN	0	1
WKD_N_DRY	1	0
WKD_D_RAIN	0	1
WKD_D_DRY	1	0
WKD_E_RAIN	0	1
WKD_E_DRY	1	0
END_N_RAIN	0	1
END_N_DRY	1	0
END_D_RAIN	0	1
END_D_DRY	1	0
END_E_RAIN	0	1
END_E_DRY	1	0

Table 25: Season Table

TIMESLICE	Daytype	
	1	2
WKD_N_RAIN	1	0
WKD_N_DRY	1	0
WKD_D_RAIN	1	0
WKD_D_DRY	1	0
WKD_E_RAIN	1	0
WKD_E_DRY	1	0
END_N_RAIN	0	1
END_N_DRY	0	1
END_D_RAIN	0	1
END_D_DRY	0	1
END_E_RAIN	0	1
END_E_DRY	0	1

Table 26: Daytype Table

TIMESLICE	Dailytimebracket		
	1	2	3
WKD_N_RAIN	1	0	0
WKD_N_DRY	1	0	0
WKD_D_RAIN	0	1	0
WKD_D_DRY	0	1	0
WKD_E_RAIN	0	0	1
WKD_E_DRY	0	0	1
END_N_RAIN	1	0	0
END_N_DRY	1	0	0
END_D_RAIN	0	1	0
END_D_DRY	0	1	0
END_E_RAIN	0	0	1
END_E_DRY	0	0	1

Table 27: Dailytimebracket

SpecifiedDemandProfile[r,f,l,y]

	Fraction
END_E_RAIN	0.02
END_E_DRY	0.03
END_N_RAIN	0.03
END_N_DRY	0.04
WKD_E_RAIN	0.06
END_D_RAIN	0.06
WKD_E_DRY	0.08
WKD_N_RAIN	0.08
END_D_DRY	0.09
WKD_N_DRY	0.12
WKD_D_RAIN	0.16
WKD_D_DRY	0.24

Table 28: Fraction of total demand per timeslice

CapacityToActivityUnit[r,t]

Since capacity is in MW and activity in TWh, the conversion becomes 0.00876

OperationalLife[r,t]

Technology	Years	Technology	Years
PWRHYDRO	50.00	PWRNUCLEAR	50.00
PWRGEO	25.00	PWRGAS	30.00
PWRWINDON	25.00	PWRGASCCS	30.00
PWRLTWP	25.00	PWRCOAL	35.00
PWRWINDOFF	25.00	PWRCOALCCS	35.00
PWRBIO	30.00	PWROIL	25.00
PWRSUN	24.00	PWROILCCS	25.00

InputActivityRatio[r,t,f,m,y]

	Efficiency	InputActivityRatio
PWRHYDRO	0.95	1.05
PWRGEO	0.80	1.25
PWRWINDON	0.20	5.00
PWRLTWP	0.20	5.00
PWRWINDOFF	0.50	2.00
PWRBIO	0.35	2.86
PWRSUN	0.20	5.00
PWRNUCLEAR	0.35	2.86
PWRGAS	0.30	3.33
PRWGASCCS	0.48	2.08
PWRCOAL	0.37	2.70
PWRCOALCCS	0.37	2.70
PWROIL	0.35	2.86
PWROILCCS	0.35	2.86
TRANSMISSION	0.95	1.05
DISTRIBUTION	0.90	1.11

All other ratios are 1.

OutputActivityRatio[r,t,f,m,y]

DISTR has 0.2 on outgoing fuels. Everything else 0.

TotalAnnualMaxCapacity[r,t,y]

”IMPELEC” as max capacity of 4800. Everything is is limitless.

B Example KPLC data

	A	B	C	D	E	F	G	H	I	J	K
1	**THE KENYA POWER & LIGHTING COMPANY LIMITED**										
2											
3	**NATIONAL CONTROL CENTRE**					**DAILY SYSTEM LOG SHEET**					
4											
5		*Half-Hour Readings in MW.*									
7	***STATION***	***00.30***	***01.00***	***01.30***	***02.00***	***02.30***	***03.00***	***03.30***	***04.00***	***04.30***	***05.00***
8	IMPORT FROM UETCL	9.000	9.000	8.650	8.650	8.224	8.224	9.300	9.300	11.140	11.140
9	EXPORT TO UETCL	7.704	7.704	4.968	4.968	4.128	4.128	6.684	6.684	0.960	0.960
10	**NET IMPORT FROM UETCL**	**1.296**	**1.296**	**3.682**	**3.682**	**4.096**	**4.096**	**2.616**	**2.616**	**10.180**	**10.180**
11	WANJII	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	TANA	20.54	19.14	19.16	19.20	19.22	19.22	19.20	19.22	19.22	19.22
13	MASINGA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14	KAMBURU	20.00	20.00	20.00	20.00	20.00	20.00	20.00	22.00	24.00	24.00
15	GITARU	52.00	52.00	54.00	54.00	54.00	54.00	56.00	58.00	58.00	60.00
16	KINDARUMA	24.00	24.00	22.00	24.00	24.00	22.00	10.00	10.00	10.00	10.00
17	KIAMBERE	152.00	156.00	142.00	124.00	128.00	136.00	130.00	130.00	130.00	132.00
18	MESCO	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38
19	SOSSIANI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
20	SAGANA	1.39	1.39	1.39	1.39	1.39	1.39	1.39	1.39	1.39	1.39
21	SANGORO	22.54	19.84	19.76	19.74	19.74	19.74	19.74	19.74	19.74	19.74
22	GOGO	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71
23	SONDU MIRIU	84.00	60.00	60.00	60.00	60.00	60.00	60.00	60.00	60.00	60.00
24	TURKWEL	16.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25	GIKIIRA	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
26	TEREM SHP	2.20	2.20	2.20	2.20	2.20	2.20	2.20	2.20	2.20	2.20
27	CHANIA- KTDA SHP	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
28	GURA- KTDA SHP	1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.20
29	**TOTAL HYDRO+UETC IMP**	**406.423**	**366.323**	**351.913**	**335.933**	**339.527**	**345.527**	**330.583**	**334.603**	**338.443**	**342.443**
30											
31	FUTURE PLANT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
32	IBERAFRICA 2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
33	OLKARIA 1	27.88	27.88	27.76	27.68	27.60	27.56	27.44	27.40	27.58	27.66
34	ORPOWER4 STEAM I	53.300	53.580	53.940	55.300	55.120	54.940	50.400	39.940	39.940	39.940
35	MUMIAS POWER	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
36	THIKA POWER	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
37	MUHORONI GT 1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
38	MUHORONI GT 2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
39	KDP1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	A	L	M	N	O	P	Q	R	S	T	U	V	W
1	**THE KENYA POWER & LIGHTING COMPANY LIMITED**	**Doc. No. KP1/7A.1/4/15**											
2													
3	**NATIONAL CONTROL CENTRE**	**DAY:**	Wednesday										
4		**DATE:**	2020-01-01										
5													
7	***STATION***	***05.30***	***06.00***	***06.30***	***07.00***	***07.30***	***08.00***	***08.30***	***09.00***	***09.30***	***10.00***	***10.30***	***11.0***
8	IMPORT FROM UETCL	11.680	11.680	5.712	5.712	11.392	11.392	5.200	5.200	3.900	3.900	9.100	9.10
9	EXPORT TO UETCL	1.992	1.992	6.768	6.768	2.016	2.016	7.776	7.776	9.528	9.528	4.704	4.70
10	**NET IMPORT FROM UETCL**	**9.688**	**9.688**	**-1.056**	**-1.056**	**9.376**	**9.376**	**-2.576**	**-2.576**	**-5.628**	**-5.628**	**4.396**	**4.39**
11	WANJII	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
12	TANA	19.22	19.22	19.22	19.22	19.22	19.20	19.04	19.04	19.04	19.04	19.04	19.0
13	MASINGA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
14	KAMBURU	24.00	22.00	24.00	20.00	0.00	0.00	26.00	26.00	28.00	28.00	28.00	28.0
15	GITARU	60.00	66.00	64.00	58.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
16	KINDARUMA	10.00	12.00	10.00	10.00	18.00	24.00	12.00	12.00	10.00	10.00	12.00	10.0
17	KIAMBERE	128.00	130.00	126.00	140.00	134.00	146.00	164.00	124.00	150.00	150.00	140.00	146.0
18	MESCO	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.3
19	SOSSIANI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
20	SAGANA	1.39	1.39	1.39	1.39	1.39	1.39	1.39	1.39	1.39	1.39	1.39	1.3
21	SANGORO	19.74	19.74	19.74	19.76	19.74	19.78	19.84	19.84	19.96	20.06	19.66	20.1
22	GOGO	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.7
23	SONDU MIRIU	60.00	60.00	60.00	60.00	60.00	60.00	62.00	60.00	60.00	60.00	60.00	60.0
24	TURKWEL	0.00	0.00	0.00	0.00	0.00	0.00	4.00	40.00	40.00	42.00	40.00	42.0
25	GIKIIRA	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.3
26	TEREM SHP	2.20	2.20	2.20	2.20	2.20	2.20	2.20	2.20	2.20	2.20	2.20	2.2
27	CHANIA- KTDA SHP	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.1
28	GURA- KTDA SHP	1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.2
29	**TOTAL HYDRO+UETC IMP**	**338.983**	**346.983**	**335.015**	**339.035**	**268.695**	**286.715**	**318.423**	**312.423**	**337.243**	**339.343**	**334.143**	**340.62**
30													
31	FUTURE PLANT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
32	IBERAFRICA 2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
33	OLKARIA 1	27.80	27.80	27.66	27.60	27.48	27.86	27.48	27.56	27.52	27.60	27.62	27.5
34	ORPOWER4 STEAM I	39.440	39.440	39.440	39.540	39.380	38.800	39.140	42.440	43.980	51.460	51.760	50.42
35	MUMIAS POWER	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
36	THIKA POWER	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
37	MUHORONI GT 1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
38	MUHORONI GT 2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
39	KDP1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0

LOGSHEET | ANALYSIS | EXEC. SUMMARY | THIKA POWER | OLKARIA V | NAIVASHA&MUSAGA | TESTFLOWS | HYDROLOGY DATA | Generation Dispatch Sheet. | BIOJOULE | MUMIAS SUGAR | WELLHEADS - ALL | KDP 3

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