Master's Thesis

Development and Evaluation of a Simplified Approach for Modeling Country Energy Systems

In partial fulfillment of the requirements for the degree
Master of Science
at the department Electrical and Computer Engineering
of the Technical University of Munich.

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Submitted on	Munich, September 10, 2019

Abstract

The need for a shift towards renewable energies has driven countries to analyze which policies could be implemented in order to reach a specific decarbonization goal. Due to the time intensiveness required to develop a complete country model and to the problem of missing data, a standardized and simplified approach for modeling country energy systems is developed and evaluated.

The categorization of energy systems is not a new idea, however, these are normally performed in a higher resolution and do not span countries that transcend continental borders. The idea of clustering countries with similar characteristics in order to derive general energy models is explored. To determine the accuracy of this approach, an archetype (or cluster) model is analyzed in parallel with a simplified country model. This allows to determine whether under the same conditions, the archetype and the country model can lead to similar results when determining the transition pathways of different energy systems.

It is found that for the modeled countries, the archetype tends to identify the base technologies that appear for all the countries within a certain cluster. this might help determine market entrance possibilities, as well as obtain a first orientation for system planning. The challenges and limitations are identified in the model and analyzed in order to better develop the idea.

After the analysis of the results, it was identified that the important parameters that need careful consideration are the time series used for the load profile and for the modeling of renewable energy resources. The scaling parameter used to convert normalized and relativized data back to absolute values played a very important role when determining the present and future archetype demand. Since the limitations are done based on general geographic information, the allowed expansion of the renewable energy resources must be considered carefully. This is because the model has a tendency of choosing the cheapest technology until the expansion limit has been reached, and then chooses the next cheapest available technology.

From the results, it is also observed that the two most important technologies for the future energy mix will be wind onshore and Photovoltaic (PV). These two technologies are normally compensated by gas power plants in order to provide energy when wind and PV are not enough and when the CO_2 emissions are not totally restricted in the energy system. Therefore, in the periods of transition towards renewable energies, gas power plants can play a very important role to compensate for the variability of renewable energy sources.

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Chapter 1

Introduction

1.1 Background and Motivation

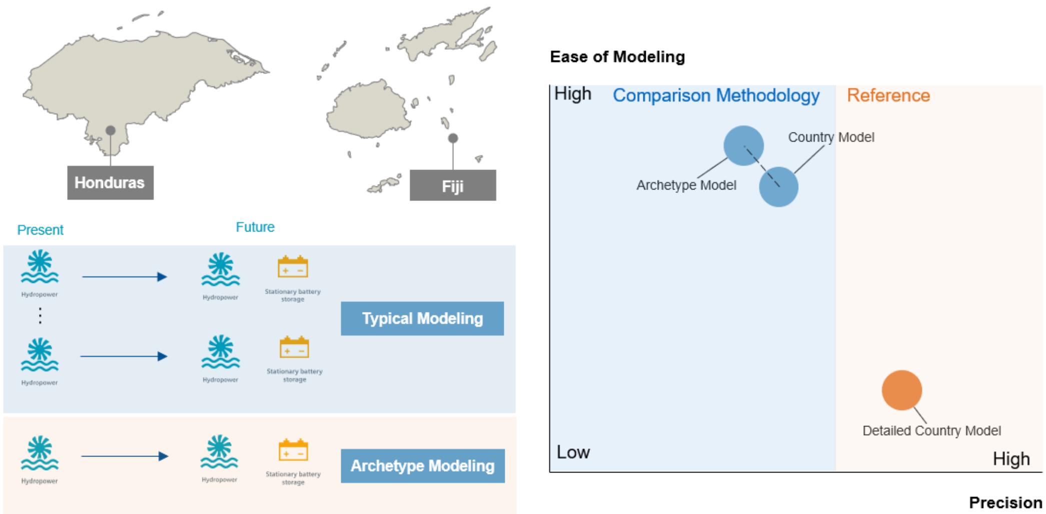
In light of the consequences of climate change, countries around the world have committed to limit their CO_2 emissions by decarbonizing their energy systems. The goal is to maintain the global temperature increase below 2 °C (ideally 1.5 °C) compared to pre-industrial levels. One of the requirements after the 21st Conference of Parties (COP21) in Paris, is for member countries to develop an action plan for the mitigation of climate change [1]. In order to develop a cost-effective transition pathway, it is important to model a country's energy system to obtain the optimal path for decarbonization.

To meet future goals and develop effective energy policies for the decarbonization of an energy system, the energy backcasting technique can be used. This method works backwards to determine which policy measures can be taken to reach a specific "future". Since forecasts through long periods of time are relatively hard to make, it is useful to analyze the effects or implications of policy goals instead [2]. In order to perform this analysis, different energy modeling approaches exist that require an extensive knowledge of a country's energy system to achieve a good estimate of the system's evolution. However, one of the greatest challenges for scientists is the access to data to build these models. To address this problem [3] has summarized the energy system of countries into what is defined as an "energy system archetype". Through this approach, countries are classified into clusters based on their energy system, geographical conditions, and economic development. Although each country is unique, and more detailed data is needed to generate an accurate representation, this approach provides a first orientation for system planning and a common data basis for country modeling.

Since modeling different countries around the world is a time intensive task, the idea of modeling through archetypes can help reduce this burden, while providing with a first overview as to how an energy system might develop without having to model the individual countries. It also presents several advantages as mentioned by [3] which are listed below:

- It gives the ability to model countries with insufficient data by modeling it with its respective archetype.
- It allows to identify similar challenges of different countries not limited to geographical regions.

– It aids in the evaluation of the potential of different technologies and markets for a specific type of energy system (determined by the archetype).



(a) Hypothetical Application Example (b) Ease of Modeling vs Precision

Figure 1.1: Modeling motivation and ease of modeling comparison

Figure 1.1 (a) shows a ***hypothetical*** example of this approach. If two countries are modeled under the same archetype, it means that their energy system, their socio-economic development, and geographic conditions are similar. The main hypothesis of this thesis states that, if these countries were to be modeled individually, similar conclusions could be derived with regards to the evolution of their energy system given their current similarities. The purpose of modeling the archetype is to reduce these two modeling processes (and potentially more) into one.

As mentioned before, since gathering detailed information of the countries is not an easy task due to a lack of governmental transparency or to security reasons, only general information that is freely available online can be used. Most of it can be obtained from the International Energy Agency (IEA), the World Bank (WB), the Energy Information Administration (EIA), and other international agencies in charge of monitoring the energy, geographical, and socio-economic data of countries around the world. Although these sources are not 100% accurate, it provides a basis for the clustering and modeling of the countries' energy system. Since general information is used, the time intensiveness is decreased and consequently the ease of modeling can be improved. It is important to mention that as the quality of the sources increases, more accurate results in both the clustering and the modeling can be obtained. Figure 1.1 (b), illustrates how the simplified country and archetype model have a high score in ease of modeling, but a lower score in precision than that of a detailed model. The more information is added to the basic model, or the more the source's quality is improved, the better the precision.

1.2 Literature Review

The transition towards decarbonized energy systems has been addressed in diverse studies. For example, the IEA provides with a world energy outlook in which several scenarios are evaluated to determine how the energy mix will look in the future under different circumstances [4]. IRENA provides with a Roadmap to 2050 in order to meet the Paris Agreement goals by this year [5]. Additionally, a study by the EWG [6] analyzed the global transition pathway towards decarbonization. However, the analyses were carried out per region, and not by individual countries. In the latter, 9 regions were studied, and their transition pathways determined. These nine regions were solely derived based on their geographic location. The analysis presented in this study involves all the energy sectors and offers a global outlook for the energy transition towards a 100% renewable-dependent energy system. They assume that most of the sectors will be highly electrified due to its economic benefits and efficient use of energy sources. This method relies solely on geography and not on energy system types. The tendency found in the region might not represent the one of some countries within it. This differs from the archetype's concept objective, where countries do not necessarily belong to the same geographical region, rather transcend continental barriers.

An attempt to cluster regions with regards to their energy system has been made by [7], where the energy mixes of European Union members were analyzed in order to cluster and characterize the major energy profiles. The analysis here performed, determined that countries can indeed show a pattern towards their energy mix evolution. Overall, it was found that the energy systems have a tendency to reduce their dependence on fossil fuels over time when the available resources and geographical constraints allow it. The idea that the countries could show a similar behavior towards the development of their energy systems is entertained in this paper, however, the clustering was done based on past behavior and did not extrapolate it into the future. In total, 7 clusters were made based on 7 main technology types. The tendency towards a renewable future indicates that the number of clusters might be reduced later on due to the convergence in the use of renewable energy technologies. Again, the approach operated under the same archetype idea, where a classification of countries regarding their energy system was made. However, no modeling is done so as to observe whether this cluster would also show the same behavior when determining a future transition pathway.

Furthermore, the classification of countries could be performed based on their demographic and socioeconomic characteristics. The study presented by [8] indicates that the energy productivity and the rate of improvement is correlated to these parameters. Therefore, a clustering was made using econometric parameters to determine that the greatest rates of improvements can be found in developing countries, nevertheless, they remain less productive than the developed nations. This study expands the clustering criteria used in [7], in which the countries were classified solely on their energy mix. They provide an insight that the country development in the energy sector might be linked to different energetic and socioeconomical information. This is why the clustering done by [3] integrates these two aspects in order to further narrow the possible development paths of similar countries.

Another dimension for clustering based on the energy system type is within buildings and districts to identify cost-effective low-carbon solutions [9]. The dimension of these analyses, however, do not correspond to the spatial dimension of the clustering in a resolution such as the one attempted by [3]. A more similar approach would be that of [10], where a higher spatial aggregation is used by analyzing villages to identify the optimal location of biomass power plant generations. Although of a higher aggregation level than the others, it still remains too small compared to the one done by [3]. Since the model is built within a geographical region, the transport capacities can be calculated and included in the total system cost. In the case of the clustering irrespective of geographical location, the analysis of the integration of transmission capacities is much harder, since a link between the clusters would be needed and a specific country within it determined. Other approaches involve the clustering of energy systems regarding the characteristics of the power system [11]. Although based on the energy type idea, its purpose is to determine convenient control methods for the integration of Distributed Energy Resources (DER) including the exchange of power between each unit.

Additionally, the concept of a global grid is introduced by [12] which considers that, in the future, all large power plants in the world could be connected in the global grid. Under the idea that the transition towards renewable energies is taking place, countries that are not self sufficient in satisfying their energy demand must obtain its power from generation centers in other geographical locations. These distances will be determined in a cost-optimized fashion. This paper also claims that if the interconnections were to be built irrespective of the geographical extension, the need for bulk storage could be avoided as well as reduce the volatility of the energy systems. While focusing on the same dimension, this approach doesn't intend to cluster, rather connect the different countries around the world while optimizing the chosen energy generation facilities and transmission capabilities. The principle of cost optimization, as the one involved in this thesis is also applied but with a different purpose. This idea could be applied to the clustering performed by [3] in order to include the cost optimization of transmission capacities. This would mean the integration of the ideas presented by [9], [12], and [3].

After a review of the literature on the clustering of energy systems, it was found that the level of aggregation used in this thesis and that is independent of geographic location, hasn't been used to model energy systems or determine their energy transition pathways in a cost-optimized manner. This is probably due to the low precision that will probably be obtained when modeling with restricted information. As explained in the previous section, modeling with this approach is not intended to replace a detailed model, rather to address the problem of missing data and obtain an overview of possible evolution scenarios of countries from which information is either too expensive to obtain or too difficult due to a lack of transparency.

1.3 Thesis Objective and Outline

This thesis includes four more chapters whose contents will be briefly described in this section. The two main pillars of this work are the standardized model development and the evaluation of the archetypes and their performance. Chapter 2 contains these main aspects of the methodology and a description of the standardized modeling approach. More specifically, it includes:

– A description of how the clustering of the countries was performed and how the energy model was set up.
– A brief explanation of the optimization model used to determine the cost-effective transition pathway.
– A description of the comparison methodology developed for the evaluation of the archetype results.
– An outline of the rules and assumptions used for the determination of the future scenario conditions.

Chapter 3 describes the results obtained when modeling the countries and archetypes under the simplified model approximation. This includes a validation against real data for 2015, a detailed analysis of the results of one cluster, and a comparison of the performance of the different modeled archetypes. Chapter 4 attempts to describe the consequences of the used assumptions, the archetype limitations, and also contains a discussion over the validity of the model. Finally, Chapter 5 presents a conclusion of the thesis, potential improvements, and a general outlook.

This thesis was carried out in several steps, in which the starting point was the clustering results obtained from [3]. Once a final set of clusters or archetypes was defined, the results were used to build the energy models. The Roadmap setup for this thesis can be observed in Figure 1.2, and a more structured framework can be observed in Figure 1.3. For a more detailed description of the goals of this thesis, a breakdown per major section is presented below:

1. Energy Model
    a) Generate a standardized energy model based on the clustering results and available data categories.
    b) Transition Pathway
        i. Generate a future scenario based on a set of rules for each analyzed country and archetype.
        ii. Develop a tool for the automation of the model and future scenario setup.
2. Comparison methodology
    a) Develop a comparison methodology for the evaluation of the country and archetype model results to validate the principle of archetype modeling.
    b) Evaluate the performance of the archetypes in order to determine its capabilities and limitations.
    c) Develop a tool for the automated comparison and evaluation of the archetypes.

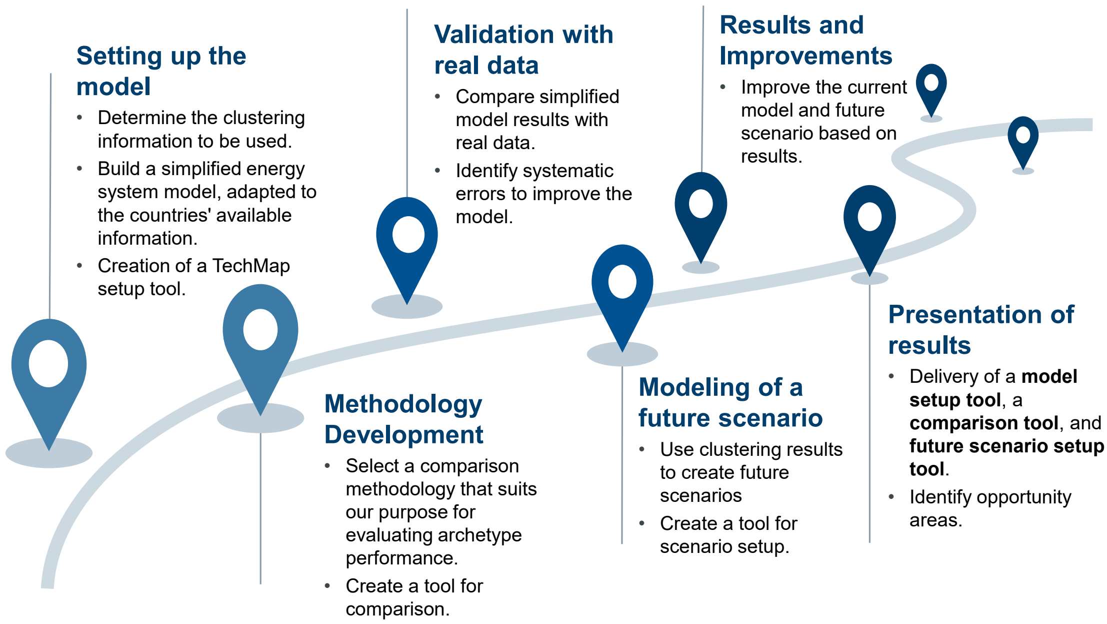


Figure 1.2: Thesis outline

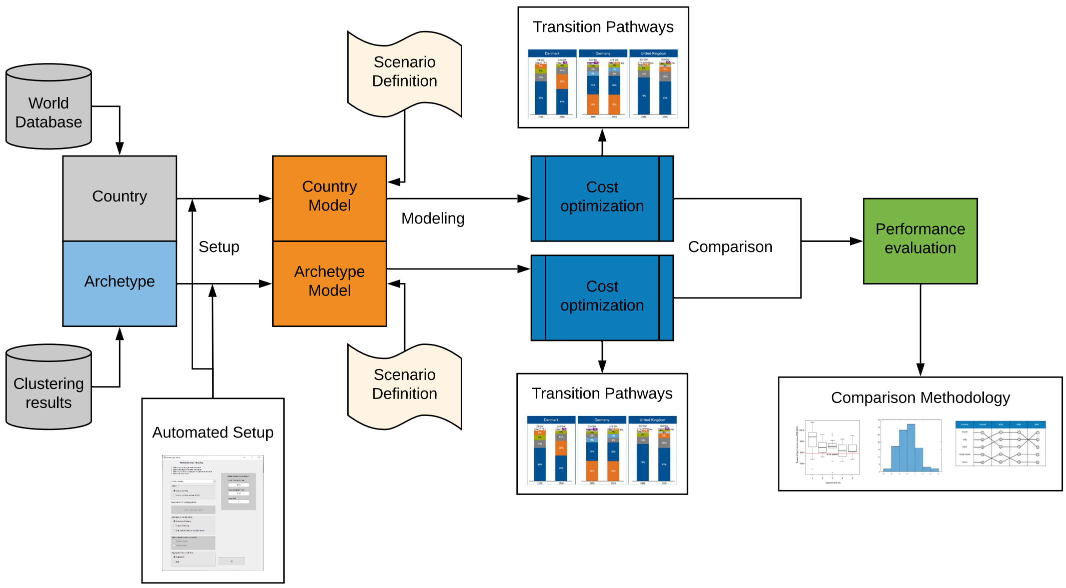


Figure 1.3: Thesis Framework

Chapter 2

Methodology

2.1 Model Setup and Assumptions

2.1.1 Country Clustering

Since the clustering results are defined as the starting point of this work, it is important to present an overview of how this was done, and which type of information was used when developing the archetypes.

According to [3], the clustering process can be summarized in three steps as shown in Figure 2.1:

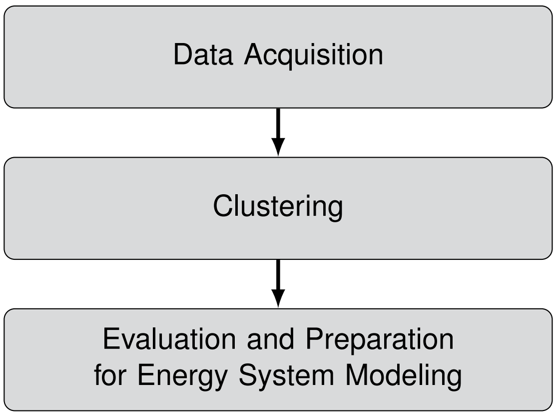


Figure 2.1: Steps towards defining the archetype

The information used as input is one of the most important aspects in energy models. The sources from which the information is taken must therefore meet a certain number of criteria in order to be considered:

1. Data from the source must be freely available for most countries around the world.
2. The data must be downloadable and processable.
3. More than one type of information parameter needs to be available, as to maintain the homogeneity of the database.
4. Information for more than one year needs to be available in order to reproduce the method for different time periods.

After a set of data is obtained, it must be cross-referenced with other sources to ensure its accuracy. After the elimination of the redundant categories, sixty-two were used in determining the archetypes. Most of these belong to the energy system characteristics of the country, followed by climatic/geographic information, and socio-economic data. An overview of the used characteristics is presented in Table 2.1[1].

Table 2.1: Data categories and exemplary data

Country List	
Category	**Exemplary Data**
Socio-economic (14)	GDP, GDP growth, GDP distribution, population, population growth, population density, urban population
Climatic/Geographic (11)	Absolute latitude, agricultural area, forest area, coast/area ratio, heating degree days, cooling degree days, average temperature, average precipitation
Energy related (37)	Consumption per capita, share net imports electricity, electricity distribution losses, installed capacity shares, CO_2 emissions intensity, emissions change from 1990, storage shares, electric vehicle sales per capita

Following the selection of categories and determining the data sources, a partitioning method is selected . To deal with a large data set, a K-means algorithm was applied due to its robustness. A relativization of the data is performed to deal with the different type of energy categories and different country sizes. For example, no absolute capacities (e.g.GW) were used, rather the share of the technology compared to the total capacity. Furthermore, the data is normalized from [0,1] according to equation (2.1) in order to weight each parameter equally when performing the clustering.

$$x'_i = \frac{x_i - \min x_d}{\max x_d - \min x_d} \tag{2.1}$$

Here, n is the number of observations, d is the number of variables, and $X = x_i, i = 1, ...n$ is a set of n d dimensional points [3].

Once the data is ready to be clustered, the K-means is applied according to Algorithm 2.1.

[1] At the time of this thesis, the data categories and the clusters described in [3] do not correspond to the ones used here. After modeling, new categories were identified as necessary and included in the clustering parameters.

Algorithm 2.1: K means algorithm

Data: Set of data items, number of cluster centers k
Result: Set of k clusters
1 Initialize cluster centers through a weighted partition;
2 **while** *The sum of the squared error has not been minimized;*
3 **do**
4 Assign each item to its closest centroid;
5 Calculate new mean of the cluster;
6 **end**

The assignment of each item to the closest centroid is done through equation 2.2, and the calculation of the new mean through equation 2.3 [13].

$$\begin{aligned}&\text{For every } i, \text{ set}\\ &c^{(i)} := \arg\min_j \left\|x^{(i)} - \mu_j\right\|^2\end{aligned} \tag{2.2}$$

$$\begin{aligned}&\text{For each } j, \text{ set}\\ &\mu_j := \frac{\sum_{i=1}^m 1\{c^{(i)}=j\}x^{(i)}}{\sum_{i=1}^m 1\{c^{(i)}=j\}}\end{aligned} \tag{2.3}$$

The criteria used to determine when the algorithm has converged, is the distortion $J(c,\mu)$. This function is calculated by equation 2.4 and is the sum of the squared distances of the points in the cluster to its center [13].

$$J(c,\mu) = \sum_{i=1}^{m} \left\|x^{(i)} - \mu_{c^{(i)}}\right\|^2 \tag{2.4}$$

Since the K-means algorithm can be susceptible to local minima, the algorithm is run many times using different initial values. The run that results in the lowest distortion $J(c,\mu)$ is selected [13].

To validate the clusters, an evaluation of the results is necessary. Once the cluster centers have been identified, the unique characteristics of each of the generated archetypes can be determined. After applying the clustering algorithm to the 196 UN countries, 141 countries were successfully assigned to 15 clusters. The countries not clustered were excluded due to insufficient data. For the modeling of the archetypes, the resulting parameters need to be prepared for input to the energy model. The process of the data preparation was within the scope of this master thesis, and therefore the procedure of transforming from the normalized data back to the original/physical data will be described with more detail in the modeling setup of Section 2.1.10.

2.1.2 Modeled Archetypes

Although the setup for the energy system models was automated, not all were simulated due to this thesis's time contraints. In total, 4 archetypes with different characteristics were chosen in order to observe the performance of the approach in different energy system types. In the archetype comparison of chapter 3, the archetypes are ranked from best to worst performance, providing with an overview as to which types of systems can be best represented by the archetypes.The chosen countries and their corresponding archetypes are listed below:

1. **Cluster 6**: Countries with high population density, fossil dependent, warm, and which have high potential for PV:
   a) Botswana
   b) Vietnam
   c) India
   d) Bangladesh
   e) Indonesia
   f) Malaysia
   g) Phillipines
   h) Sri Lanka
   i) Thailand
   j) Pakistan
   k) Dominican Republic

2. **Cluster 13**: Countries with high share of renewables, high potential for wind, and which have reduced emissions since 1990. This cluster has a highly diversified energy mix, rendering the observation of its evolution, interesting:
   a) Denmark
   b) Germany
   c) United Kingdom

3. **Cluster 14**: Countries with high share of hydropower, presence of electric vehicles, heating, and low population density:
   a) Austria
   b) Canada
   c) Finland
   d) New Zealand
   e) Norway
   f) Sweden
   g) Switzerland

4. **Cluster 15**: Fossil fuel dominated countries with PV potential and good economic growth prospects. This cluster includes countries that are in very close proximity:
   a) Kuwait
   b) Oman
   c) Qatar
   d) Saudi Arabia
   e) United Arab Emirates

Note: A complete list of the countries and their respective archetypes can be found in the appendix.

2.1.3 Temporal and Spatial Dimension

The applicability of the archetype approach is intended for countries around the world. However, due to the lack of data in general information, only 141 countries are able to be included in the clustering. As mentioned in Section 1.1, the purpose of the archetypes is to serve as a data basis for countries with missing data. Therefore, an un-clustered country can be analyzed and paired with the closest archetype to obtain a general overview of how its energy system can develop.

With regards to the temporal dimension, the data gathered for this analysis was from 2015, which serves as the starting point for the system model. Since most of the usefulness of the archetype approach lies in the determination of possible transition pathways towards decarbonization, the model is applied until year 2050 with a 7 year time step. This will allow the observation of a 35 year period evolution for the countries' energy system. A more detailed description of this setup can be found in the scenario definition of Section 2.2.1.

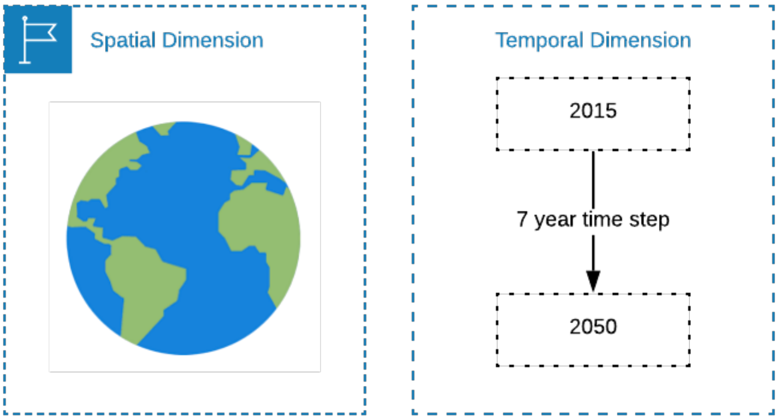


Figure 2.2: Temporal and Spatial Dimension of the Modeling

2.1.4 Optimization Model: Energy System Development Plan (ESDP)

The modeling software used for the energy optimization process was Siemens' proprietary tool, ESDP. This model simultaneously optimizes the schedule and the capacities of an energy system. It uses a multi-modal energy approach, meaning it allows for the coupling between different energy sectors such as heat, electricity, and gas. Although it is mostly used for the development of a cost-optimized transition pathway for energy systems, it can be used to model single years to determine the operation costs of a system and its ideal dispatch schedule.

To describe the energy model that needs to be optimized, the conversion processes, commodities, and the technical and financial information of the technologies need to be defined in the following data files [14]:

1. **Technology Map (Techmap)**: Document in an excel format, containing information about the available technologies and their technical and economical parameters. Information such as efficiency, investment costs, technical and financial lifetime, fuel costs, and Operation and Maintenance (O&M) costs are specified. In this file, the scenarios, as well as the carbon emission goals or carbon prices (if any) must be defined.

2. **Volume Data**: This includes datasets such as load, PV, wind, and other time dependent series.

Once the input data has been defined, the overall system is optimized considering the entire transition pathway. The optimization problem can be formulated as a

Linear Programming (LP) problem with the objective to minimize the overall system cost, as in equation 2.5.

$$\min \quad CAPEX + OPEX \tag{2.5}$$

Although in reality the problem is not linear due to discrete operational and investment decisions, it is formulated as one due to the increased complexity and computational intensity needed to solve a Mixed Integer Programming (MIP) and/or non-linear problem of this size.

To optimize the transition pathway, the problem is divided in intervals y. For every interval, a characteristic year is simulated. To achieve the optimal planning throughout the transition pathway, the investment of technologies x for all intervals y, regions i, and hourly t operational decisions is modeled in a single optimization run. Investments costs are deprecated according to an annuity factor and discounted accordingly. Operation costs for each interval are also discounted to the base year [15].

$$CAPEX = \sum_{y} F_y^{disc} \cdot \sum_{i,x} C_{y,i,x}^{inv} \tag{2.6}$$

$$OPEX = \sum_{y} F_y^{disc} \cdot \sum_{i,x,t} \left(C_{y,i,x,t}^{fiel} + C_{y,i,x,t}^{OM} \right) \tag{2.7}$$

The Operating Expenditures (OPEX) includes maintenance ($C_{y,i,x,t}^{OM}$) and fuel costs ($C_{y,i,x,t}^{\text{fuel}}$) which should be defined in the Techmap. The CO_2 emission costs are not included in the OPEX costs because they are determined from the solution of the dual problem when a limit in the annual emissions is introduced. Another alternative is to include the CO_2 price as a parameter without limitation in the annual emissions.

In this model, the transition pathway is calculated until 2050 with a 7 year time step. To determine the capacities that need to be built or retired once an initial capacity $P_{i,x}^{init}$ is used, equation 2.8 is applied.

$$P_{y,i,x} = P_{i,x}^{init} - \sum_{y=1}^{y} P_{y,i,x}^{retire} + \sum_{y=1}^{y} P_{y,i,x}^{new} \quad \forall y \in Y, i \in I, x \in X \tag{2.8}$$

After the optimization is performed, the following can be found among the model's output [14]:

1. Operation schedules for each technology.
2. Cost optimal capacities for each technology.
3. Energy, CO_2 prices, etc. for each modeled hour.
4. Total system costs and CO_2 emissions.
5. Technology specific OPEX and Capital Expenditures (CAPEX).
6. Statistics on the required flexibility of a technology's operation.

A summary of how this energy modeling tool works can be found in Figure 2.3

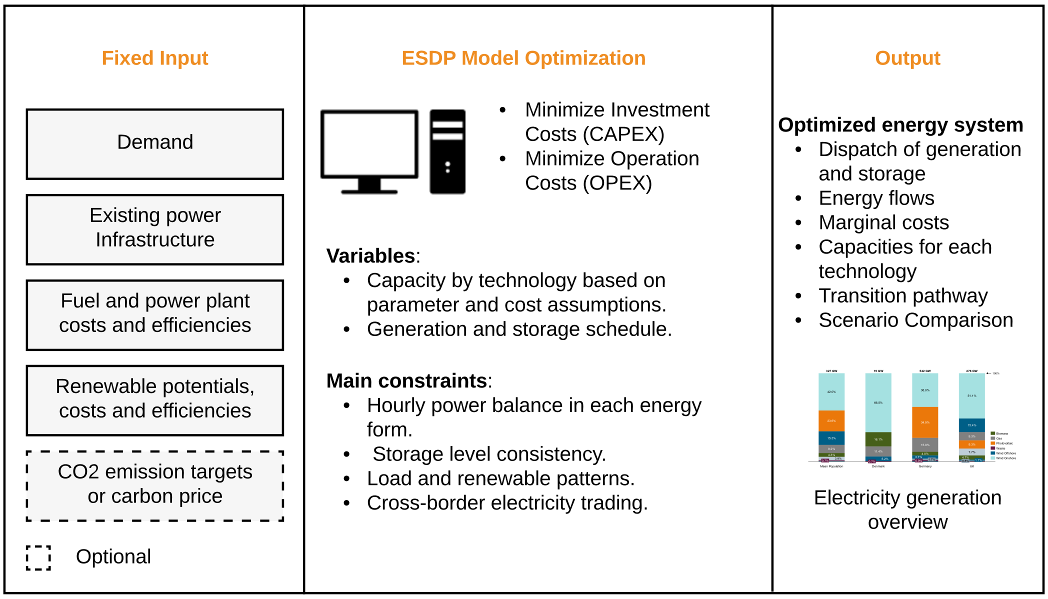


Figure 2.3: ESDP tool. *Adapted from* [14]

2.1.5 Technologies and Commodities

A country's energy mix might be conformed by different technologies to cover specific demands or to adapt to the available resources. Due to the complexity of modeling different technologies, a simplified approach is used in this thesis: technologies belonging to the same group are aggregated into one category. See Figure 2.4 The technologies here specified correspond only to the electricity sector. The coupling with the heating and transportation sectors is not considered.

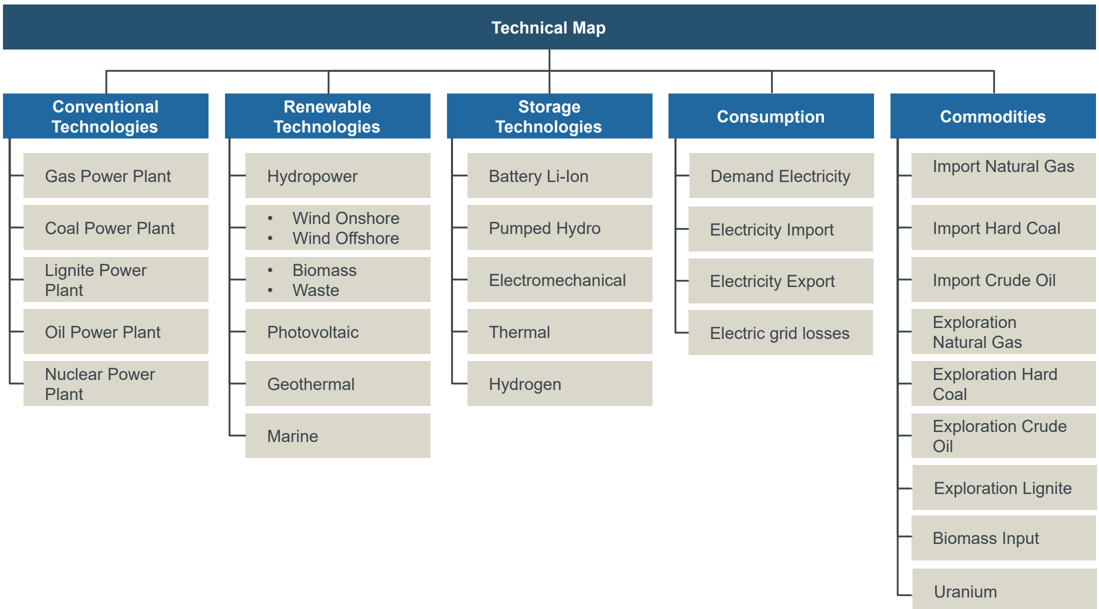


Figure 2.4: Technologies and Commodities

Conventional Technologies

Conventional technologies are denominated here as those which use non-renewable resources as their input commodity. When more than one type of power plant is aggregated into a category, an average for the technologies within that group is taken.

1. **Gas Power Plant**: includes Gas Standard Power Plants (Gas SPP), Gas Combined Cycle Power Plants (Gas CC), and the Gas Single Cycle Power Plants (Gas SC).
2. **Coal Power Plant**: is a standard coal-fired power plant with electricity as its output commodity and hard coal as its input commodity.
3. **Lignite Power Plant**: is a type of coal fired power plant but with lignite (or brown coal) as its input commodity. This is the most CO_2 intensive power plant due to its low quality input fuel.
4. **Oil Power Plant**: includes the Oil Standard Power Plants (Oil SPP) and the Oil Single Cycle Power Plants (Oil SC).
5. **Nuclear Power Plant**: has uranium as input commodity and electricity as output commodity. It is the only conventional technology with no associated CO_2 emissions.

Renewable Technologies

The renewable energy technologies are here referred to as the conversion processes that use renewable energy sources as input commodities and which produce no CO_2 emissions. All the renewable technologies, except biomass, use a 'Dummy' as input commodity.This 'Dummy' is used to represent wind, solar radiation, ocean movement, etc. It has no costs and no efficiency is considered other than in the conversion process.

1. **Hydropower**: includes all types of hydropower plants, such as run-of-the river or barrage. When modeling, it is divided into two categories: Inflexible Hydro and Flexible Hydro (See: 2.1.10).
2. **Wind Power**: is divided into wind onshore and wind offshore. The capacity factor and technology costs for each is different, therefore the model differentiates between them.
3. **Biomass**: uses biomass as its input commodity to produce electricity (See: Biomass Input in 2.1.5). It includes the standard biomass power plants, as well as the Combined Heat and Power (CHP) biogas plants.
4. **Waste**: combusts waste to produce electricity.
5. **PV**: includes the Central and Rooftop PV. No solar thermal or Concentrated Solar Power (CSP) is considered in this study.
6. **Geothermal**: involves the conversion of thermal energy stored on Earth for the production of electricity. The use of geothermal energy for heating is not considered.
7. **Marine**: encompasses wave and tidal energy.

Storage technologies

1. **Battery Li-Ion**: includes central and decentral lithium ion batteries with the ability to store electricity by means of a chemical process.

2. **Pumped Hydro Energy Storage (PHES)**: This type of hydroelectric storage device stores electricity in the form of potential energy. Its energy to power ratio is considered to be between 1 day and an hour for this study.
3. **Electromechanical Storage**: refers to the Flywheel storage device, which uses kinetic energy as a mean to store electricity [16].
4. **Thermal Storage**: comprises those technologies which can store electricity by adding energy to a material (either solid or liquid) to increase its temperature without changing its phase. [17]
5. **Hydrogen Storage**: This technology is divided into two parts in the Techmap. It is comprised of an electrolyzer which converts electricity into hydrogen, and a hydrogen storage module. The output commodity from the storage module is hydrogen, and considered as a direct input to the gas power plant. This is a simplified approach for modeling hydrogen storage. This assumption is made due to the possibility that in the future, gas turbines will be used with hydrogen for the full decarbonization of the energy system.

Commodities

The commodities in this section are either imported or extracted locally. No export of commodities was considered during the modeling.

1. **Natural Gas**: all types of natural gas that can serve as input for the gas power plant. It is both, imported and locally extracted.
2. **Hard Coal**: refers to the high quality coal that can be input to the coal power plant. It can either be imported or locally extracted depending on the country's characteristics.
3. **Lignite**: refers to the low quality coal that is input to the lignite power plant. This commodity can only be extracted locally due to its low energy density.
4. **Crude Oil**: serves as input commodity for the oil power plant and can be either imported or extracted locally.
5. **Biomass Input**: includes animal or plant material that can serve as input to the biomass power plant.
6. **Uranium**: is the raw material used by nuclear reactors for electricity production.

2.1.6 Efficiency and Costs

For the generation of a techno-economical analysis, the efficiency of the conversion processes and investment and operation costs for the different technologies are needed. Although the costs and efficiencies are country dependant, estimations for Europe were used. The Energy Technology Reference Indicator (ETRI) [17] provides with a complete evaluation of the progress and developments of different technologies from 2015-2050, as well as a complete coverage on available technologies. Since the technologies vary in sizes and types, a summarized version of the costs and efficiencies was derived based on the presented information on the report.

For some, the efficiency is assumed to improve throughout the years, others, are estimated to remain the same. Since a help 'Dummy' input commodity is used for most renewables, they are considered to have an efficiency of 1 unless a different input commodity is specified. An overview per storage technology can be found in Table 2.2 , and one for the generation technologies is provided in Table 2.3:

Table 2.2: Storage technology efficiencies

Storage Technology	**Round-trip Efficiency**
Battery Li-Ion	0.9
Pumped Hydro Storage	2015: 0.8 2030: 0.85 2050: 0.9
Electromechanical Storage	0.85
Thermal Storage	0.65
Hydrogen Storage	0.67

Table 2.3: Efficiency per technology

Technology	**Efficiency**		
Year	**2015**	**2030**	**2050**
Gas PP	0.485	0.525	0.54
Coal PP	0.45	0.48	0.48
Lignite PP	0.42	0.47	0.47
Oil PP	0.3575	0.3575	0.3575
Nuclear PP	0.33	0.34	0.355
Hydropower	1	1	1
Wind onshore	1	1	1
Wind offshore	1	1	1
Photovoltaic	1	1	1
Geothermal	0.156	0.166	0.176
Waste	0.27	0.34	0.42
Biomass	0.35	0.39	0.425
Marine	1	1	1

Most of the technology cost information was also taken from [17]. These include: investment cost per kW, O&M costs for power, O&M costs for energy production, and storage investment costs. A summary per parameter and per generation technology is presented in Table 2.4.

Table 2.4: Investments and O&M Costs for all the generation technologies

Technology	Investment Cost $[\frac{EUR}{kW}]$			O&M Cost Power $[\frac{EUR}{kW \cdot a}]$			O&M Cost Energy $[\frac{ct}{kW}]$		
Year	2015	2030	2050	2015	2030	2050	2015	2030	2050
Gas PP	755	700	700	16.99	19.25	19.25	0.7	0.65	0.65
Coal PP	1600	1600	1600	40	40	40	0.36	0.36	0.36
Lignite PP	2000	2000	2000	50	50	50	0.45	0.45	0.45
Oil PP	755	700	700	98.15	91	91	0.15	0.15	0.15
Nuclear PP	4500	4925	4516.67	94.5	100.92	81.11	0.8	0.66	0.29
Hydropower	3850	3922.5	3922.50	52.94	53.93	53.93	0.45	0.45	0.45
Wind onshore	1400	1300	1100	37.8	28.6	18.7	0	0	0
Wind offshore	3470	2580	2280	129.39	77.4	52.44	0	0	0
Photovoltaic	1243.3	885	765	24.25	17.26	14.92	0	0	0
Geothermal	8366.67	6570	5773.33	147.811	131.4	130.86	0	0	0
Waste	6080	5240	4540	182.4	157.2	136.2	0.69	0.69	0.69
Biomass	3635	2650	2160	93.60	68.24	55.62	0.465	0.465	0.465
Marine	10005.71	3646.25	1996.98	323.04	127.01	88.65	0	0	0

For storage technologies, all costs corresponds to those presented in [17], except the electrolyzer used in hydrogen storage. These prices were taken from [18]. An overview of the overall costs is presented in Table 2.5 and 2.6.

Table 2.5: Storage Costs (a)

Technology	Investment Cost $[\frac{Euro}{kW}]$			O&M Cost Power $[\frac{EUR}{kW \cdot a}]$		
Year	2015	2030	2050	2015	2030	2050
Battery Li-On	490	140	140	6.86	1.96	1.96
Pumped Hydro	2250	2250	2250	33.75	33.75	33.75
Electromechanical	600	600	600	8.4	8.4	8.4
Thermal	1200	1200	1200	2.4	2.4	2.4
Hydrogen	1500	500	500	30	10	10

Table 2.6: Storage Costs (b)

Technology	O&M Cost Energy $[\frac{ct}{kWh}]$			Storage Capacity Cost $\frac{EUR}{kWh}$		
Year	2015	2030	2050	2015	2030	2050
Battery Li-On	0.26	0.26	0.26	752	205	245.5
Pumped Hydro	0	0	0	0	0	0
Electromechanical	0	0	0	0	0	0
Thermal	0	0	0	24	24	24
Hydrogen	0	0	0	9	9	9

Two more technology types are considered to have an input commodity: nuclear and biomass. As mentioned in section 2.1.5, the input for the biomass plant is denominated as Biomass Input; the Nuclear power plant input is uranium. For both, costs from [19] were used. A small table is shown with the costs assigned to each of these commodities:

Table 2.7: Commodity Prices: Biomass and Uranium

Commodity	Cost $[\frac{ct}{kWh}]$		
Year	2015	2030	2050
Biomass	0.5	0.2035	0.0729
Uranium	0.8	0.8	0.8

2.1.7 Fuel Prices

Fuel prices fluctuate yearly and depend on the country and available resources. In the World Energy Outlook, [4] fossil fuel prices are calculated based on the expected demand and available resources. However, precisely modeling the future trend of fossil fuel prices is a complicated task. It is assumed that the prices remain constant and that the order from cheapest to most expensive is maintained. For the exploration, prices of hard coal, gas, and oil, information from the EIA were used [2]. The lignite exploration prices were derived from [20]. It represents only the production prices, as this fuel is not traded.

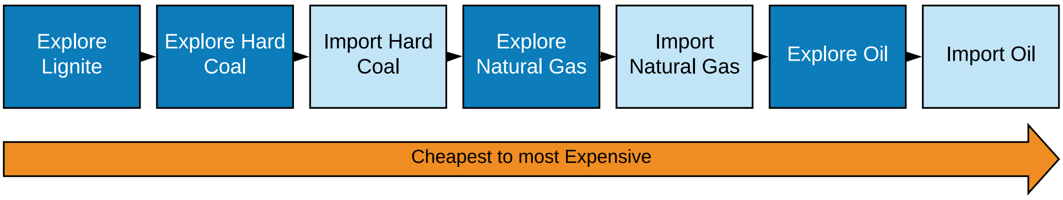


Figure 2.5: Fuel price from cheapest to most expensive

2.1.8 Time Series

Energy models are sensitive to time series information, therefore it is important to use real time series for the country's generation and load profile when possible. In this model, time series were obtained for:

- Load Profile
- Wind Onshore
- Wind Offshore
- PV

Load Time Series

Load profiles are an important aspect for system planning and operation of power systems. They drive the generation necessities throughout the year and determine peak demand [21]. For this approach, most European countries are modeled with the load profiles provided by the European Network of Transmission System Operators (ENTSO) [22]. For New Zealand, the time series was obtained from [23]. The profiles were then normalized according to equation 2.9 for model input. The model then scales back by using the total energy consumption.

[2] The information presented here is in 2011 US dollars. A conversion rate of 1.39 $ per euro was taken.

$$\text{Time Step Value } = \frac{\text{Load } [\text{MWh}]}{\text{Max Value in Time Series}[\text{MWh}]} \tag{2.9}$$

In the event where no time series were available, the time series of the country nearest to the cluster center and with available information was used.

For Cluster 15, the time series of United Arab Emirates was selected to represent the load profile of all the countries in the cluster. For cluster 8, the time series of India was used. Both of these time series were synthetically created by using the profile of a typical day, month, and week during winter and summer. The load series were aggregated using a weighting factor that depends on the time of the year to account for seasonal variations. Information for the profile of cluster 15 was obtained from [24], [25], [26], and [27]. For India, information of the typical demand was obtained from [28]. Since one of the goals of the archetype approach is to increase the ease of modeling, and since the countries are clustered based on geographic, climatic, economical, and energetic information, it is assumed that the countries are similar enough to use the time series of a country in another of the same cluster.

PV and Wind Time Series

For the wind and PV time series, a mix of sources and methods were used. For wind offshore, information of the hourly capacity factor for European countries was available in Renewables Ninja [29]. For those in which it was not, disaggregated information from the same source was used. The data there presented was based on the work of [29], [30], [31], [32], and [33]. For non-European countries, the data was available for specific geographical points, therefore a specific methodology was followed to determine the aggregated time series of the country.

The general methodology can be observed in Figure 2.6.

- **Wind**: To obtain information about the FLH of wind, a wind turbine of 80m of height was considered. Five points were selected, each with a different weighting factor. The weighting factors are based on [34]. The point on the center is given 50% of weight. The other 4 points are given weights depending on their FLH. From best to worst (more FLH the better), they are assigned a weight of: 20%, 15%, 10%, and 5% respectively.

- **PV**: For this profile, a standard solar panel with direction to optimal infeed and with no adjustable axes is considered. Again, five points are selected: one in the center and the rest in the country's border. The weighting factors are assigned in a similar fashion as in wind, but without giving more value to the center point. From best to worst location, they are assigned the following factors: 30%, 25%, 20%, 15%, and 10%.

After the profiles have been aggregated using these weighting factors, they are validated and then used in the model.

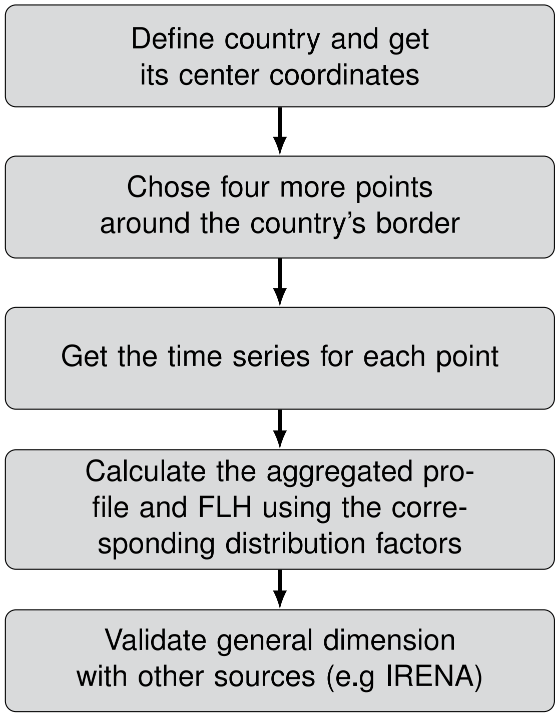


Figure 2.6: Profile generation methodology

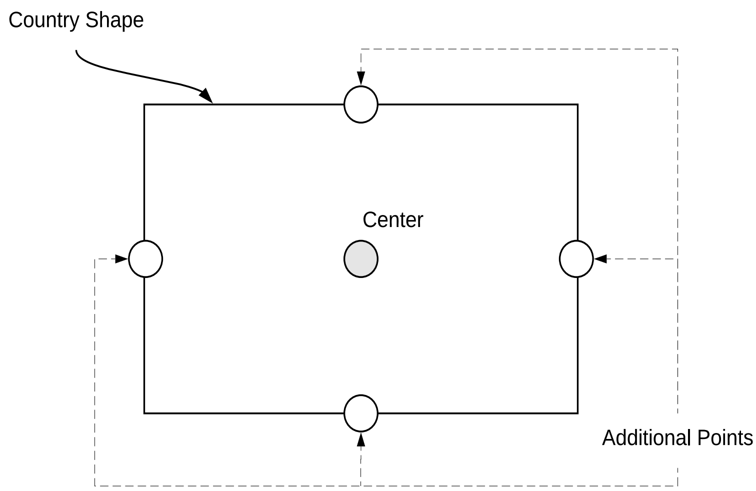


Figure 2.7: Point Selection Representation for Time Series Generation

2.1.9 Scaling back from the normalized data

As mentioned in 2.1.1, all the data was normalized and relativized to prevent the country's size to influence the results. In order to scale back to absolute data, the following information was needed:

1. Population
2. Capacity [GW]
3. Consumption [TWh]

For the country's model, entering this information from 2015 was enough to scale back from the relativized values accordingly. The archetype, however, presented a problem because the relation capacity/consumption was not maintained. This caused a lack of capacity to meet the demand. Due to this reason, the relationship of these two variables was analyzed for all clusters and was included into the clustering parameters.

Figure 2.8 shows that the relationship was almost linear for most of the clusters. Although in the future these relation might not hold true due to the penetration of renewable energies, it is adequate for the determination of the current state of the energy system. Only one cluster presented a low correlation in these two variables, Cluster 5. This cluster is mostly composed of countries that export a considerable amount of electricity, therefore its capacity is higher than that required to meets its demand.

Once the relationship capacity/consumption is obtained, only the country's or archetype's population is needed. The consumption and capacity are calculated as follows:

$$\text{Ratio} \;=\; \frac{\text{Total Installed Capacity}}{\text{Total Consumption}}\left[\frac{\mathrm{GW}}{\mathrm{TWh}}\right] \tag{2.10}$$

$$\text{Consumption} \;=\; \text{Consumption per capita} \;\cdot\; \text{Population}\;[\mathrm{TWh}] \tag{2.11}$$

$$\text{Capacity} \;=\; \text{Consumption} \;\cdot\; \text{Ratio}\;[\mathrm{GW}] \tag{2.12}$$

To set up rules in the future scenario building, information such as the country's area and its coastal line extension was necessary to limit the expansion of renewables. These limitations are furthered explained in section 2.2.2. In order to scale the geographical data, the following steps were performed:

1. Calculate the area using the population density and population:

$$\text{Area} = \frac{\text{Population}}{\text{Population Density}}[\mathrm{km}^2] \tag{2.13}$$

2. Calculate the coastal area using the coastline/area ratio:

$$\text{Coastline} = \text{Coastline/area ratio} \cdot \text{Area}\;[\mathrm{km}] \tag{2.14}$$

With regards to economic information, the GDP was also necessary for the calculation of future economic growth and for the determination of CO_2 emissions (See: 2.2.2). This was calculated using the Gross Domestic Product (GDP) per capita from the clustering results.

$$\text{GDP} = \text{GDP per capita} \cdot \text{Population [Billion \$ PPP]} \tag{2.15}$$

Table 2.8 shows the factors that were scaled with the calculated parameters from the previous equations.

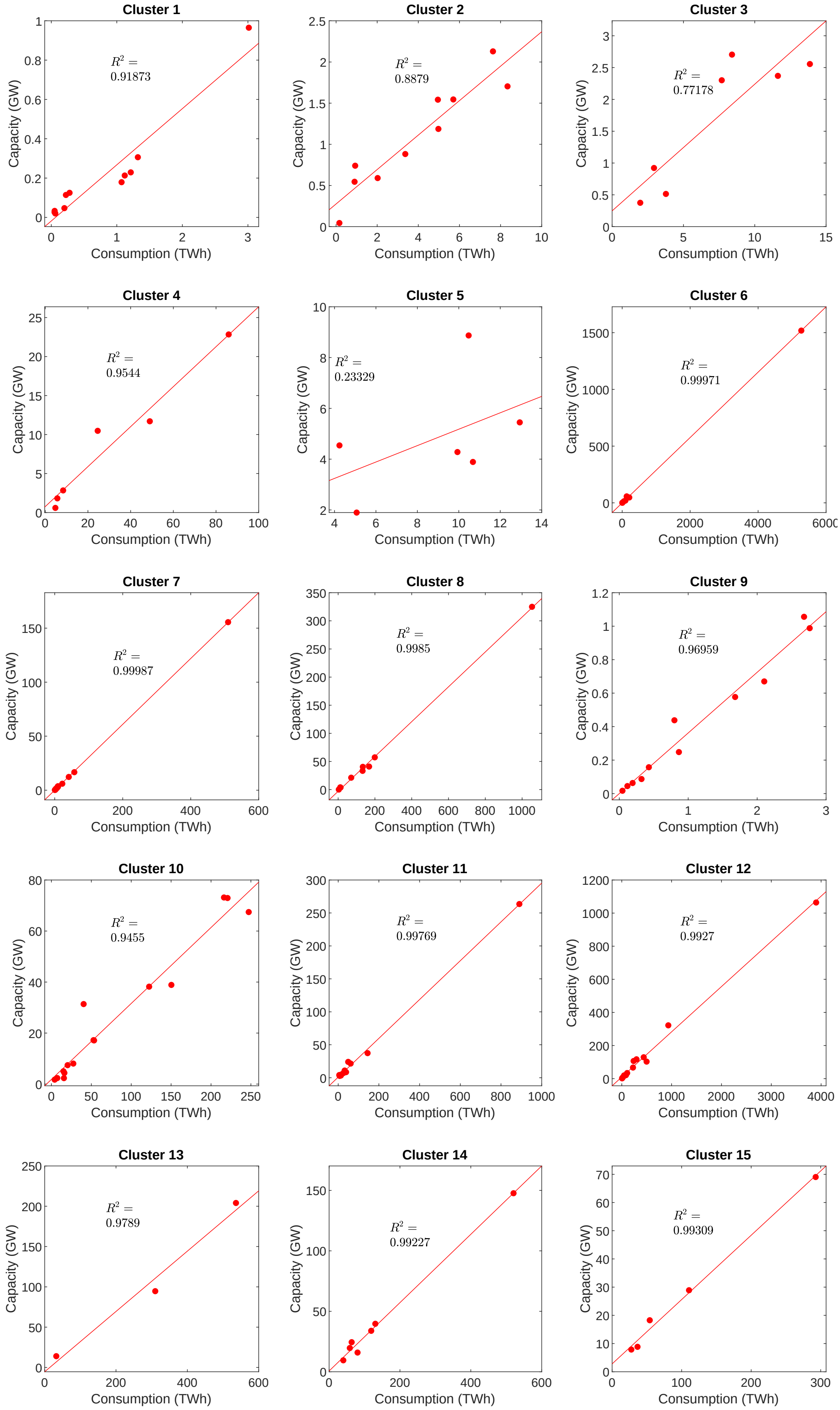


Figure 2.8: Correlation between Capacity and Consumption per cluster [35], [36]

Table 2.8: Scaling of relativized data

Clustering Parameter	Scaling Parameter	Absolute Value
Share of Installed capacity	Capacity	Installed Capacity (GW)
Net Import/Consumption	Consumption	Net Import (TWh)
Consumption per capita	Population	Demand (TWh)
Population Density	Population	Area (km^2)
Coastline/Area ratio	Area	Coastline (km)
GDP per capita	Population	GDP (Billion $ PPP)

2.1.10 Base Modeling Assumptions

Besides the already discussed parameters, several assumptions were made for the base modeling approach. For the purposes of this thesis, the assumptions used for modeling and that were not obtained from the clustering results were taken as global or archetype dependent for simplification. These can be changed according to specific data availability and to the modeler's criteria.

– **Assumption 1:** To model the non-optimal dispatch of power plants due to outages, linkage to the heating sector, and transmission constraints, a minimum FLH is specified for technologies installed before 2015. The technologies with this constraint are: gas power plants, oil power plants, and coal power plants.

  The FLH are specified by cluster and represent the minimum value found among the countries within the cluster for the year 2015. They were calculated using the generation and capacity of 2015 according to equation 2.16:

$$\text{FLH} = \frac{\text{Generation [GWh]}}{\text{Capacity [GW]}} \tag{2.16}$$

  Table 2.9 shows the results for each technology and archetype.

Table 2.9: Minimum FLH per cluster [37], [35]

Archetype	Oil PP	Gas PP	Coal PP
Archetype 8	0	0	1293
Archetype 13	495	2095	1911
Archetype 14	0	1113	0
Archetype 15	0	1289	0

– **Assumption 2**: The existing power plants must be decommissioned due to the different years in which the current fleet was built. Using the lifetime of the technologies and the initial installed capacity, a linear function is used to determine the remaining capacities every year.

$$\text{Remaining Capacity} = \text{Initial Capacity} - \frac{\text{Initial Capacity}}{\text{Lifetime}} * \Delta t \text{ [GW]} \tag{2.17}$$

An example is illustrated in Figure 2.9, assuming a lifetime of 30 years and an initial installed capacity of 40 [GW].

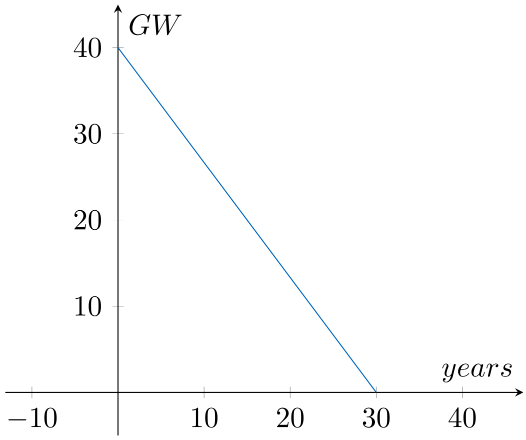


Figure 2.9: Power plant decommissioning methodology

– **Assumption 3**: A Weighted Average Cost of Capital (WACC) of 7% was used for all technologies [19].

– **Assumption 4**: The maximum CO_2 emissions per country were obtained from [36] for 2015. For the archetype, the CO_2 emission limit is dictated by the CO_2 emission intensity [Mio t CO_2/ Billion $ PPP] and the GDP calculated with equation 2.15.

$$\text{CO}_2 \text{ emissions limit} = \text{CO}_2 \text{ intensity} \cdot \text{GDP [Mio t CO}_2] \tag{2.18}$$

– **Assumption 5**: It is assumed that the net imports do not change over the years. Since transmission requirements are not calculated nor optimized, it is considered that the current transmission capacities are the ones available in the future.

– **Assumption 6**: The electric grid and losses percentage of the generated energy is also maintained the same throughout the analyzed period.

– **Assumption 7**: The CO_2 emissions are assigned to the fossil fuel commodities and slightly improve throughout the years. The emissions assigned to them are displayed in table 2.10.

Table 2.10: CO_2 emissions assigned to commodities [17]

Commodity	**CO_2 Emissions** $[\frac{kg}{kWh}]$		
Year	**2015**	**2030**	**2050**
Gas	0.49	0.44	0.43
Hard Coal	0.89	0.84	0.84
Crude Oil	0.69	0.64	0.63
Lignite	1.01	0.91	0.91

– **Assumption 8**: The lifetime for each technology is the average of the lifetimes estimated by [17] for 2015, 2030, and 2050. An average is taken due to the limitation of ESDP, which allows to assign only one value for the entire study period (See Table 2.11).

Table 2.11: Lifetime per technology

Technology	**Lifetime (years)**
Gas PP	30
Coal PP	40
Lignite PP	40
Oil PP	48
Nuclear PP	53
Hydropower	60
Wind onshore	23
Wind offshore	30
Photovoltaic	25
Geothermal	30
Waste	25
Biomass	24
Marine	20
Battery Li-Ion	10
Pumped Hydro Storage	60
Electromechanical Storage	20
Thermal Storage	20
Hydrogen Storage	20

– **Assumption 9**: The maximum FLH of the different technologies are mostly the same for all countries, except for gas. In countries that are not gas dependant, the power plants are used for different purposes, such as to cover peak demand or in CHP. Because of this reason, the maximum FLH attributed to this technology group is the average of the FLH of the different power plants it comprises (See Section: 2.1.5). For cluster 15 and 8, however, the maximum FLH for gas are much higher because of their dependance on fossil fuels. This assumption was very important, since the investment in Gas PP capacity is heavily influenced by this factor. The higher the full load hours, the lower capacity installed; the lower the FLH, the more capacity is needed. Because of this reason, this parameter should be considered carefully. With regards to renewable energies, the FLH for Wind and PV are determined by their respective time series FLH (See: Table 2.12).

– **Assumption 10**: The hydropower category is divided into two: Flexible and Inflexible. The total installed capacity is divided in half and assigned to each respectively. This approach was taken to portray more accurately the behavior of hydro production due to a lack of time series information for most countries around the world. The flexible category is allowed to produce when the optimizer sees more convenient; the inflexible category is only able to

Table 2.12: Maximum FLH per technology [17]

Technology	Max FLH
Fixed	
Gas	Clusters 8,15: 7446
	Clusters 13,14: 4390
Coal	7446
Lignite	7446
Oil	7446
Nuclear	7095
Geothermal	8322
Waste	7008
Biomass	6132
Marine	2015: 2452
	2030: 3087
	2050: 3750
Variable	
Hydropower	From clustering results
Wind Power	Given by time series
PV	Given by time series

produce in an uniform time series, meaning that its production is the same throughout the year.

2.2 Future Scenario

As mentioned in 2.1.3, the transition pathway until 2050 was modeled. The future scenario selected was an 80% decarbonization from the 2015 energy system. For Cluster 13, a Business as Usual (BAU) scenario was modeled to obtain a reference case. In order to build these scenarios, the CO_2 goals and the maximum allowed expansion was calculated for all the countries and archetypes in a methodological manner. These are furthered explained in section 2.2.2.

2.2.1 Scenario Definition

In order to quantify the decarbonization goal, the CO_2 emissions were calculated for the year 2015 based on the results from equation 2.18. The goal for 2050 was set to 20% of the emissions calculated for 2015:

$$\text{CO}_2 \text{ emissions limit}_{\,2050} = \text{CO}_2 \text{ emissions}_{\,2015} \cdot 0.2 \tag{2.19}$$

For the BAU scenario, the CO_2 emissions were also calculated to model the current trends in emissions per economic intensity. The estimation of the future economic growth, demand, and model expansion limits are explained in more detail in section 2.2.2.

2.2.2 Assumptions

Demand growth

As with the base model setup, a set of assumptions was used for the modeling of the future scenario. Two main aspects determined the growth of the country's energy demand: population and economic growth. From the clustering results, the values for population growth and GDP growth can be obtained for each archetype. Since values for the current GDP and population are known information (See: Section 2.1.10), an interpolation for 2050 was performed. The determination of the future demand follows a series of steps, which are outlined below:

- **Step 1**: Determine the future population with the projected population growth [38]. This value represents the growth compared to the population of 2015. The future population can therefore be determined through equation 2.20.

$$\text{Population}_{\text{ 2050}} = (1 + \text{population growth}) \cdot \text{Population}_{2015} \tag{2.20}$$

- **Step 2**: Determine the GDP per capita for 2050. As with the population calculation, the GDP for 2050 can be determined through equation 2.21.

$$\text{GDP}_{\text{cap}}{}^{2050} = \text{GDP}_{\text{cap}}{}^{2015} \cdot (1 + \text{Growth rate} \cdot \Delta t) \tag{2.21}$$

- **Step 3**: Calculate the energy intensity for 2050 based on the estimated GDP. According to [21], a correlation between electricity demand and GDP per capita exists. This correlation is much stronger in wealthier countries than in poorer ones, therefore a margin of error is expected when estimating the demand for countries with low economic development. The study also shows that the energy intensity decreases with higher GDP, meaning that in future years, there might be a decline in energy intensity per capita after a GDP threshold. Combining this information, [21] has derived a two-term exponential equation describing the relationship between the energy intensity and the GDP per capita of several countries. It uses the estimated GDP for a specific year to determine the energy intensity of the country.The values of a, b, and c were obtained through a two-term exponential fitting of the curve of GDP vs electricity consumption per capita.[3]

$$E_{cap}^{2050} = a \cdot \left(e^{\left(b \cdot GDP_{cap}^{2050}\right)} - e^{\left(c \cdot GDP_{cap}^{2050}\right)} \right) \tag{2.22}$$

$$a = 7.721 \cdot 10^4 [\text{kWh}], \quad b = -1.95 \cdot 10^{-6} \quad 1/[\text{EUR/capita}], \quad c = -5.655$$
$$10^{-6} 1/[\text{EUR/capita}]$$

- **Step 4**: Determine the total energy demand for 2050 by multiplying the energy intensity by the total population in the country/archetype.

$$\text{Demand} = E_{cap}^{2050} \cdot \text{Population} \quad [\text{TWh}] \tag{2.23}$$

[3]The GDP calculated in equation 2.15 is in Billion $ PPP. The formula presented in this section assumes the GDP to be in €. For currency conversion an exchange rate of 1.3 €/ per US $ was employed.

After these estimations were performed, the results were validated with other sources to evaluate whether the estimations were reasonable. The GDP of Canada and Germany was compared with results from *PWC* [39]. The comparison can be seen in 2.10:

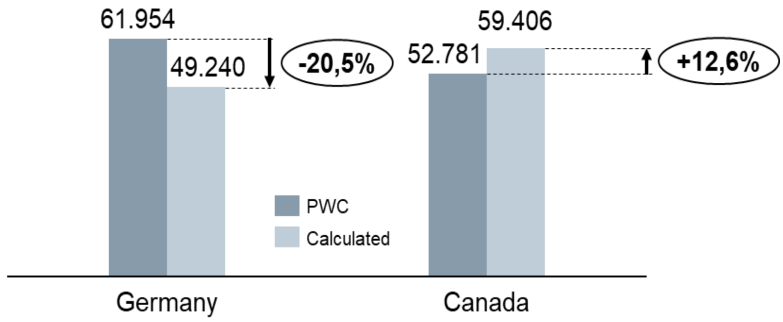


Figure 2.10: GDP Comparison. Values are expressed in Billion $

As seen from figure 2.10, the values are not the same due to the use of different growth rates throughout the years in *PWC*'s study, whereas the growth rate used for this model is constant for the entire evaluation period. The GDP growth was also considered to be the same as that from 1995-2015, which leads to an approximation, but not an accurate representation of the possible future economic growth. However, if another estimation from this parameter can be obtained, the clustering results can be improved, but the methodology for demand estimation remains the same. Another methodology for estimating future GDP is suggested in [21]. However, this approach assumes that the GDP of all countries will be the same in 2100. This can lead to an overestimation of the GDP and the demand. If selected, it should be employed with caution.

For the validation of future demand, a comparison with other studies was performed. For example, the demand for Germany was estimated for 2050 and compared against [15]. There is a discrepancy in the estimated demand, which can be attributed to the overestimation of the GDP. The difference , however, is not greater than 10% and considered tolerable.

Of course, this methodology is not foolproof, but attempts to develop a rule that can be applicable for all the analyzed countries based on the available information from the clustering results.

Expansion Limitations

The evaluation of renewable energy potential requires extensive research and varies according to the technology. The use of multiple sources such as statistics, digital data, remote sensing, and satellite digital images is necessary for the determination of the technical potential [40]. The approach taken in this thesis, however, is simplified due to the spatial dimension of the problem. To avoid the installation of resources where it is not technically feasible, the expansion for renewables is limited annually. A specific set of rules was used for all the countries and archetypes analyzed. Some are own assumptions, others depend on the country/archetype size, and others on the of the resource's availability (FLH).

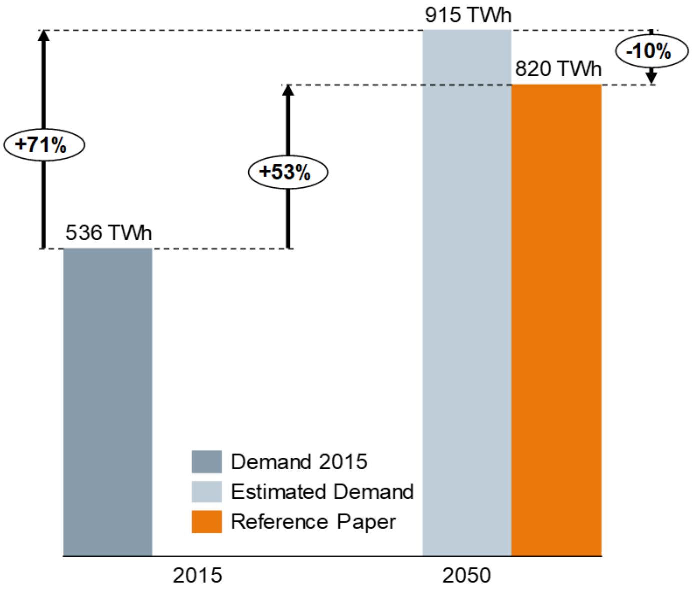


Figure 2.11: Validation of estimated demand

- **Assumption 1**: No new installations of nuclear power plants are allowed. Although nuclear energy is a source of carbon neutral energy and contributes to the system's reliability due to its availability, there are many hurdles today that prevent their development. According to [41], government policies have failed to value the security that nuclear can provide, and new projects have been delayed and their costs overrun. The current trends indicate that nuclear power can be on decline, and the world is at risk of losing two-thirds of the current nuclear fleet. Because of this reason, this study considers a future in which no new nuclear capacity is installed.

- **Assumption 2**: Analyzing the development of hydropower over the years and given that it is an old and established technology, new power plants will be allowed to be installed only in places where hydropower currently exists. The allowed expansion per annum is of 6.5% of the capacity installed in 2015 when the installed capacity is higher than 500 MW. For countries that have less than 500 MW installed, the maximum allowed expansion is 10 MW per annum. This increase was obtained by analyzing the growth of hydropower plants in recent years [42].

- **Assumption 3**: The installation of wind resources requires considerable infrastructure, therefore the land area is considered when allowing the expansion of this resource. The expansion rate in $\left[\frac{\text{MW}}{\text{km}^2 \cdot a}\right]$ was calculated for Denmark, Germany, and the United Kingdom. The estimated capacity installed for 2050 for these countries was obtained from [43], [44], and [15]. From the three values, Germany's expansion rate was the fastest and therefore taken as the maximum rate allowed.

  The expansion rate was obtained by considering the installed capacity per km^2 in 2015 for every country. According to [15], the expected installation of wind onshore by 2050 for Germany is around 170 GW. Expressing the installed capacity in these two years per unit area yields two points in time, as illustrated in figure 2.12.

The slope of the line connecting these two points determines the growth rate per year necessary to reach the desired installed capacity by the end of the study period. To be included in the model, the value in MW per year is calculated by multiplying by the area of the country or archetype. The densities per year and the calculated slope are shown in Table 2.13.

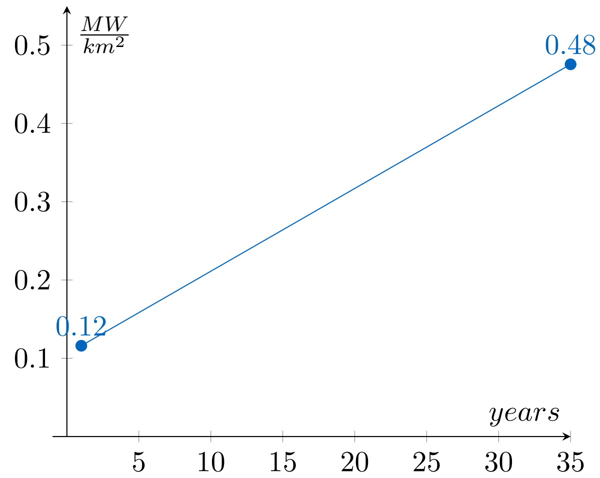


Figure 2.12: Slope calculation for wind onshore expansion

Table 2.13: Wind Onshore Density [$\frac{\text{MW}}{\text{km}^2}$] for Germany, Denmark, and the United Kingdom

Country	Capacity 2015 [GW]	Capacity 2050 [GW]	Current Density [$\frac{MW}{km^2}$]	Future Density [$\frac{MW}{km^2}$]	Slope [$\frac{MW}{km^2 \cdot a}$]
Germany	41.38	170	0.116	0.476	0.010
Denmark	9.22	22.5	0.038	0.092	0.002
UK	3.81	4.3	0.088	0.01	3×10^{-4}
		Average	0.081	0.222	0.004

– **Assumption 4**: The development of wind offshore has risen over the past years. Most of the installations have taken place in Europe. European countries account for 98% of the installed capacity worldwide [45]. The top 3 countries are UK, Denmark, and Germany which account for 85% of the total installed capacity. Because of this reason, these countries were analyzed for the wind offshore expansion limit. A similar approach as for wind onshore was used, except that the coastline extension was considered as the limiting factor, and not the area. The density in $\frac{\text{MW}}{\text{km}}$ was calculated for the present and the future to determine the necessary expansion rate per annum. The fastest growing rate was again Germany, and therefore taken as the reference. (See:

Table 2.14). To convert to MW, the slope is multiplied by the total coastline extension obtained through equation 2.14.

Table 2.14: Wind Offshore Density [$\frac{\text{MW}}{\text{km}}$] for Germany, Denmark, and the United Kingdom

Country	Capacity 2015 [GW]	Capacity 2050 [GW]	Current Density [$\frac{MW}{km}$]	Future Density [$\frac{MW}{km}$]	Slope [$\frac{MW}{km \cdot a}$]
Germany	3.29	20	1.37	8.36	0.2
Denmark	5.09	30.2	0.41	2.429	0.057
UK	1.27	7.73	0.174	1.06	0.025
		Average	0.651	3.95	0.094

– **Assumption 5**: Wind onshore and offshore expansion is somewhat limited by the "potential" due to the consideration of the available geographical area and extension. For PV, a similar "potential" approach is used to determine the annual limits. In this case, the load estimated for 2050 was considered, as well as the FLH calculated when determining the time series of PV. The necessary capacity to meet the total demand by just PV is calculated and divided by the number of years of the study period. This established the maximum limits for yearly PV expansion.

$$\text{PV Limit} = \frac{\text{Demand}_{2050}}{\Delta t \cdot \text{FLH}} \text{ [GW]} \tag{2.24}$$

– **Assumption 6**: For the expansion of the other renewables, a 10% increase of the capacity in 2015 is allowed to be installed every year. The technologies to which this assumption applies are: Geothermal, Waste, and Marine.

– **Assumption 7**: For the biomass limit, a share in the total installed capacity is assumed. Biomass power plants are not limited by the area as wind, nor limited by the FLH and time availability as PV. The allowed expansion of biomass is then determined by the current share in the energy mix, assuming countries will continue to invest in the same proportion as in the past, given the lower limitations biomass presents.

$$\text{Biomass Limit} = \text{Current share} \cdot \text{Installed Capacity}_{2015} \text{ [GW]} \tag{2.25}$$

– **Assumption 8**: Since the current share of renewables plays a significant role in the rate of expansion, a correction factor was calculated for the simulated countries in order to achieve the goals for 2050. This correction factor is applied to all the technology limits, except PV and hydro. This means that countries with lower share of renewables in 2015 are allowed to install more per year than countries which have a higher share (See Table 2.15).

– **Assumption 9**: Pumped Hydro Storage can only be installed when there is evidence that hydro resources exist (i.e. only when there is an initial installed capacity of hydro).

Table 2.15: Correction factors based on the share of renewables

Share of Renewables (%)	Correction Factor
x <10	4
10 <x <30	3
30 <x <50	2
x >50	1

2.3 Comparison Methodology

For the evaluation and performance quantification, a methodology was developed in order to evaluate the accuracy with which the archetype model portrays a country's development. Due to the great number of criteria to be compared, a more systematical method for comparing and ranking was required. Using concepts from Multiple-Criteria Decision Making (MCDM), a ranking methodology called Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) II was selected. Other methodologies were also explored for the validation of the results. An overview of these methodologies is provided in the appendix.

2.3.1 Performance Metric

The first step towards performance evaluation is the selection of a performance metric. These are defined as "the logical and mathematical constructs designed to measure how close the actual results are from what was expected" [46]. With a variety of performance metrics available, most are categorized based on common characteristics and properties. For the description of the ones employed in this thesis, the categorization based on [46] is used. The performance metrics here described are classified in: primary metrics, extended metrics, composite metrics, and hybrid metrics.

Primary metric calculation involves three steps: calculating point distance, normalizing, and aggregation of the point results over a data set. For the ranking of the countries within a cluster, only one primary metric is used because only one estimation value per comparison criteria exists. For the archetype, the use of an extended metric is possible, since the number of estimations is greater than one and equal to the amount of countries it encompasses.

For the primary metric calculation, a formula can be defined in a generic form [46], where A represents the actual value, P the predicted value, $\mathbb{D}$ the method of determining point distance, $\mathbb{N}$ the normalization method, $\mathbb{G}$ the method for aggregation of point distances, and n the size of the data set.

$$\mathbb{M} = \underset{i=1,n}{\mathbb{G}} \left\{ \mathbb{N} \left[\mathbb{D} \left(A_i, P_i \right) \right] \right\} \tag{2.26}$$

The methods referred to in equation 2.26 are chosen based on the information that can be derived from them. For the method of point distance determination, the absolute value error is chosen and defined as $|A_i - P_i|$. This error metric is classified by [47] as pessimistic since it focuses mainly on determining how large the error is. As with other error measures, this metric has pros and cons. For example, when determining the absolute error, there is a clear physical interpretation and thereby easily understood. However, as mentioned before, this type of error focuses on determining how bad the performance is and can sometimes bias the results. Since the error measures are applied to different technologies with different levels of importance in an energy system, a normalization method had to be chosen to show these differences. For this application, the reference values are those obtained from the country model results. To include the relative importance of the technologies, the reference value becomes the total energy output and the total capacity installed for the corresponding parameters (i.e. the capacity errors are normalized by total installed capacity, and the energy output errors are normalized by the total energy output). The aggregation method for the country error values is non-existent. For the archetype error values, the mean aggregation method is selected, meaning that an arithmetic mean over all the countries within an archetype is taken as the error measure for every criteria in the archetype.

The resulting error formula can be summarized as in equation 2.27 , where M is the amount of criteria in each category mentioned in Table 2.16 and i refers to each evaluated criteria.

$$\text{Error}_i = \frac{|A_i - P_i|}{\sum_{j=1}^{M} A_j} \tag{2.27}$$

For the archetype, the error for every criteria i is defined as in equation 2.28 where N is the number of countries within the archetype.

$$\text{Error Archetype}_i = \frac{1}{N}\sum_{k=1}^{N} \text{Error}_{\text{i,k}} \tag{2.28}$$

Table 2.16: Evaluated parameters and normalization categories

Category	Units	Number of Parameters
Capacity	GW	18
Energy	TWh	18
OPEX	EUR	1
CAPEX	EUR	1
CO2 Emissions	Mio ton	1
Total Parameters		39

Although other error measures were explored and applied to the evaluation of the archetype's performance, their advantages were invalidated when applying the PROMETHEE methodology with a linear preference function (See section 2.3.2). Because of this reason, the other error metrics are not shown when presenting the results, however, an overview of the applicable error metrics is presented in the appendix.

2.3.2 PROMETHEE Methodology

The PROMETHEE methodology is part of the outranking methods in multi-criteria analysis. It has six extensions which can be applied on different situations depending on the required flexibility or complexity of the problem. PROMETHEE I and

II were created in 1982 by J.P. Brans and further developed with the help of B. Mareschal. These two first extensions provided with the possibility to partially rank projects and to create a total preorder of a set of possible alternatives. The other extensions further develop the decision process by including more complex aspects in the decision making: PROMETHEE III allows for a ranking based on intervals; PROMETHEE IV studies the continuous case; PROMETHEE V allows to include segmentation constraints; and PROMETHEE VI attempts to represent the human brain when making decisions [48].

For the understanding of the applicability of the archetype, a ranking methodology was chosen to identify whether a certain type of energy system is more closely represented by the approach. One of the main advantages of the selected methods, is that no relativization is needed for the ranking based in multiple criteria. What is most appealing about the PROMETHEE methodology, is the introduction of the intensity of preference when comparing criteria, allowing for a quantification of how much better or worse an alternative is. To do this, a set of preference functions are suggested depending on the decision maker's criteria. As will be shown in the next chapter, the selection of the preference function can have a strong effect when ranking the alternatives and should be carefully considered.

The concept of ranking can be thought of as a competition among the countries within an archetype and a competition among the archetypes themselves based on performance. The criteria compared are the errors for the different categories mentioned in Table 2.16. The countries and the archetypes are considered the alternatives or possible set of actions when describing the methodology. An overview of the principle is observed in Figure 2.13.

Principle of the Methodology

The multi-criteria problem can be defined as in equation 2.29, where K is a finite set of possible alternatives and $f_1(\cdot)...f_n(\cdot)$ a set of evaluation criteria. Some criteria can be either minimized or maximized depending on the aspect it evaluates (e.g. costs can be minimized and revenues maximized). At the end, the goal of the decision maker is to identify the alternative that optimizes all the criteria [48].

$$\mathrm{Max}\,\{f_1(a), f_2(a), \dots, f_h(a), \dots, f_k(a) | a \in K\} \tag{2.29}$$

Consider two alternatives a and b. The notion of preference is introduced, categorizing whether an alternative is preferred (P) over another, or if the two alternatives are the same (I).

$$\begin{array}{ll} a\ P\ b & \text{iff } f(a) > f(b) \\ a\ I\ b & \text{iff } f(a) = f(b) \end{array} \tag{2.30}$$

This preference can be quantified from [0,1], depending on the preference function chosen by the decision maker. This allows the quantification of how much an alternative is preferred over the other. The preference value is a function of $f(a)$ and $f(b)$ [49]. When there is no preference, a score of 0 is assigned:

$$P(a,b) = \begin{cases} 0 & \text{if } f(a) \leqslant f(b) \\ p[f(a), f(b)] & \text{if } \quad f(a) > f(b) \end{cases} \tag{2.31}$$

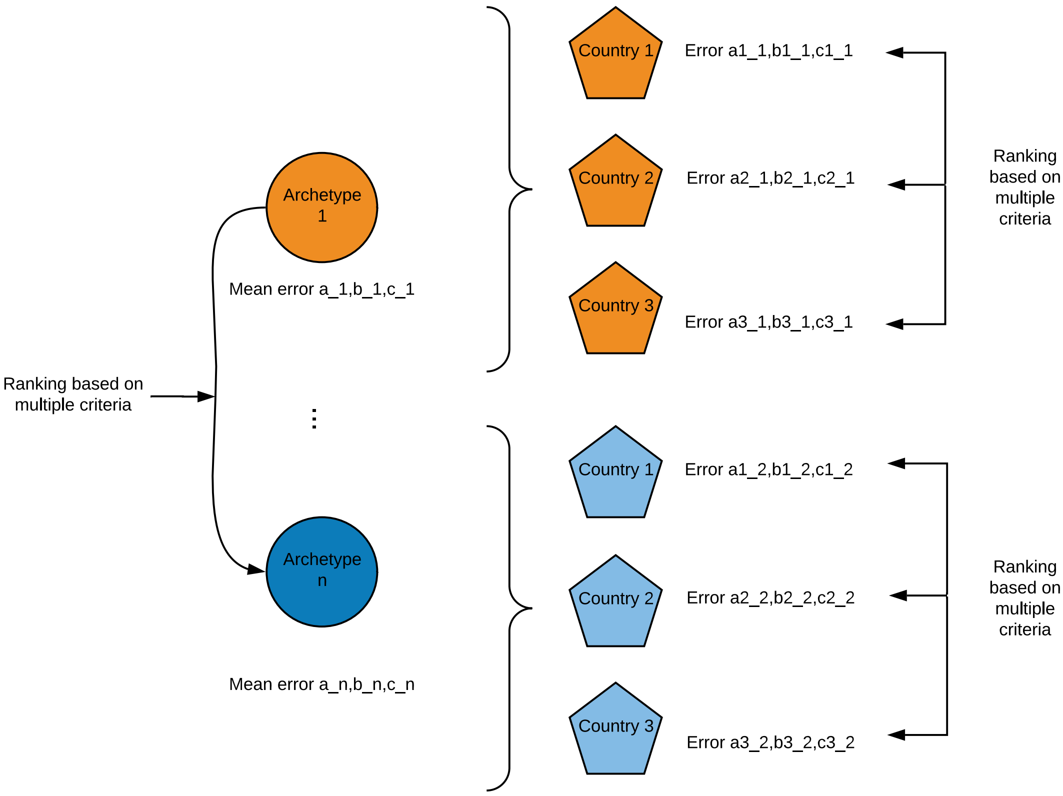


Figure 2.13: Ranking Principle using the PROMETHEE Methodology

$$p[f(a), f(b)] = p[f(a) - f(b)] \tag{2.32}$$

In order to compute the preference level based on the parameter obtained in equation 2.32, a preference function is selected. In the PROMETHEE methodology, a set of preference functions are suggested. Among them, the following can be listed [49]:

– Type I: Usual criterion

$$p(x) = \begin{cases} 0 & \forall x \leqslant 0 \\ 1 & \forall x > 0 \end{cases} \tag{2.33}$$

– Type II: Quasi-Criterion

$$p(x) = \begin{cases} 0, & x \leqslant l \\ 1, & x > l \end{cases} \tag{2.34}$$

– Type III: Criteria with Linear Preference

$$p(x) = \begin{cases} x/m, & x \leqslant m \\ 1, & x \geqslant m \end{cases} \tag{2.35}$$

– Type IV: Level-Criterion

$$p(x) = \begin{cases} 0, & x \leqslant q \\ 1/2, & q < x \leqslant q + p \\ 1, & x > q + p \end{cases} \tag{2.36}$$

– Type V: Criterion with Linear Preference and Indifference Area

$$p(x) = \begin{cases} 0, & x \leqslant s \\ (x-s)/r, & s \leqslant x \leqslant s+r \\ 1, & x \geqslant s+r \end{cases} \tag{2.37}$$

– Type VI: Gaussian Criteria

$$p(x) \begin{cases} 0, & x \leqslant 0 \\ 1 - e^{-x^2/2\sigma^2}, & x \geqslant 0 \end{cases} \tag{2.38}$$

For the evaluation in this thesis, the preference function type III is selected to quantify precisely the magnitude by which a country or archetype performs against the others. With this function, the decision maker is allowed to prefer progressively a to b for progressively larger deviations between $f(a)$ and $f(b)$ [49]. The preference function type IV is also applied to illustrate the effects of choosing a function type. With this function, an area of indifference is introduced: the alternatives are considered indifferent as long as the difference between $f(a)$ and $f(b)$ does not exceed q. The preference becomes then weaker, when the difference is found between q and $q + p$, and stricter when the difference is greater than p.

Following the selection of the preference function, a preference index is calculated for the alternative a with regards to b over all the criteria.

$$\pi(a,b) = \frac{1}{k} \sum_{h=1}^{k} P_h(a,b) \tag{2.39}$$

As mentioned before, the PROMETHEE I allows for a partial ranking to identify whether two alternatives are incomparable or if a total outranking can be done. According to [50], the notion of incomparability is important because it allows the method to avoid to decide when there is insufficient availability of data. Incomparability can arise when, for example, a is good on a set of criteria where b is weak, and a is weak on a set of criteria where b is good. To perform a partial ranking, a set of positive and negative flows is calculated. The positive flows represent how much better an alternative is than the others, and the negative flow represents how much better the other alternatives are than the one currently analyzed. The higher the positive flow is, the better the alternative. The lower the negative flow, the less the other alternatives outrank the current one. To calculate the total preorder, a net flow is derived. This flow can be defined in terms of the positive and the negative flow and can be interpreted in this case, as how much better in average the alternative is than the others by taking the difference of the strengths and weaknesses [51].

$$\varphi^+(a) = \frac{1}{n-1} \sum_{x \in K} \pi(a,x) \tag{2.40}$$

$$\varphi^-(a) = \frac{1}{n-1} \sum_{x \in K} \pi(a,x) \tag{2.41}$$

$$\varphi(a) = \varphi^+(a) - \varphi^-(a) \tag{2.42}$$

For a partial ranking, the following rules hold true:

$$\begin{array}{lll} aP^+b & \text{iff} & \varphi^+(a) > \varphi^+(b) \\ aP^-b & \text{iff} & \varphi^-(a) < \varphi^-(b) \\ aI^+b & \text{iff} & \varphi^+(a) = \varphi^+(b) \\ aI^-b & \text{iff} & \varphi^-(a) = \varphi^-(b) \end{array} \tag{2.43}$$

In this case, a outranks b if aP^+b and aP^-b, OR aP^+b and aI^-b, OR aI^+b and aP^-b. The alternatives are indifferent if aI^+b and aI^-b. In any other case, they are incomparable.

The concept of positive and negative flows can be visualized as a set of nodes that represent the alternatives, and where the arcs represent the weaknesses and strengths compared to the other alternatives.

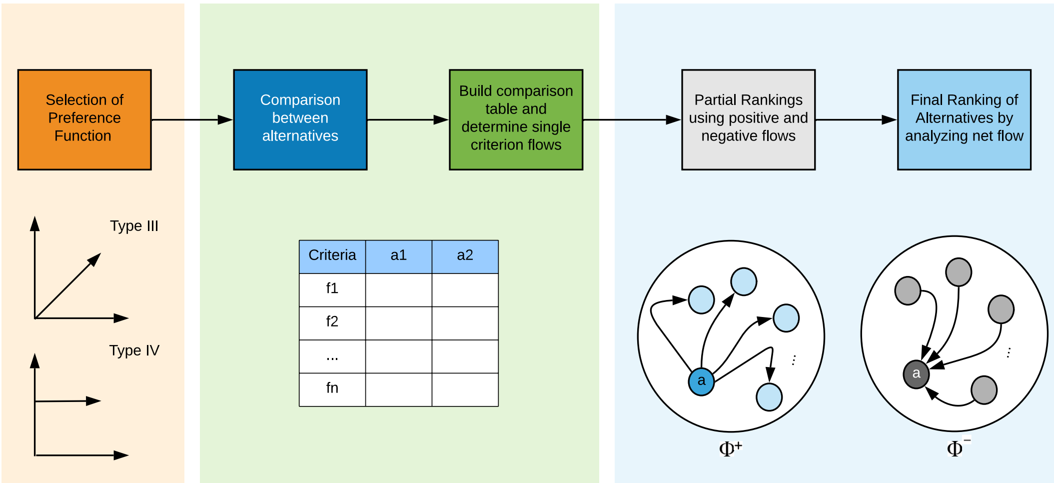


Figure 2.14: PROMETHEE Methodology Flowchart and Flows Visualization

2.3.3 PROMETHEE Parameters

For the complete definition of the preference function, the parameters defining the linear and the level function (Type III and Type IV) must be specified. A summary of the assigned parameters can be visualized in table 2.17. The parameters for the preference function were chosen so as to prefer according to the error level. If the error difference is greater than 100%, then full preference was given, otherwise, a preference according to the error difference is assigned. For the level criterion, the preference of 0.5 was assigned when the two options presented the same amount of error and a total preference when the error in a parameter was lower than in the other.

Table 2.17: Preference function parameters

Function	p	q	m
Type III	n/a	n/a	1
Type IV	0	$f(a) - f(b) + 10^{-9}$	n/a

For example, given two alternatives a_1 and a_2 with criteria f_1 and f_2, the flows can be calculated for the set of errors shown in 2.18 as follows:

Table 2.18: PROMETHEE example using preference function III

	a_1	a_2
f_1	5%	10%
f_2	2%	1%

To calculate the positive flows for a_1, the following calculations can be performed:

$$\pi(a_1, a_2) = \frac{1}{2} \times \left[\frac{10-5}{1} + 0\right] \tag{2.44}$$

$$\pi(a_2, a_1) = \frac{1}{2} \times \left[0 + \frac{2-1}{1}\right] \tag{2.45}$$

The positive, negative, and net flow can be therefore calculated as:

$$\varphi^+(a_1) = \frac{1}{2-1} \sum_{x \in K} \pi(a_1, a_2) = 2.5 \tag{2.46}$$

$$\varphi^-(a_1) = \frac{1}{2-1} \sum_{x \in K} \pi(a_2, a_1) = 0.5 \tag{2.47}$$

$$\varphi(a) = \varphi^+(a) - \varphi^-(a) = 2.5 - 0.5 = 2.0 \tag{2.48}$$

Since the sum of net flows must be equal to 0, the net flow for a_2 can be defined as the negative of the net flow of a_1 when only two actions are considered. The result can be interpreted as: a_1 is 2.0% better than a_2 in average for all criteria. This is a simple representation of how the methodology is applied and can seem trivial in this case, however, it becomes useful when the number of criteria is much higher and more difficult to manage.

In theory, it is possible to assign a weight to each criteria depending on the relative importance. Since an intrinsic weighting was done when calculating the errors, no additional weighing is assigned in this step. For further extension of the presented formulas, [48] is recommended as complementary reading.

2.3.4 Descriptive Statistics

Statistics can be either inferential or descriptive. Descriptive statistics deal with the presentation and organization of data. Within the descriptive statistics, measures such as the mean, median, standard deviation, and range can be found. These statistics aim at summarizing numerical information [52].

For the evaluation of the performance within the countries in the archetype, a statistical evaluation was performed to describe the different errors to be expected when modeling a country with the archetype model. The statistical tools used to describe these errors are briefly discussed in this section.

Averages

Averages can be defined as a single number that describes an entire collection and which provides with information about the central tendency of the dataset. Among the different type of averages, the mean, median, and mode are the most commonly used. The mean value can be determined by adding all the numbers in the collection and dividing by the amount of terms in the sum. The median is a number in the middle of the set. Its unique characteristic is that the same amount of numbers are found above and below this number. The other type of average measure is the mode. This is defined as the most common number in a collection of observations [53]. For every country in the archetype, a set of these averages is provided to obtain an overview of the typical expected errors within all the evaluated criteria.

Variance measures

To evaluate the level of data dispersion, tools such as the variance and standard error are used. These parameters are calculated for the errors in each country and can be serve as an indication of how much the data differs from the mean μ. When the standard deviation assumes a small value, it means that the data is grouped around the mean. When the value is high, the data occupies a much larger range, and the values might differ greatly from the mean.

For the calculation of the dispersion measures, the variance is firstly calculated from equation 2.49. This is the average squared deviation from the mean [52]. This must be calculated first in order to avoid the problem of negative deviations from canceling the positive deviations. The standard deviation, then, can be calculated by taking the square root of the variance as in equation 2.50. In both these equation, N represents the number of data points used.

$$\sigma^2 = \frac{\sum_{i=1}^{N} (x_i - \mu)^2}{N} \tag{2.49}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \mu)^2}{N}} \tag{2.50}$$

Statistical Distributions

For the evaluation using probabilities, a normal distribution was fitted to the errors presented within the archetype. Based on a constructed histogram and on the information of the mean μ and the standard deviation σ of the data set , the distribution was completely defined. The normal distribution is the most commonly used distribution and has a range of $-\infty$ and + ∞. Based on the distribution, the probability density function can be defined as in equation 2.51, were x is the evaluated random variable (in this case, the errors) [54]:

$$\mathrm{f(x)} = \sqrt{\left(\frac{1}{2\pi\sigma^2}\right)} e^{-0.5[(x-\mu)/\sigma]^2} \tag{2.51}$$

With this function, the error value for a certain probability can be derived. For example, Figure 2.15 shows the evaluation for New Zealand for 2050, in which the expected error with a probability of 0.7 can be determined. Furthermore, information about the probability that the error lies below 30% is also displayed with the help of the cumulative probability function as defined in equation 2.52. The metrics aid in the description of the errors typically found, and what to expect when modeling the countries with the archetype. It is also a way of determining whether or not the error meet the criteria of error tolerance when modeling energy systems. It is part of the feedback loop in which the model can be further tuned, as it indicates the achieved level of precision in the modeling process.

$$\mathrm{F}\left(\mathrm{x_o}\right) = \mathrm{P}\left(\mathrm{x} \leq \mathrm{x_o}\right) \quad = \int_{-\infty}^{x_o} f(x)dx \tag{2.52}$$

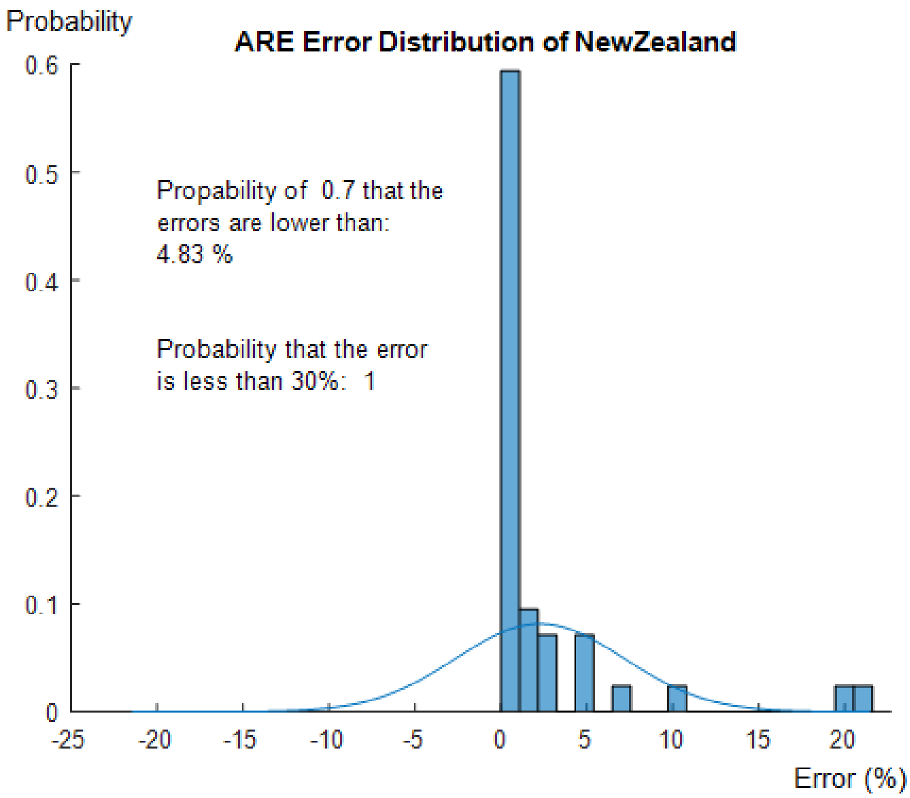


Figure 2.15: Expected error of New Zealand for 2050. Application of the Probability Distribution Function and the Cumulative Distribution Function

Box and Whisker Plots

For an overview of the errors within the archetype, an extra statistical tool was implemented in order to visualize the expected errors. The box and whisker plot is a graphical representation of a set illustrating the lower values, the mean, median, and the quartiles in which the data can be found [52]. In this case, the length of the box represents the interquantile range, meaning that the data within this box is between 75% - 25% of the distribution. Any information outside this box is categorized as an outlier. Additionally, the end of the whiskers represent the 9th and 91th percentile, providing a fuller visualization of the expected errors. The evaluation for all the archetypes, as well as their corresponding descriptive statistics can be found in the appendix. An example for archetype 15 is displayed in 2.17, where the expected errors for 2050 can be observed for every country.

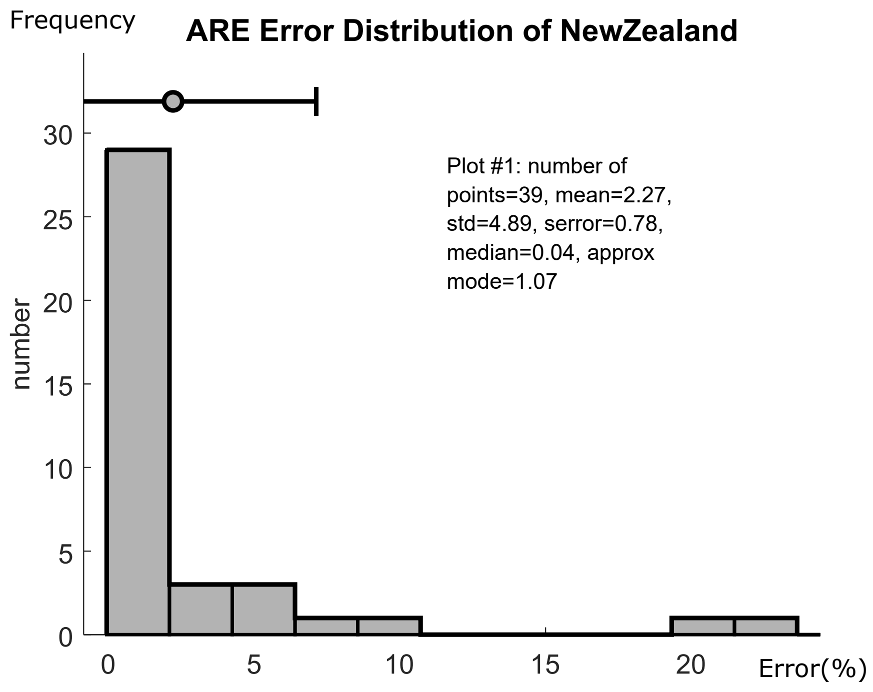


Figure 2.16: Histogram of New Zealand for 2050

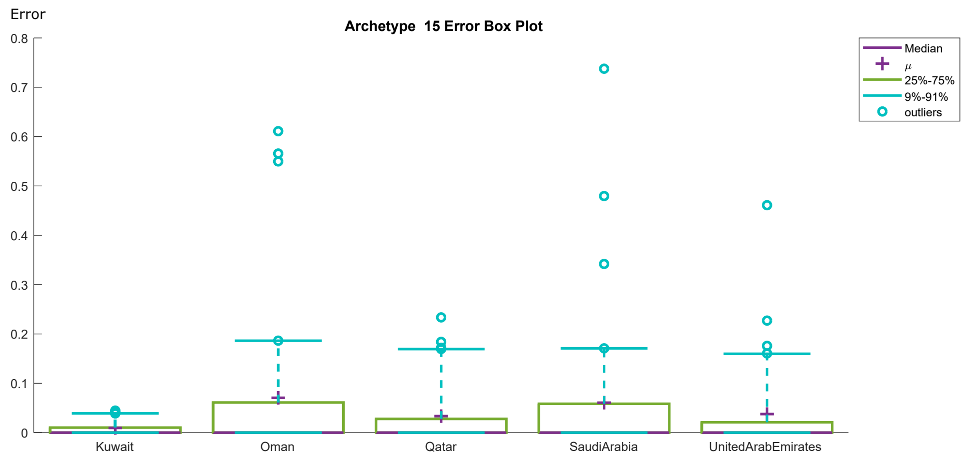


Figure 2.17: Box and Whisker Plot for Archetype 15

Chapter 3

Results

3.1 Model Validation

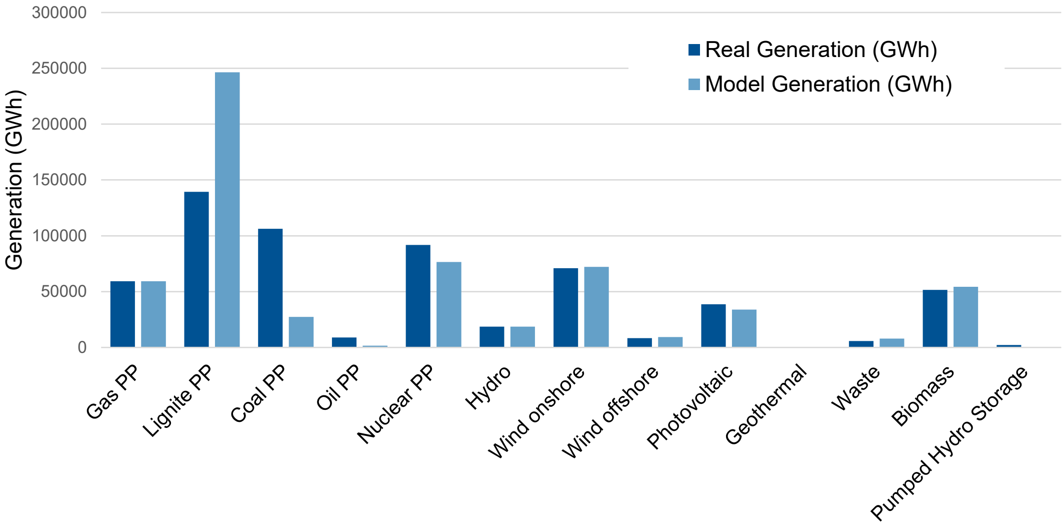
To validate the model output for 2015, a comparison against real generation was performed for Germany, Denmark, and the United Kingdom. To generate the complete basic model, a tuning of the assumptions had to be done so as to reflect the real operation of the energy systems. The information for comparison was gathered from [35], [41], and [55] and the results can be visualized in Figure 3.1.

In the case of Germany, most of the technologies are correctly portrayed. The weaknesses observed in this model are associated with the lignite and hard coal power plants. These technologies present a weighted error of 23% and 17% respectively, while the other technologies are below 4%. Since the model does not consider sector coupling, outages, or specific plant availability, not all technologies can be 100% correctly estimated. Given that the model tries to meet the demand to the lowest possible cost, it chooses lignite to provide this energy and not hard coal when these factors are not taken into account.

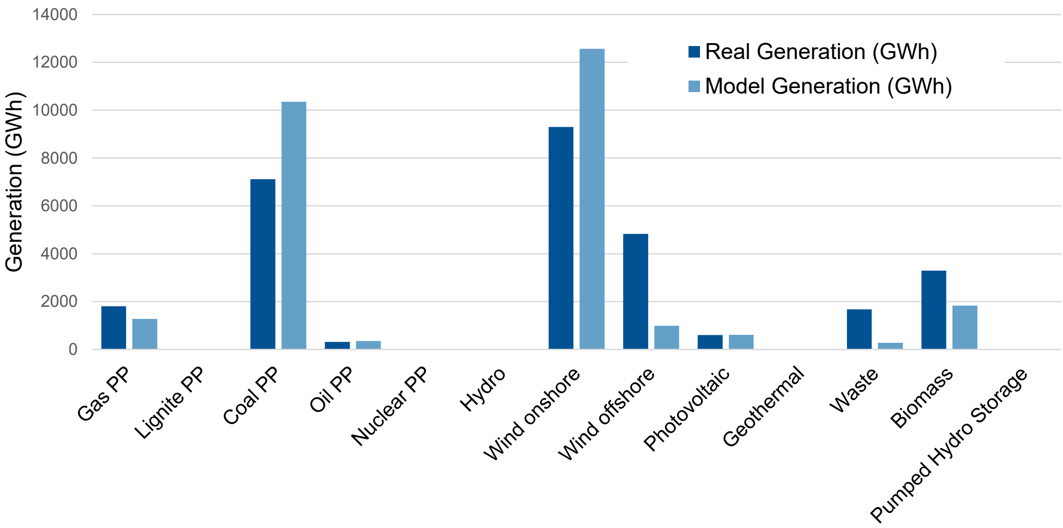
For Denmark, higher errors are observed. The over and under estimation of the wind technologies can be partly attributed to the approach taken when obtaining the time series, leading to miscalculations of the real FLHs. For gas, the model underestimates the production and assigns the generation to cheaper technologies, possibly coal or renewables. When calculating the errors per technology based on their importance in the energy mix, it is observed that they do not surpass 15% and are considered acceptable for this simplified approach.

United Kingdom's model presents good estimations for the all of technologies during this year, with weighted errors lower than 7%. The error in the fossil fuel power plants is due to the optimizer's preference towards cheaper technologies. In this case, nuclear and wind onshore. For PV and wind offshore, the FLH appear to be correctly estimated and do not differ greatly compared to reality.

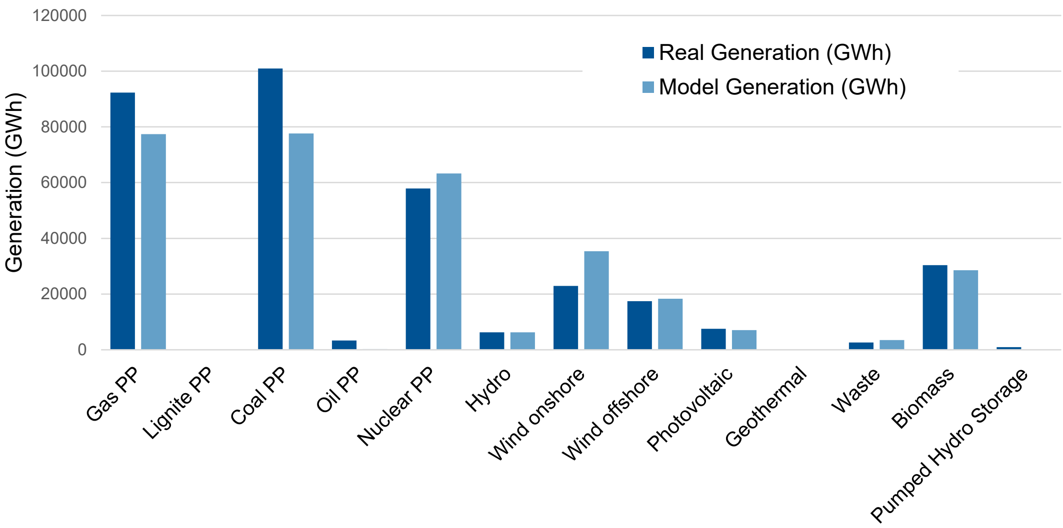
The availability estimation for most of the technologies, such as time series and FLHs, was validated by analyzing the generation in 2015. Some discrepancies can occur, as with the case of Denmark, indicating that the approach might have some flaws for certain countries. Of course, no global solution can be found and the set of assumptions may fit some countries' profiles, but not others. Based on the results presented in this section, the case can be made that the standardized approach is good enough to portray a country's energy system.



(a) Germany Generation 2015



(b) Denmark Generation 2015



(c) United Kingdom Generation 2015

Figure 3.1: Data Validation for Germany, Denmark, and the United Kingdom

3.2 Model Results and Transition Pathways

After the validation has been made, the model is further extended to obtain the transition pathways for every country and its corresponding archetype. Except for cluster 13, only the decarbonization scenario is modeled for the 23 countries analyzed. In the case of cluster 13, an extra scenario - BAU - was modeled to provide a reference case for the evolution of the energy system assuming less strict limitations in CO_2 emissions.

Although this chapter contains only the results from cluster 13, the resulting energy mix for all countries can be found in the annex for the years 2015, 2029, and 2050. In each figure, the country's and the archetype's results are displayed together for easier comparison.

3.2.1 Detailed model Results for Cluster 13: Germany, Denmark, United Kingdom

Decarbonization Scenario

As mentioned in Section 2.2, the decarbonization goal for the model was 80% compared to the emissions in 2015 and optimized in a seven year time step. The resulting energy mix for the archetype and the country was compared to determine whether the future energy mix estimated by these two models was similar.

When comparing the installed capacities for the year 2050, a few remarks can be made (See Figure 3.2 for an overview of the installed capacities). For all three countries, the chosen base technologies are gas, biomass, and wind onshore. Biomass and gas act as the designated technologies to cover base load and peak demand, which compensate for the variability of renewable energies. In the case of Denmark, the archetype has a higher consumption for 2050 due to the difference in the consumption per capita estimated by the archetype and the country model. Due to the higher demand, PV starts to be chosen when the wind installation limit has been reached. For Germany, the installed capacity in the country model is higher than that of the archetype. This discrepancy does not affect the installation of PV, rather the installation of gas power plants. In this case, almost all the chosen technologies match between the country and the archetype. When analyzing the shares, the technologies occupy almost the same level of importance in both of these cases. For UK, the difference between the estimated necessary capacity of the country is much higher than that of the archetype (33% discrepancy).- higher than the over\under estimation of the other two countries. In this case, the amount of PV chosen does not match between the two models.

With regards to energy generation, the archetype matches very closes the energy production of the three most important technologies for all countries (See Figure 3.3). When comparing the total generation between the archetype and the country, the difference is much lower than when comparing total capacities. The difference between the estimated consumption for 2050 was between 8-9%, reducing the difference between the generation of the chosen technologies. As with capacities, the biggest discrepancy lies in the generation for UK with regards to wind offshore, and PV. These technologies partake a much higher role in the country model generation than in the archetype model. In absolute values, the difference in generation for UK between the country and archetype is 80 TWh , accounting for a great part of the energy provided by wind offshore and PV that the archetype model fails to estimate.

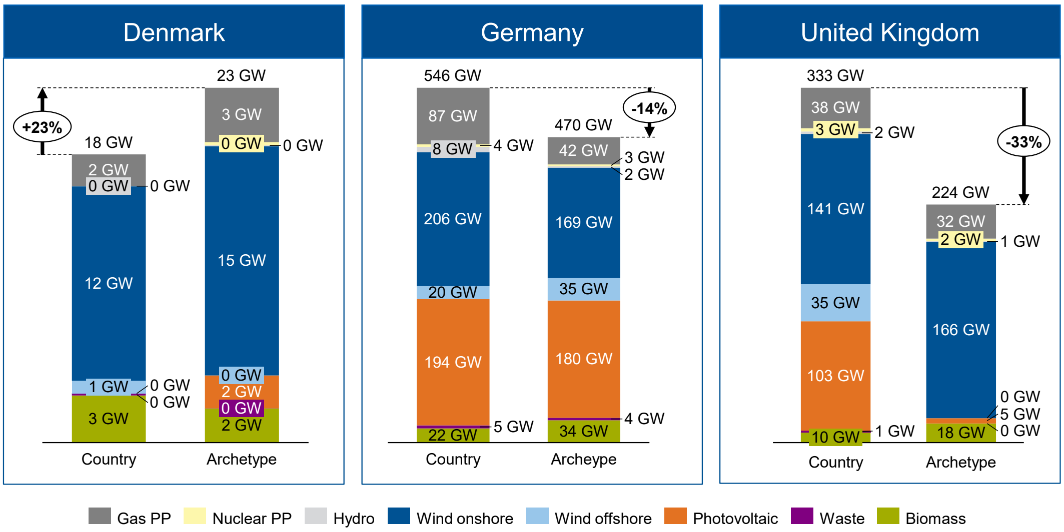


Figure 3.2: Installed Capacities for 2050: Germany, United Kingdom, and Denmark

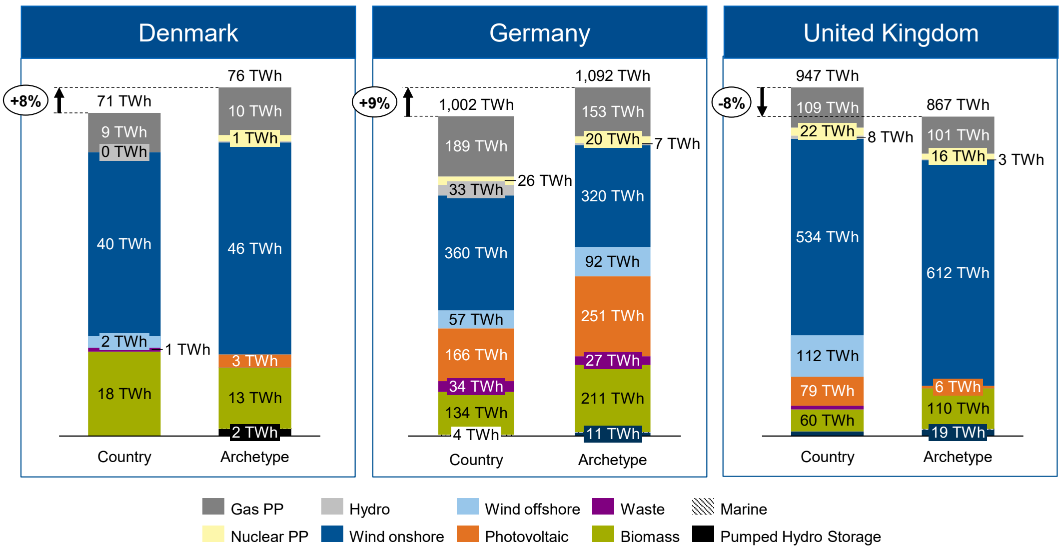


Figure 3.3: Generation for 2050: Germany, United Kingdom, and Denmark

Finally, a ranking regarding the performance of the countries within this cluster is presented in Figure 3.4. This portrays Germany as the country with the best performance, and the United Kingdom as the worst. This is probably due to the incapability of the UK's archetype model to estimate correctly the installation of PV and wind offshore.

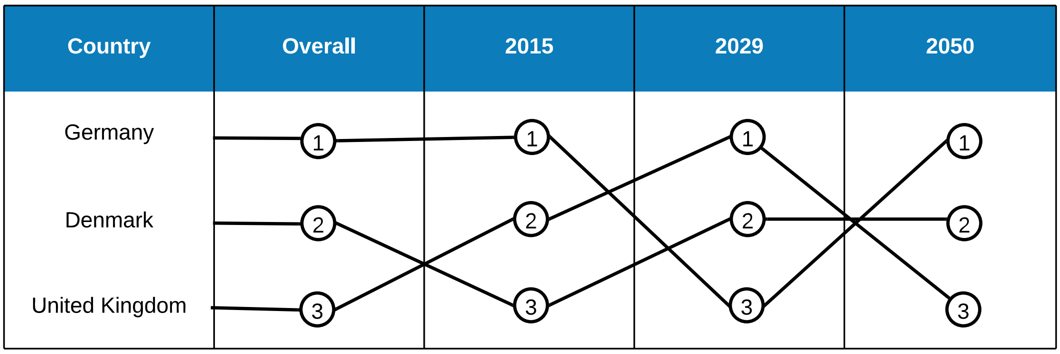


Figure 3.4: Performance Ranking of Cluster 13

Business as Usual

In order to obtain an overview as to how the system might develop when no CO_2 emissions goal is introduced, a business as usual scenario for cluster 13 was analyzed. In this case, a CO_2 limit was used but only to reflect current emissions intensity. That is to say that based on the present limitations and the current enacted policies, a limit for the future was established. This enables to prevent the unrealistic installation of cheap and CO_2 intensive technologies that wouldn't have been installed under the current energy framework of the countries. In order to calculate the limit, equation 2.18 was used with the GDP value corresponding to the one estimated for 2050 through equation 2.21.

Once the limits have been set, the model is simulated for the archetype and country model. As observed from Figure 3.5, the countries tend to use renewable energies in the future energy system due to low cost of producing energy. In the case of Denmark and the United Kingdom, Wind onshore, gas, coal, and biomass are chosen as the necessary technologies to cover the energy demand. In United Kingdom, nuclear energy that has not been decommissioned remains as part of the mix and allows to provide base load. In the case of Germany, however, the results from the archetype and the country are very different. Analyzing the initial installed capacities, and the remaining capacities from conventional energies, it is observed that the remaining capacities for coal, lignite, and nuclear are enough in the country to cover the demand without installing too many gas power plants or renewable energy resources other than biomass.

An interesting behavior is that, if allowed to emit CO_2 emissions, the amount of new installed capacities is not as high as in the decarbonization scenario. The ability of coal to produce energy throughout most of the year reduces the needed installed capacity, and therefore a lower diversification of the energy mix is obtained. Wind onshore remains as the number one technology for providing clean and cheap energy, while gas power plants are being installed to compensate for the variability. Due to the lower capital costs of gas power plants, and their lower CO_2 emissions, this technology is often selected to reduce the amount of installed renewable energy resources.

In this scenario, the performance of the countries and archetypes differ greatly, as the energy mix in Germany does not match the one the archetype due to the initial set of installed capacities of conventional energies. This leads to a different

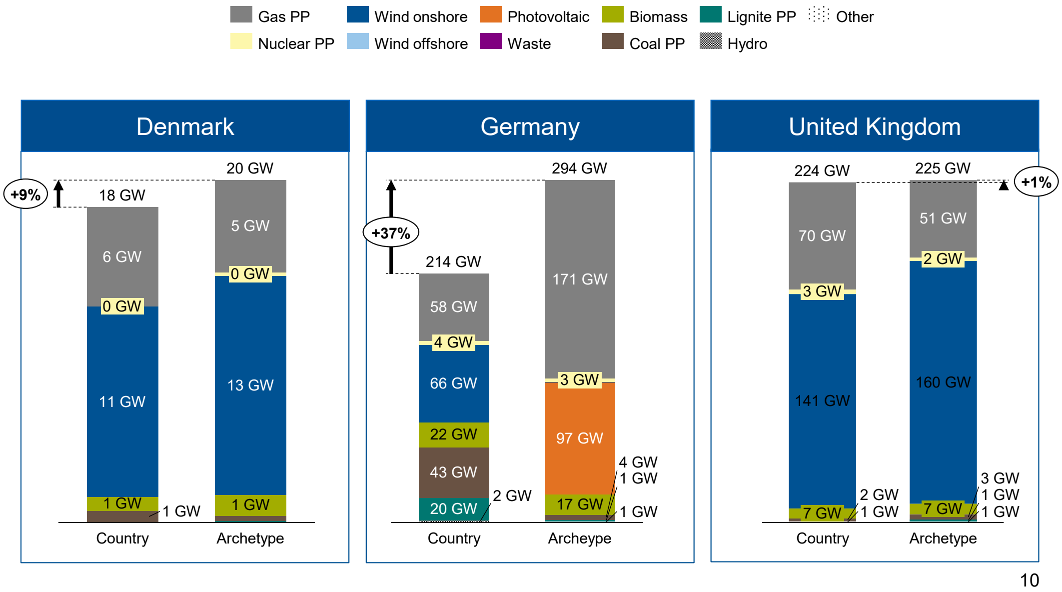


Figure 3.5: Installed Capacities in the Business as Usual Scenario for Cluster 13

behavior, in which Denmark's archetype estimations are much closer to the country model. Germany takes the last place, leaving United Kingdom in the second place. For this scenario, only the final energy mix is considered, and therefore the rankings were only made for this year. For 2015, the ranking corresponds to that shown in Figure 3.4.

3.2.2 Comparison Business as Usual and Decarbonization Scenario

When comparing both scenarios, it is observed that the installed capacities for Denmark are very close for the country model. The difference is mostly on the amount of installed capacity in gas and biomass power plants. The model, if allowed, chooses gas instead of biomass. For the archetype model, there is no PV capacity installed and the amount of wind onshore in the BAU is lower than in the decarbonization scenario. Gas replaces the PV installations and some of the wind onshore capacity. The difference in the outlook of the system is not that drastic due to the available FLH of wind onshore, which translates into lower installed capacity necessary.

In the case of the United Kingdom, the model decides to not install wind offshore nor PV and instead chooses gas. As with Denmark's archetype behavior, gas replaces some of the capacity installed in wind onshore and biomass. This can be explained due to the higher FLH with which the gas power plant can operate, which lowers the capacity needed to be installed. There is a limit in which it is more economical to install capacities with wind, but for instances where more flexibility is required, gas power plants turn out to be the best option.

For Germany, the situation is very different. The country model contains higher installed capacities for lignite, coal, and nuclear. Although these power plants are decommissioned throughout the years, the remaining capacity were high enough to make the model not go through a total system restructuring. In the archetype's case, the system decides to install PV as the first choice of renewables and gas power plants. In this case, an insight about the selection of technologies in the model is obtained. Since the limit for CO_2 emissions is much higher than in the decarbonization scenario, it appears that in some cases PV is cheaper to install than wind onshore when combined with a certain amount of gas. This means that in order to reduce the system's installed capacities and costs, these two technologies are a good combination. The choice of using wind onshore is most likely determined by the higher availability of this resources if a reduction in emissions is imposed, which doesn't allow too many installations of CO_2 emitting sources. For the decarbonization scenario this means that in order to reduce the amount of installed capacity, wind onshore is chosen instead of PV. Whereas in the BAU scenario, PV is chosen if allowed to be compensated by a less variable resource such as gas.

In general, the lower limitations of the CO_2 emissions allows a lower amount of installed capacity in the system. This, however, comes with the price of increasing CO_2 emissions and contributing to climate change. In the end, due to the consequences of climate change, the money that was saved by reducing the amount of installed capacity will probably have to be used in mitigating the damage caused by the environmental changes. Therefore, a quantification of the externalities in which the system might incur if allowed to emit great amounts of Greenhouse Gases (GHG) should be included in future models in order to obtain a more unified vision of the real costs of choosing a certain energy transition path.

It is also evident that the difference in total energy demand of the UK no longer means a huge difference in the necessary installed capacities. In the BAU scenario, the difference in installed capacities is only about 1%. This is a big difference compared to the 33% difference shown in Figure 3.2. Denmark experiences a similar reduction in the installed capacities, where the 23% difference experienced in the decarbonization scenario is reduced to around 8%. Unfortunately, for Germany the difference in installed capacities widen due to the presence of more conventional technologies with higher FLH.

As observed in the previous results, whenever PV is chosen, the system requires more capacity installation than with wind onshore. The conventional energies compared to renewable sources is also quite big, where 1GW capacity of conventionals provides much more energy than 1GW of renewables depending on the achievable FLH.

3.2.3 Effects of scaling in Archetype Results

As seen in the previous sub-section, the estimation of the annual energy consumption can make a significant difference when estimating the energy mix of the future. A deviation of just 8% meant for the UK an installation of almost 100 GW more of PV to cover for the extra demand.

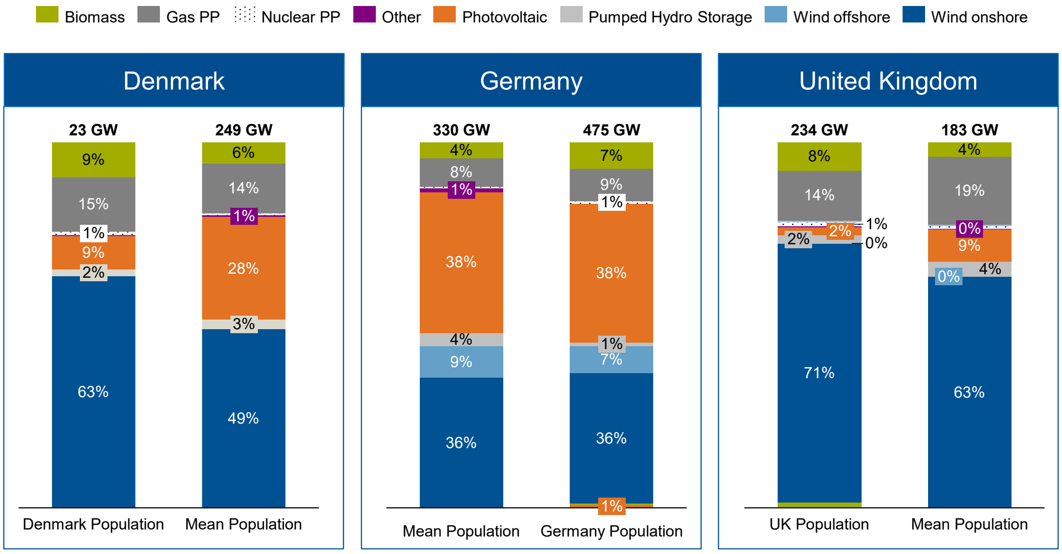
Since the population used as input for the model scaling determines the annual energy consumption, the total country area, and the coastline extension, it is worthwhile to evaluate the impact this can have when modeling a country with the archetype. An assessment was thus performed using the country's population and an arbitrary value for model scaling. For this analysis, the mean population of the three countries was selected as the arbitrary population. This has a two-fold purpose: first, assess the effect of population when scaling; second, observe whether one model scaled to an average value of the population was enough to observe the evolution of all countries within the archetype effectively.

For this experiment, two archetype models where built using the same base characteristics for the setup (i.e the same capacity shares, consumption per capita, area/coastline ratio, population density, and net imports share). This also includes the same time series for load, wind, and PV. The only varied input was the population used in scaling. An analysis of the archetype model using the three country time series of cluster 13 was carried out, leading to six different simulation results.

Using Figure 3.6 as reference, it is clear that the population used for Denmark was significantly different than its actual population, which is obvious by the higher demand requirements. This translated into a great amount of PV installation. Because of this reason, PV becomes one of the most important technologies in the final energy mix with 28% of the installed capacity in 2050, when in reality, the share is more around 9% if Denmark's real population is used. Due to the increase in the installed PV capacity, the share of wind onshore lowers, and the share of gas and biomass decrease, but not considerably. This confirms the assertion made when explaining the discrepancy observed with UK in the previous section.

The fact that the mean population used for scaling Germany and the UK didn't differ greatly from the actual population, the difference in the share of the installed technologies did not change dramatically. The chosen technologies were the same and the relative importance was maintained within the energy mix. For Germany, a lower population mean a lower share in the installed wind offshore, biomass, and gas power plants. The model also sees more importance placed in storage, as pumped hydro accounts for 4% of the installed capacity, possibly to compensate for the decrease in gas and biomass. United Kingdom's model lower population, in contrast, mean a lower installed capacity of wind onshore due to the lower area for wind expansion, meaning that the model recurs to PV to meet the demand, as well as gas power plants to compensate for the lower FLH that PV provides compared to wind.

Ultimately, the scaling method does not only affect the annual demand, but also lowers the limit for expansion in technologies that depend on physical constraints, such as territorial extension. The modeler must understand the consequences this has on the energy mix in order to determine the robustness of the results. With these results, it is possible to conclude that the modeling processes might not be reduced to one when using this approach, but rather it might be convenient to model the archetype in smaller batches based on the the population of the countries within.



***Mean Population**: Average of Denmark, Germany, and UK*

Figure 3.6: Population sensitivity analysis results

3.2.4 Effects of Time Series in Archetype results

From the results obtained in section 3.2.1, a difference between the archetype installed capacities was observed in spite of having used the same base model parameters. Although these parameters were the same,the population used for scaling and the time series for load, PV, and wind were different. Previously, an analysis of the effects of scaling was performed to observe the effect this parameter has on the chosen technologies for every country. To check the sensitivity against the other variable parameter, the used time series were also varied to observe the possible effects they have on the system model's output.

For this analysis, the archetype model used a constant population for scaling, meaning all the model parameters were scaled to the same values. The mean population was again used, as in the previous section. The results using the time series for Denmark, Germany, and the UK were analyzed. The installed capacities for 2050 are shown in figure 3.7.

The results vary considerably when using different time series for this cluster. Although the annual energy consumption and the expansion limitations were the same, different capacities were installed for the different time series. In the case of Germany, the installed capacity is much higher than observed in Denmark and the UK. This can be attributed to different factors, such as the full load hours of the demand and available resources, as well as the correlation between the time series. This can mean that Germany's peak demand requirements are much higher than the other countries, or that the renewable energy resources availability do not correlate to the demand requirements.

For every country, the full load hours with regards to the demand were calculated, as well as the number of instances where the normalized time series values were higher than 0.9. This provides an overview as to how much of the year the demand requires the system to provide energy at more than 90% full capacity. An overview of these values can be observed in table 3.1. After analyzing this information, it is determined that Germany's energy system demand is much higher than in the other countries, therefore it requires more capacity of renewables to be able to meet its demand. The technologies that are chosen first for all three systems are gas, wind onshore, and some of PV. The level of PV, however, increases as the capacity requirement does. When the PV limit is reached, or more capacity is needed outside of the range in which PV provides energy, wind offshore is installed to cover for the demand.

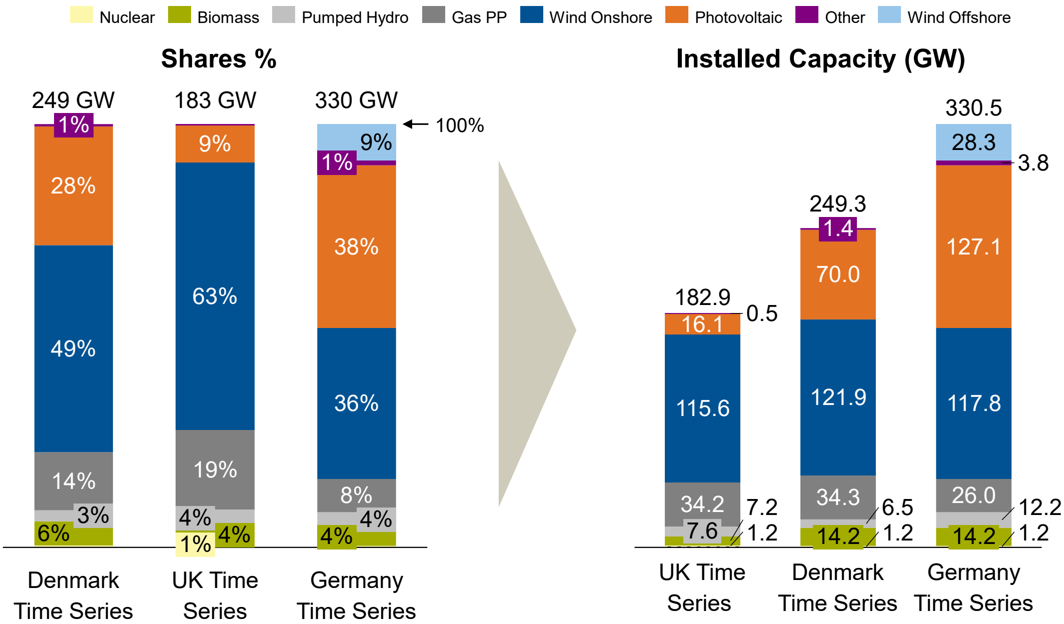


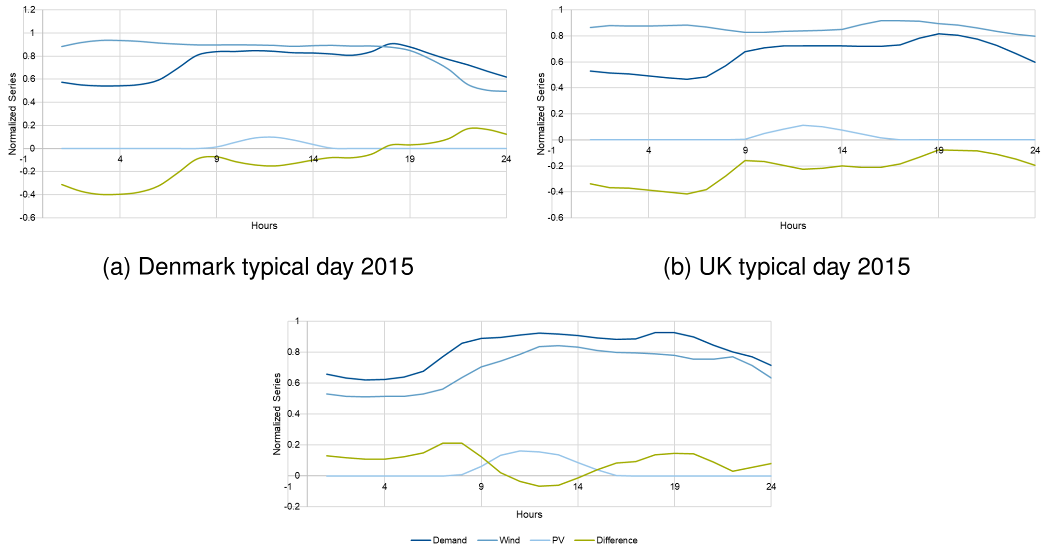
Figure 3.7: Time series sensitivity analysis results

Table 3.1: Analysis of the demand time series for countries in cluster 13

Country Series	Full Load Hours	Instances >0.9
Germany	6486.62	1088
Denmark	6006.54	331
UK	5262.16	82

A typical day for the three countries was also analyzed to observe the effect of the renewable energies availability in combination with the demand series. If all were scaled to the same energy values, UK would be able to meet the demand with the wind onshore and PV. As seen in Figure 3.8 (b), UK's difference line between the demand and the [Wind + PV] time series lies below the 0 axis, meaning that the demand can be met with these two technologies. For Denmark, the same behavior is observed for most of the day, with an exception during the last hours, where the demand is higher than the availability of both resources combined. This means a little more capacity is needed for Denmark to fill this gap. For Germany, most of the difference line lies above the 0 axis, meaning that more capacity is needed to fill the gap during the beginning and end of the day.

The importance of this analysis is that, when modeling the countries with the same time series, a sensitivity analysis must be carried out. A variation to the generalized time series must be applied in order to capture the effect of digressing from real life operation. Information about which technologies will start to be chosen under different cases is also obtained, providing with a more complete view as to how the system is likely to evolve under different factors. For example, if the demand FLH were to increase in the future, the installed capacity that will be chosen first to meet the demand in a cost effective fashion would be PV and wind offshore. Similar conclusions could be derived for other clusters and archetype models.



(a) Denmark typical day 2015

(b) UK typical day 2015

(c) Germany typical day 2015

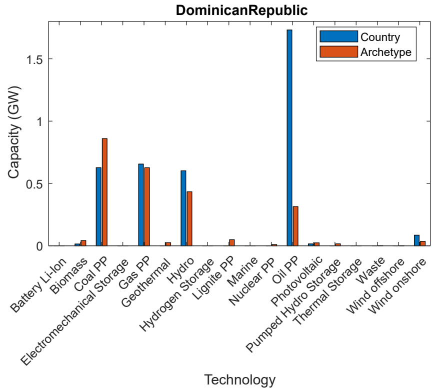
Figure 3.8: Typical day analysis for Germany, Denmark, and the United Kingdom

3.3 Comparison Country-Archetype Results

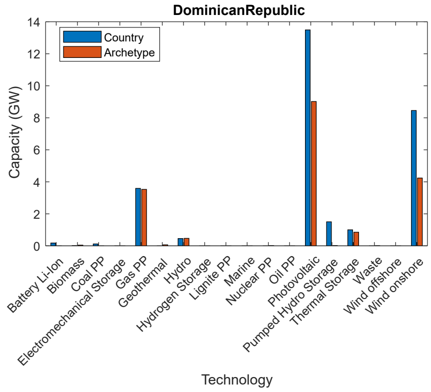
The model evolution for 20 more countries besides the already analyzed were also modeled. The most interesting results will be presented in this section, as well as the distinct technologies chosen per cluster (See Section 2.1.2 for information of the modeled archetypes).

Cluster 6: Warm, densely populated, and fossil dependent countries

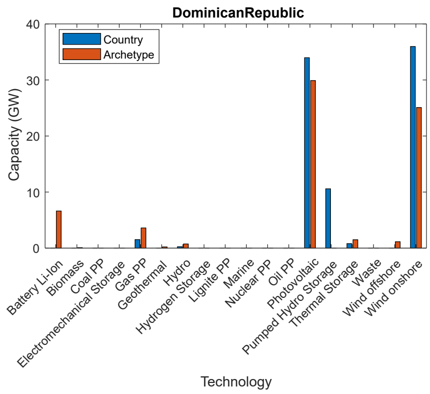
TCluster 6 is the largest of all the modeled clusters. It includes 11 countries in total and favors PV and wind onshore for the decarbonization of the energy system. For the compensation of the variability of renewable energy, the chosen technology in this cluster is pumped hydro. The results in this archetype start to differ when the total annual demand is over- or underestimated. If this is the case, the chosen base technologies are the same, and other technologies start being chosen to meet the extra demand. A ranking among the countries in this cluster was made to determine which country performed the best of all as a way of determining if this approach tends to benefit a country with specific characteristics. From the 11 countries, the Dominican Republic performed best. Its transition pathway with regards to installed capacities per technology can be observed in Figure 3.9. It is important to remember that the installed capacities were not the only parameter compared when ranking the archetypes and the countries within it. The correct estimation of the CO_2 emissions, as well as the annual energy output, CAPEX, and OPEX were also considered.



(a) Dominican Republic Installed Capacity 2015



(b) Dominican Republic Installed Capacity 2029



(c) Dominican Republic Installed Capacity 2050

Figure 3.9: Dominican Republic Decarbonization Pathway

In 2029 gas power plants start to get installed in order to start meeting peak and base demand for 2050. PV and wind onshore are built as well, but increase considerably the installed capacity for 2050. This cluster has a very high estimated future demand, which explains the amount of total installed capacity. It is expected that in the future, this countries will start the electrification process and have a very steep economic growth, leading to a much higher demand than the current one.

When modeling, the base model had to be modified for the the archetype. Based on the cluster center, the CO_2 emissions for 2015 were limited based on the value obtained for CO_2 emissions per economic intensity. For the country model this was acceptable, however, the archetype model required some extra modifications. Instead of the calculated CO_2 emissions for 2015, an extra allowance had to be made in order for the model to solve to optimality. This can be attributed to the archetype's under estimation of the emissions intensity of the cluster. Since this established the limits for 2015, from which the decarbonization goal was set, it

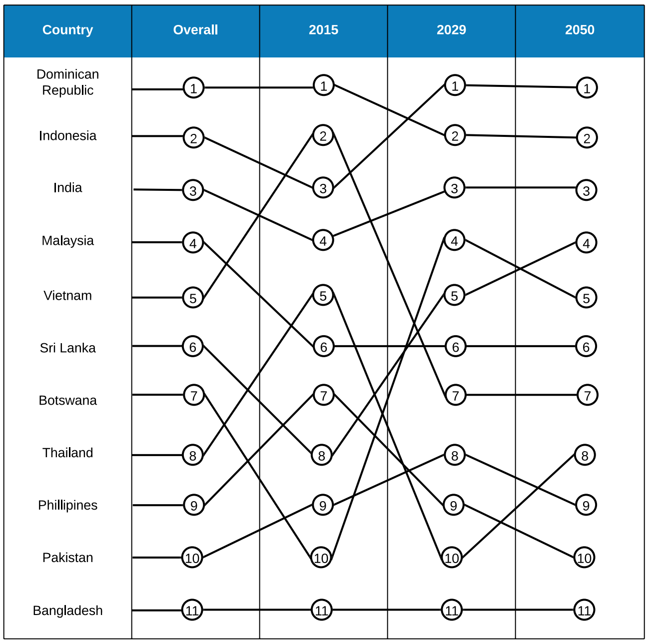


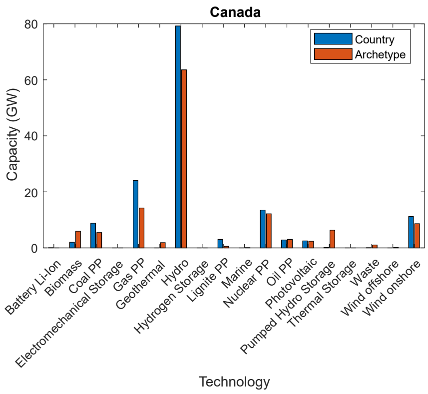
Figure 3.10: Performance Ranking of Archetype 6

is probable that the decarbonization for 2050 was much larger than with the other clusters. All the countries were ranked per year, and the results can be seen in Figure 3.10.

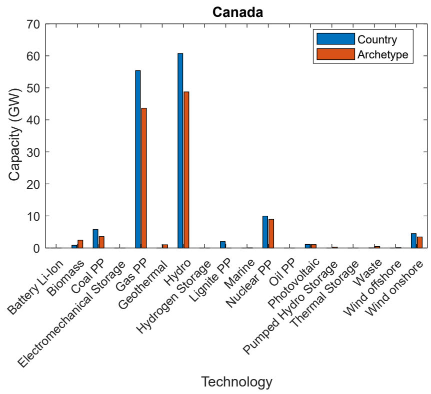
One last aspect has to be noted. Although they were all modeled with the same load time series, the behavior in the future was not exactly the same. They all showed a similar trend for all the technologies. However, at this stage and given all the different variables that can affect the outcome, no conclusive assertion can be made with regards to the consequences of using the same time series in the model.

Cluster 14: Hydro dependent countries

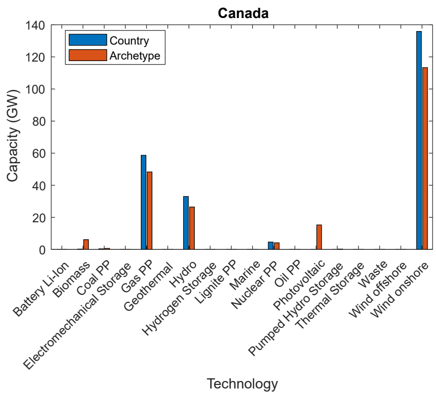
This cluster is the second largest, containing 7 countries. This archetype is characterized as having most of its energy in 2015 provided by hydro power plants. This power plants can be used to cover base load, however, they also depend on the available precipitation the country gets per year. The marginal costs for energy production using hydro are not as high as using fossil fuel based generation facilities. Therefore, it was interesting to observe that the optimizer did not benefit this technology to provide for the future energy demand. However, due to the long lifetime attributed to this technology, the remaining hydro capacity was enough to compensate for the variability of renewable energies. This reduced the amount of gas power plants installed in the countries, as well as the need for large storage necessities. In 2050, then, the countries within this archetype are characterized as having most of its energy provided by hydropower, wind onshore, and gas. Photovoltaics are used to a lower extent, and is only chosen when the estimated load becomes larger so that the limit for the other technologies is reached, or when the CO_2 limits for the fossil fuel technologies has been capped out. The country with the best overall performance was Canada. Although in 2050 it didn't occupy the first place in this regard, its errors in the other years were lower and the ones observed for 2050 were not significant to bump it down from the first place in the overall ranking. Its transition pathway can be observed in Figure 3.11.



(a) Canada Installed Capacity 2015



(b) Canada Installed Capacity 2029



(c) Canada Installed Capacity 2050

Figure 3.11: Canada Decarbonization Pathway

For this cluster, it is interesting to see that although in 2015, Finland was the best country regarding the country-archetype performance, for 2050 it was one with the largest errors. This indicates that, although the country might be very close to the archetype's values during the initial year, there are parameters that are more important when determining the future development. In Finland's case, it had to do with an over estimation of the archetype's demand, in which the gas power plant was one of the chosen technologies, whereas in the country model, all of the energy was supplied by renewable resources or carbon neutral ones, such as nuclear. As with cluster 6, the ranking of the countries within this cluster is presented in Figure 3.12. The effect of installing gas power plants not only increased the error in this parameter. Due to the need to buy natural gas, the OPEX was miscalculated. Since the country model does not have high CO_2 emissions, using gas power plants also increased the error for this parameter. It is therefore important to consider that the analyzed parameters are also linked to each other, and during the evaluation, this can worsen the performance evaluation.

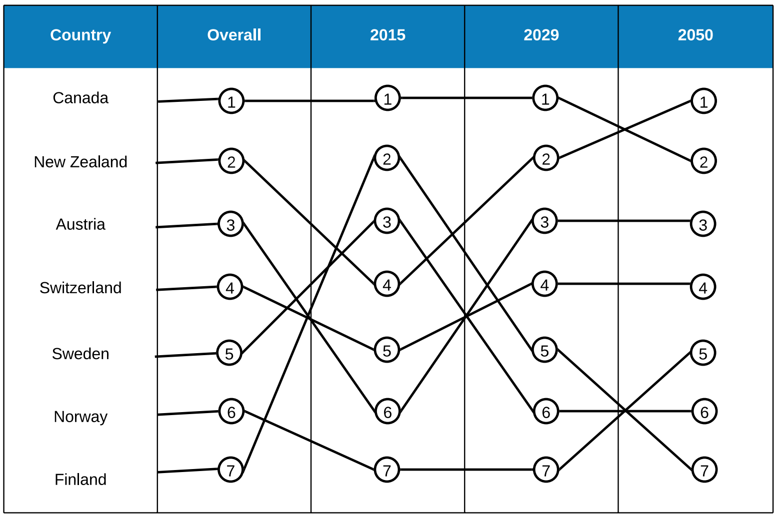


Figure 3.12: Performance Ranking of Cluster 14

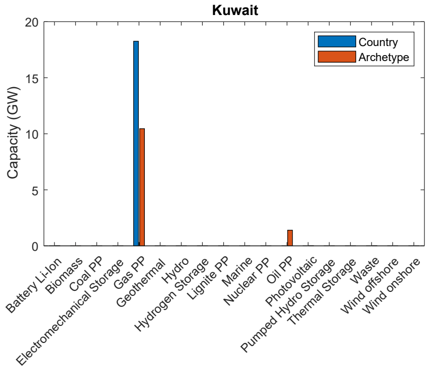
Cluster 15: Oil and gas dependent countries

Cluster 15 includes countries that rely heavily on fossil fuels, and have little to none renewable energies as part of the current energy system. This cluster has a very high potential for PV and therefore it was expected that the model would choose this technology based on the FLH for this resource. In 2050, this technology occupied the highest share in the energy mix. The cluster showed similar behavior and chooses PV as the number one runner, followed by wind onshore, gas power plants, and wind offshore to complement the energy mix. The behavior of the countries within this cluster was more constant with regards to capacities, and all of the countries tend to choose the same technologies, confirming in a way that countries that share similar characteristics, are likely to develop their energy systems towards the same direction if a cost optimization is performed.

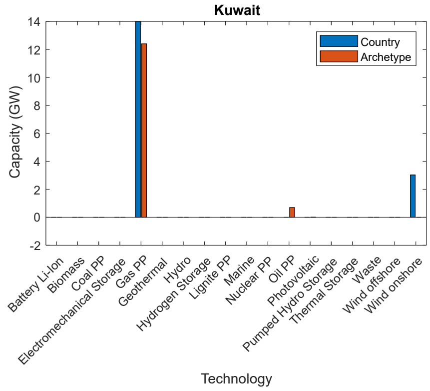
Due to the low current share of renewables, this cluster was allowed to expand 4 times faster than the other countries. This means that the process of replacing most of their current fossil fuel power plants towards a 80% renewable energy fleet, needed more installations per year than other countries, such as Denmark, for example. This had to be considered, otherwise the model was not able to find a solution in order to meet the estimated demand for 2050.

The country that performed best for this cluster was Kuwait, and its results can be observed in Figure 3.13. It is interesting to see that unlike the other clusters, this cluster chose two different storage resources,thermal storage and lithium ion batteries, as means for compensating for the variability of renewable energies. Since all countries within the archetype choose these storage technologies , it can be concluded that possible markets for them might develop, and manufactures of these products can benefit from this type of knowledge - showcasing the utility of the archetype concept.

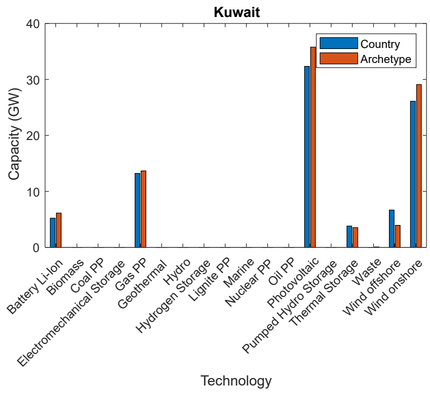
The ranking of the countries within this archetype show an interesting behavior. Although the energy system estimation for Kuwait was not ranked first for 2015 and 2029, it was number one in 2050. The errors obtained for 2050 were enough to compensate for the errors in previous years, rendering this country as the one



(a) Kuwait Installed Capacity 2015



(b) Kuwait Installed Capacity 2029



(c) Kuwait Installed Capacity 2050

Figure 3.13: Kuwait Decarbonization Pathway

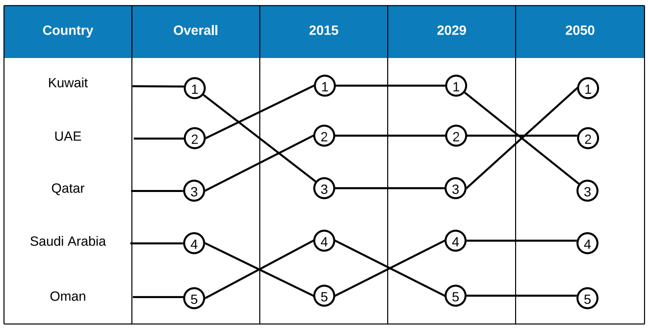


Figure 3.14: Performance Ranking for Cluster 15

with best performance combined. The overall ranking for all years can be found in Figure 3.14. Two countries always remained in the last positions, Oman and Saudi Arabia. The larger errors for this countries are attributed to the overestimation of the demand in the archetype model. Due to this over estimation, technologies not chosen by the country model appear in the archetype results. To get a better estimation for these countries using the archetype, it might be convenient to scale it with a lower population.

3.4 Comparison Archetype - Archetype Results

Finally, the performance between the archetypes was compared with the same parameters used when calculating the ranking between the countries. In this case, the average of the errors for every parameter was calculated and assigned to the error of the corresponding parameter in the archetype. As seen 3.15, the best ranked archetype was Archetype 13, which included Germany, Denmark, and UK. Based on the ranking, it is concluded that for future years, the performance is related to the cluster's size. The smallest archetype performed the best, whereas the largest one performed the worst among all. When the cluster is larger, one or more countries might present higher errors, and with that, the overall error for the archetype increases. It is more likely for this behavior to happen when the archetypes are larger, therefore smaller sized clusters are more likely to exhibit lower errors overall.

For 2015, cluster 15 was ranked first. This was because for this year, there were only one or two main technologies (gas and oil) installed in the countries. Due to this reason, there was little leeway for the cost optimizer to choose other technologies. This leads to lower errors when estimating the present energy system's operation.

Another trend observed within all archetypes was that the net flows obtained with PROMETHEE became smaller for the countries in 2029. This means that during this year, the difference between the errors of the countries within the archetype were not as different. A possible explanation can be that during this year, a mixture of real information and assumptions was the ideal combination for there to be lower differences among the country errors. This does not mean that this year was the best or the one with the lowest errors. The best years for every archetype differed, and presented no real insight as to which year is likely to be the best for all.

As previously discussed, cluster 15 and 6 were modeled using the load time series of only one country within the archetype. Observing how they occupy different rankings, and that the oil and gas cluster (cluster 15) ranked pretty high, this parameter didn't affect the behavior with regards to errors between the country and the archetype.

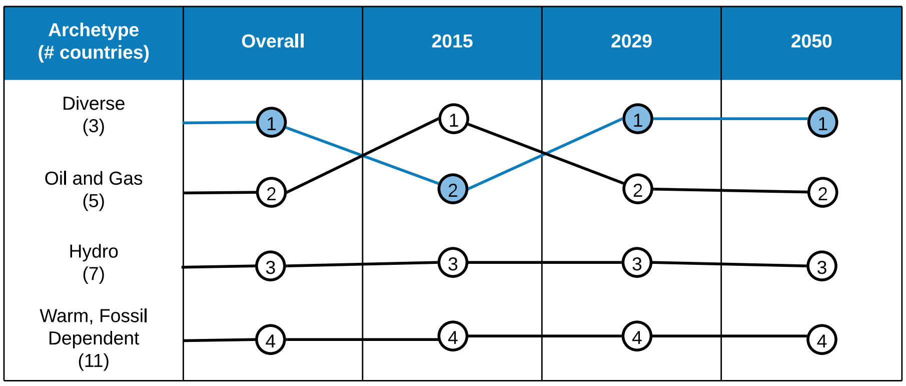


Figure 3.15: Performance Ranking for all Archetypes

Chapter 4

Discussion

The obtained results are discussed in this section. The consequences of the assumptions used during modeling, as well as the validity of the archetype approach and its limitations are analyzed.

4.1 Assumption consequences

The assumptions listed in Section 2.1.10 are simplifications used when modeling. As mentioned before, this assumptions were made due to several factors. The first being the spatial dimension of this approach. It is a first attempt to summarize an energy system's behavior for several countries around the world as realistically as possible. The second factor was the information that could be obtained from the clustering results. Since the archetype does not represent a specific country, only general information could be used as to encompass the behavior of the countries that belonged to it. Also, since the model addresses the lack of detailed information, the goal was to obtain a model that could correctly represent a country based on freely available information from reliable sources. Because of this reason, the precision of modeling is greatly reduced, however, a general overview of the energy system and its development can be obtained.

Some of the assumption consequences are listed below, so that the reader understands the effect these might have in the modeling of energy systems.

– The use of the minimum full load hours, although having improved the results, do not capture the entire complexity of the coupling with the heating sector or the real behavior of the electricity sector. In real life, the system doesn't operate in a cost-optimized fashion. This can be observed in the data validation, where production from the oil power plants existed even though the costs are much higher than other technologies.

– When modeling a country, power plants are either divided in age categories or modeled individually because the age of the installed power plants and their possible decommissioning year is known. In the current model, only information about the total installed capacity is obtained, with no insight as to how many power plants are installed to add up to that capacity, or information as to when they were built. Because of the assumption used in this work, the remaining capacity in future years might be higher or lower than estimated.

– Another assumption that might critically impact the behavior of the energy system is the one regarding net imports. For example, if a country in 2015 is a great exporter, it is assumed that in the future, it remains the same. This assumption translates into a higher generation requirement for the country in order to meet future demand. It might be that in reality, a country becomes an importer of electricity because it might be cheaper or because their available natural resources and expansion rate is not enough to meet the demand. As observed from the results of the previous section, the amount of demand assigned to a country determines greatly the selection of the technologies, which makes this assumption of great consequence to the model results.

– The expansion limits are normally determined by Geographic Information Systems (GIS), and country specific information regarding available exploitable resources is used. When using general information such as area and coastline extension, the true availability for renewable energy resource installations is not considered. This might lead to an overestimation of the real available sites for wind or PV installations.

– The use of a single set of costs for all technologies does not reflect the correct prices in every region. For example, cluster 15 has lower gas and oil prices than other countries because of their location and available reserves. For other technologies, the prices depend on market penetration [56]. This means that for countries that already have an established market for PV, for instance, lower prices for the installation of this technologies can be achieved. Using only one set of prices for all countries, disregarding market penetration or region and country specific resources, might lead to a wrong energy mix. The optimization performed by ESDP is cost based, meaning that the chosen technologies will be the cheapest ones when available. If the prices are wrongly set, then the final energy mix is also compromised.

– The electrification of the transport sector is not considered in this model. Due to the different consequences this might have, such as a change on fossil fuel prices due to the lower demand or the higher need of electricity for charging electric vehicles, it might make a great difference in the future energy mix. The coupling with the transportation sector is also required to obtain a fuller view of the real development for the energy systems.

4.2 Archetype Limitations

Given the consequences previously explained, the archetype model has many limitations. However, the goals established for the archetype approach were also limited. Recapitulating, the idea of modeling with an archetype does not intend to replace a complete and detailed model of a country, rather to provide an overview of the possible evolution of a system, to serve as a common data basis for system modeling, and to simplify the modeling of global challenges. Since the archetype attempts to model different countries at once, the individuality of each country is not kept. The model strips these individualities and uses the common and most important information of the countries to develop an analysis of the possible evolution of the system. A fuller picture can therefore be obtained by adding archetype or country specific information to complete the model.

It is very likely that due to the attempts to have an integrated regional electricity market, and to the transformation towards renewable energy, that the need for new transmission capacities will be present. This means that the cost-optimization of extensions is also needed to obtain the full costs towards the transition to a sustainable energy system.

For this first approach, only 62 data categories were available to create a working model. Since not all were relevant when modeling the system, not all were used (in total, 29 data categories). Although for some countries more data is available, the country model was also limited to these categories in order for the country and the archetype model to be comparable. The least amount of external data was used, and limited to the time series and population information. This way, just the fundamental principle of the archetype was tested since only the data categories used for clustering were used to create the energy model.

As seen by the sensitivity analysis, the model is sensitive to the estimation of the demand (especially overestimation) and therefore, with the estimation of the future energy mix. Consequently, sensitivity analyses must be performed in order to obtain a fuller understanding of the evolution of the system. The development of load time series for countries within the archetype that don't have any information available in this regard would also be crucial when determining the amount of capacity needed to cover the demand.

The simplification of the used technologies is another identified limitation of the system. When the results indicate that PV becomes an important technology, the type of PV installation is not specified or determined. Also, when installing gas power plants, it is not clear which type of technology is needed (e.g Gas SC, Gas CC, or Gas SPP). This simplification then, limits the model to provide with an orientation as to what type of technology can be used but not specifically which within the same category. A solution to this problem could be to analyze the time series in characteristic hours, as well as the capacity factors of the technologies. This could help determine for which purpose these power plants were installed and infer which type of technology was chosen for that use.

4.3 Validity of Archetype Modeling

Having observed the evolution of the countries within the archetype, similar conclusions for all the countries could be made. In general, the same technologies were chosen for 2050 in most of the countries in every archetype. For some, there were exceptions because of the demand mismatch. It was also identified that the approach is valid for both, mid-term and long-term planning, as the rankings between the countries do not differ as much from 2029 to 2050. This proves that the systems do not tend to change as much and tend to keep a status-quo.

As a first estimation for system planning, it was proved that under the same assumptions, the country and archetype model could lead to similar results. There were countries with errors in a few parameters that were higher than ideal. However, the weaknesses have been identified, and consequently, the decision-maker can act accordingly after performing the necessary analyses to address the archetype's problems.

This was a successful first attempt in modeling energy systems using this approach, in which areas of opportunities were identified in order to improve the model. An insight into the implication of several parameters that affect the energy modeling process is also obtained, which can prove valuable when determining transition pathways and for the correct analysis of the implication of several policies.

Chapter 5

Conclusion and Outlook

Recapitulating on the goals set up for this thesis, there were two main pillars that were important for the evaluation of the hypothesis. First, the development of the model using a set of rules for the use in all the clustered countries was necessary. Because the setup of the specific models could be time intensive, and given that the ease of modeling was one of the benefits of using this approach, an automation of the process was performed. This automation used the set of rules established during the scenario definition, as well as allowed for the change of certain parameters such as the modeled years, the time steps in which the optimization was carried out, and the decarbonization goal for each model.

The second main goal was the development of the comparison and evaluation methodology used to evaluate the performance of the different countries. Due to the same reason as before, it was important that the procedure was automated in order to assess all countries in a time efficient manner. The adaptation of the ranking methodology for the purposes used on this thesis were novel, and its implementation for this purpose was flexible and also applicable even though the number of criteria or the number of countries per archetype change.

When analyzing the results, the system is imperfect, but the idea that similar countries might develop in a similar fashion was demonstrated. Most countries, under the same set of assumptions tend to choose the same technologies. Also, every cluster presented a special technology in its energy mix, and PV and Wind onshore tend to always be chosen as the key technologies for the supply of the energy demand. Assuming no new technologies will appear as competitors for these two, it is safe to assume that they will compose most of the global energy system. After the presented sensitivity analyses, it is possible to conclude that it might be necessary to model countries within an archetype under different scaling. This is due to the effect it can have on the selected technologies when the demand is not correctly estimated. This would require partitioning the archetype with regards to the consumption per capita or population. An alternative to this process would be to model the archetype under different scaling to determine the base technologies that are robust to population changes. When varying the scaling, an analysis of demand sensitivity is performed which allows to determine which base technologies will be chosen regardless of the change in demand.

This thesis used a set of rules and assumptions with the intent that they would be easily applied to all the analyzed countries. Although as a first effort this proved useful, it could be beneficial to compare the annual limitations based on a technical potential analysis with GIS. This will allow to determine whether the generalized assumptions had a basis on reality. If the results prove to differ greatly, the potential information could be integrated into the clustering criteria. Moreover, the geographic information available for the use in the model setup is not enough for the limitation of certain technologies. For example, there was no limitation for pumped hydro other than the requirement for there to be evidence that there was hydro potential. This might not be enough, because the installation of pumped hydro depends on the available altitudes within a country, as well as on the fact that the hydro potential might have already been used up.

It could also be appreciated that in most cases, a technology would only be chosen when a technology has reached its limit for installations. This gives an insight to the importance the limitation criteria have when modeling these countries. It is therefore important to consider real values when setting the model up, instead of using general information when deriving a set of rules. Additionally, the same base assumptions were applied to all the analyzed countries for the purpose of doing a first comparison and evaluation of whether the idea would work. However, this can also be modified so that the prices and costs mirror the situation of the countries within an archetype. This means that a different set of costs would need to be defined for the technologies and fuels for an archetype. This can reflect, for example, the cheap prices obtained for PV when there is already market presence and penetration. Or, in the case of the oil and gas dependent countries, the fuel prices should reflect the low prices of fossil fuels that can be found in the region due to the vast availability of these resources in this region.

The results presented in this thesis, with regards to how the energy mix might look in the future is only ideal. It is important to consider that, the integration of renewable energies into the energy mix depends on many factors. This includes the policies implemented in the countries for the installation and interconnection of renewable sources into the grid, social acceptance when installing wind turbines, the available resources and investment potential for network reinforcement measures and for the replacement of the conventional power plants. The results here presented do not necessarily reflect these behaviors, and only focuses on determining a path of minimal cost to reach the final decarbonization goal. The usefulness of this thesis, however, is in providing a first insight into which technologies are best from a cost perspective, as well as help policy makers and investors make decisions in order to reach their decarbonization goals. Although of a simplified nature, it is possible to obtain useful conclusions about the most probable path of development with regards to the energy transition.

List of Abbreviations

BAU Business as Usual. 26, 45

CAPEX Capital Expenditures. 12, 79

CHP Combined Heat and Power. 14, 25

COP21 21st Conference of Parties. 1

CSP Concentrated Solar Power. 14

DER Distributed Energy Resources. 4

EIA Energy Information Administration. 2, 18

ENTSO European Network of Transmission System Operators. 18

ERV Estimating Ranking Vector. 76, 77

ESDP Energy System Development Plan. ix, 11, 13, 25, 62

ETRI Energy Technology Reference Indicator. 15

FLH Full Load Hours. xi, 19, 23, 25, 26, 28, 31, 43, 48–50, 53, 57

GAE Geometric Average Error. 75, 76

Gas CC Gas Combined Cycle Power Plants. 14, 63

Gas SC Gas Single Cycle Power Plants. 14, 63

Gas SPP Gas Standard Power Plants. 14, 63

GDP Gross Domestic Product. 21, 23, 24, 27, 28

GHG Greenhouse Gases. 49

GIS Geographic Information Systems. 62, 66

HAE Harmonic Average Error. 75, 76

IEA International Energy Agency. 2, 3

LP Linear Programming. 12

MCDM Multiple-Criteria Decision Making. 32

MIP Mixed Integer Programming. 12

O&M Operation and Maintenance. 11, 16

Oil SC Oil Single Cycle Power Plants. 14

Oil SPP Oil Standard Power Plants. 14

OPEX Operating Expenditures. 12, 56, 79

PCM Pairwise Comparison Matrix. 76, 77

PHES Pumped Hydro Energy Storage. 15

PROMETHEE Preference Ranking Organization Method for Enrichment Evaluations. 32–36, 59, 76, 79

PV Photovoltaic. i, 10, 14, 18, 19, 25, 31, 43, 45, 46, 49–54, 57, 62, 63

RMSE Root Mean Square Error. 75

SSA Simple Score Addition. 76, 77

Techmap Technology Map. 11, 12, 15

WACC Weighted Average Cost of Capital. 24

WB World Bank. 2

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[59] E J G Pitman Hobart. “The “closest” estimates of statistical parameters”. In: *Communications in Statistics - Theory and Methods* 20.11 (1991), pp. 3423–3437. DOI: 10.1080/03610929108830714. URL: https://doi.org/10.1080/03610929108830714 (cit. on p. 76).

Appendix A

Additional Performance Metrics and Ranking Methodologies

A.1 Performance Metrics

Due to the different benefits the use of several performance metrics can provide, some of them were considered and could be applied for the evaluation of the archetype's performance.

In [47], a summary of the different performance metrics is provided, classifying them as either pessimistic, optimistic, or balanced. In total, this section describes 3 additional performance metrics that could be used in addition to the error defined in 2.3.1: the Root Mean Square Error (RMSE), the Geometric Average Error (GAE), and the Harmonic Average Error (HAE).

The RMSE is one of the most popular used error metrics. Its main feature is its approximation to the standard error, which is related to the standard deviation. Because of this reason, the RMSE is very useful for probabilistic analysis. It can be defined by equation A.1, where $\hat{x}$ is the estimation, x the reference value, and $\tilde{x} = x - \hat{x}$ [47]:

$$\mathrm{RMSE}(\hat{x}) = \left(\frac{1}{M} \sum_{i=1}^{M} \|\tilde{x}_i\|^2 \right)^{1/2} \tag{A.1}$$

Its main advantages are its popularity and its strong tie to the standard deviation. Its disadvantages are its unclear physical interpretation and the dominance of large errors.

The HAE is one of the metrics that concentrate on the estimation's good behavior, therefore, it can be classified as an optimistic metric. It focuses on how good the performance of the estimator is, and is suitable for averaging rates. It is defined by:

$$\begin{aligned} \mathrm{HAE}(\hat{x}) &= \left(\frac{1}{M} \sum_{i=1}^{M} \|\tilde{x}_i\|^{-1} \right)^{-1} \\ &= \frac{M}{1/\|\tilde{x}_1\| + \cdots + 1/\|\tilde{x}_M\|} \end{aligned} \tag{A.2}$$

Being robust with regards to large errors is one of the biggest advantages of this metric, however, it has an unclear physical interpretation, it is dominated by small errors, and lacks popularity. Its usefulness can be found when averaging rates and when measuring and comparing good performance [47].

The GAE can be considered as a balanced measure for performance because it is less affected by extreme values. It is based on the geometric average and can be defined by:

$$\ln[\mathrm{GAE}(\hat{x})] = \frac{1}{M}\sum_{i=1}^{M} \ln \|\tilde{x}_i\| \tag{A.3}$$

As with the HAE, it is useful for the averaging of ratios and lacks popularity. Its main advantage is its robustness against extreme errors and has nice properties.

A.2 The Estimating Ranking Vector and the Simple Score Addition Methods

For ranking projects or estimators, different methods exist in the area of operations research and in control applications. The PROMETHEE methodology has been mainly employed in this thesis, however, the validation of the information obtained with this method was corroborated with the use of the Estimating Ranking Vector (ERV) and the Simple Score Addition (SSA). These methods are described in [57] and further developed in [58].

ERV

The ERV is a solution provided by [58] to solve the intransitivity problem that can occur when using the method developed in [59] to rank estimators based on performance. The ERV uses the information obtained from pairwise comparison. In order to get over the intransitivity problem, [58] proposes the use of a C-matrix which contains all the information regarding the comparison or competition of one estimator against another. To build this matrix, the following criteria is used:

$$p(1,2;x) = \begin{cases} 1 & \text{if } \hat{x}_1 > \hat{x}_2 \\ 0.5 & \text{if } \hat{x}_1 = \hat{x}_2 \\ 0 & \text{if } \hat{x}_1 < \hat{x}_2 \end{cases} \tag{A.4}$$

Here, $p(1,2;x)$ denotes the measure of difference between estimator 1 against 2 compared to x. When calculating this value, the following rule must hold:

$$P(1,2;x) + P(2,1;x) = 1 \tag{A.5}$$

Once the preference values are gathered for all the estimators, the Pairwise Comparison Matrix (PCM) is built in the following manner:

$$X_{\mathrm{PMC}} \triangleq \begin{bmatrix} P(1,1;x) & \cdots & P(1,N;x) \\ \vdots & \ddots & \vdots \\ P(N,1;x) & \cdots & P(N,N;x) \end{bmatrix} \tag{A.6}$$

After the matrix has been formed, the ERV can be obtained by calculating its eigenvectors and selecting the one with all positive real values. The numbers obtained in the vector provide the score for every estimator. The one with the highest score corresponds to the one with the best performance.

SSA

The method of ranking through SSA can be expressed in terms of the PCM matrix as calculated in Section A.2. Once the PCM matrix is obtained, the following equation can be used to calculate the score for all the estimators [58]:

$$\mathrm{SSV1} = \frac{X_{\mathrm{PMC}}[1,\ldots,1]'}{\|X_{\mathrm{PMC}}[1,\ldots,1]'\|} \tag{A.7}$$

The SSA addition presents, however, a problem. This method treats all the estimators the same at the beginning, without considering prior goodness. Therefore, the method can be extended and performed several times in order to obtain a more robust vector. The higher the number of k, the better the estimation of the score assigned to the estimators [58].

$$\mathrm{SSVk} = \frac{X^k_{\mathrm{PMC}}[1,\ldots,1]'}{\left\|X^k_{\mathrm{PMC}}[1,\ldots,1]'\right\|} \tag{A.8}$$

A.3 List of Countries and Clusters

Table A.1: Countries and Clusters (a)

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
Benin	Ethiopia	Afghanistan	Albania	Belize	Bangladesh	China
Burkina Faso	Kenya	Angola	Georgia	El Salvador	Botswana	Kazakhstan
Chad	Malawi	Cambodia	Kyrgyzstan	Fiji	Dominican Republic	Moldova
Comoros	Mozambique	Cameroon	Laos	Guatemala	India	Mongolia
Gambia, The	Namibia	Central African Republic	Paraguay	Honduras	Indonesia	South Africa
Liberia	Uganda	Congo (Brazzaville)	Tajikistan	Mauritius	Malaysia	Ukraine
Niger	Zambia	Cote dIvoire (IvoryCoast)		Nicaragua	Pakistan	Uzbekistan
Sao Tome and Principe		Ghana		Samoa	Philippines	
Senegal		Guinea			Sri Lanka	
Togo		Mali			Thailand	
Vanuatu		Nigeria			Vietnam	
		Papua New Guinea				
		Tanzania				
		Zimbabwe				

Table A.2: Countries and Clusters (b)

Cluster 8	Cluster 9	Cluster 10	Cluster 11	Cluster 12	Cluster 13	Cluster 14	Cluster 15
Brazil	Algeria	Bahamas, The	Armenia	Australia	Denmark	Austria	Kuwait
Colombia	Argentina	Cape Verde	Belarus	Belgium	Germany	Canada	Oman
Costa Rica	Azerbaijan	Guyana	Bosnia and Herzegovina	Chile	United Kingdom	Finland	Qatar
Ecuador	Bolivia	Jamaica	Bulgaria	France		New Zealand	Saudi Arabia
Gabon	Cyprus	Malta	Croatia	Greece		Norway	United Arab Emirates
Panama	Egypt	Saint Kitts and Nevis	Czech Republic	Ireland		Sweden	
Peru	Iran	Seychelles	Estonia	Italy		Switzerland	
Suriname	Iraq	Tonga	Hungary	Japan			
	Israel		Latvia	Korea, South			
	Jordan		Lithuania	Luxembourg			
	Lebanon		Poland	Netherlands			
	Mexico		Romania	Portugal			
	Morocco		Russia	Spain			
	Tunisia		Slovakia	United States			
	Turkey		Slovenia	Uruguay			

Appendix B

Results for 2050

B.1 Installed Capacities

In this section, the installed capacities in 2050 for all the countries are shown. The descriptive statistics, the PROMETHEE rankings, the CO_2 emissions, the OPEX, and the CAPEX are included in the electronic annex.

Cluster 13

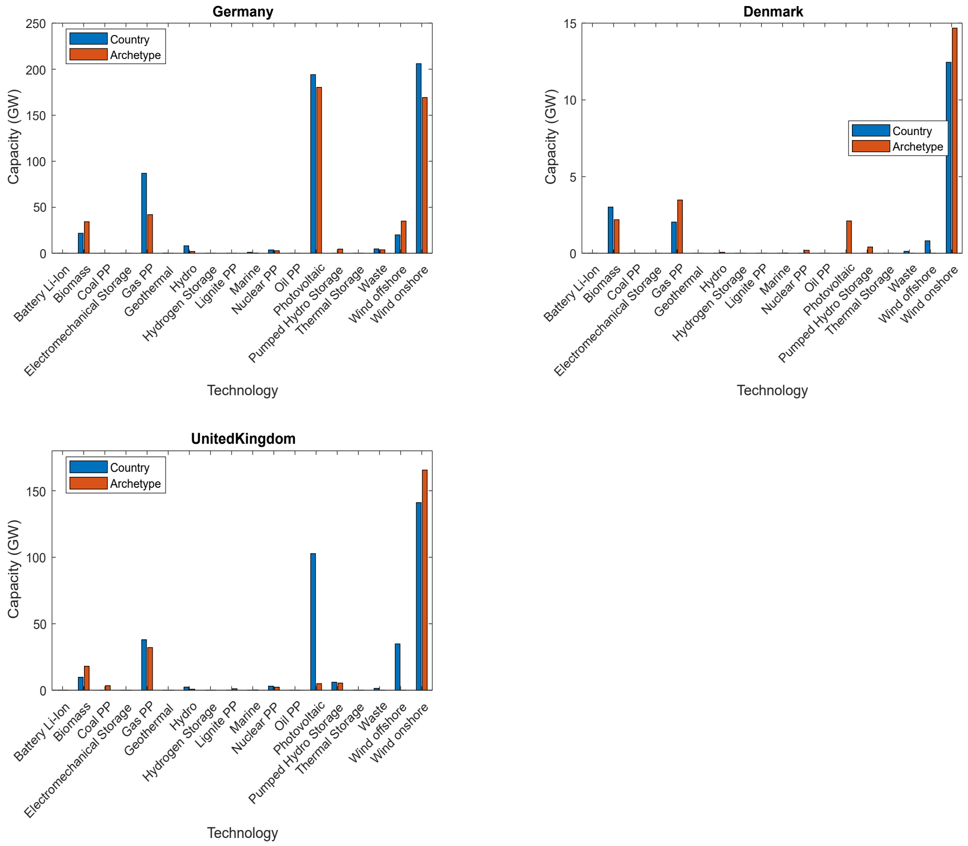
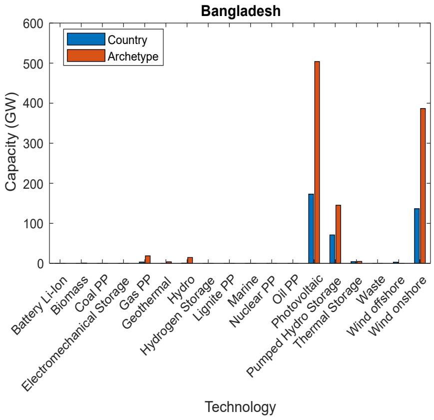
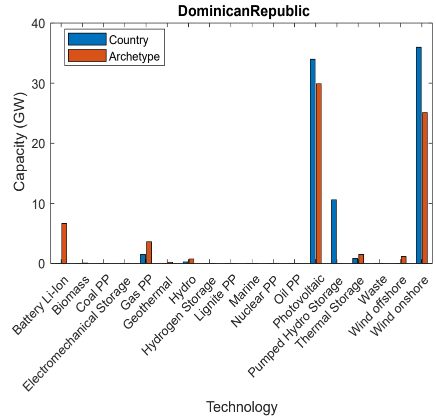


Figure B.1: Installed capacities for cluster 13

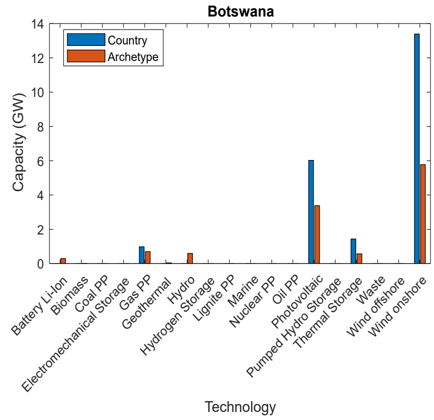
Cluster 6



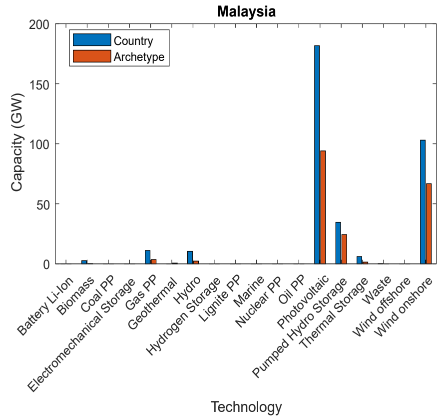
Bangladesh
Country
Archetype
Capacity (GW)
Technology
Battery Li-Ion
Biomass
Coal PP
Electromechanical Storage
Gas PP
Geothermal
Hydro
Hydrogen Storage
Lignite PP
Marine
Nuclear PP
Oil PP
Photovoltaic
Pumped Hydro Storage
Thermal Storage
Waste
Wind offshore
Wind onshore



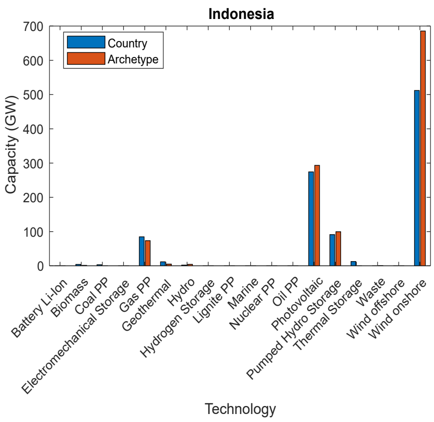
DominicanRepublic
Country
Archetype
Capacity (GW)
Technology



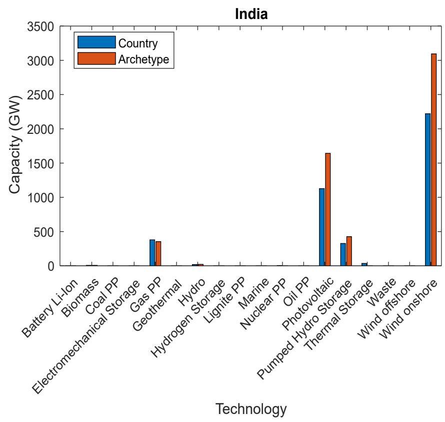
Botswana
Country
Archetype
Capacity (GW)
Technology



Malaysia
Country
Archetype
Capacity (GW)
Technology



Indonesia
Country
Archetype
Capacity (GW)
Technology



India
Country
Archetype
Capacity (GW)
Technology

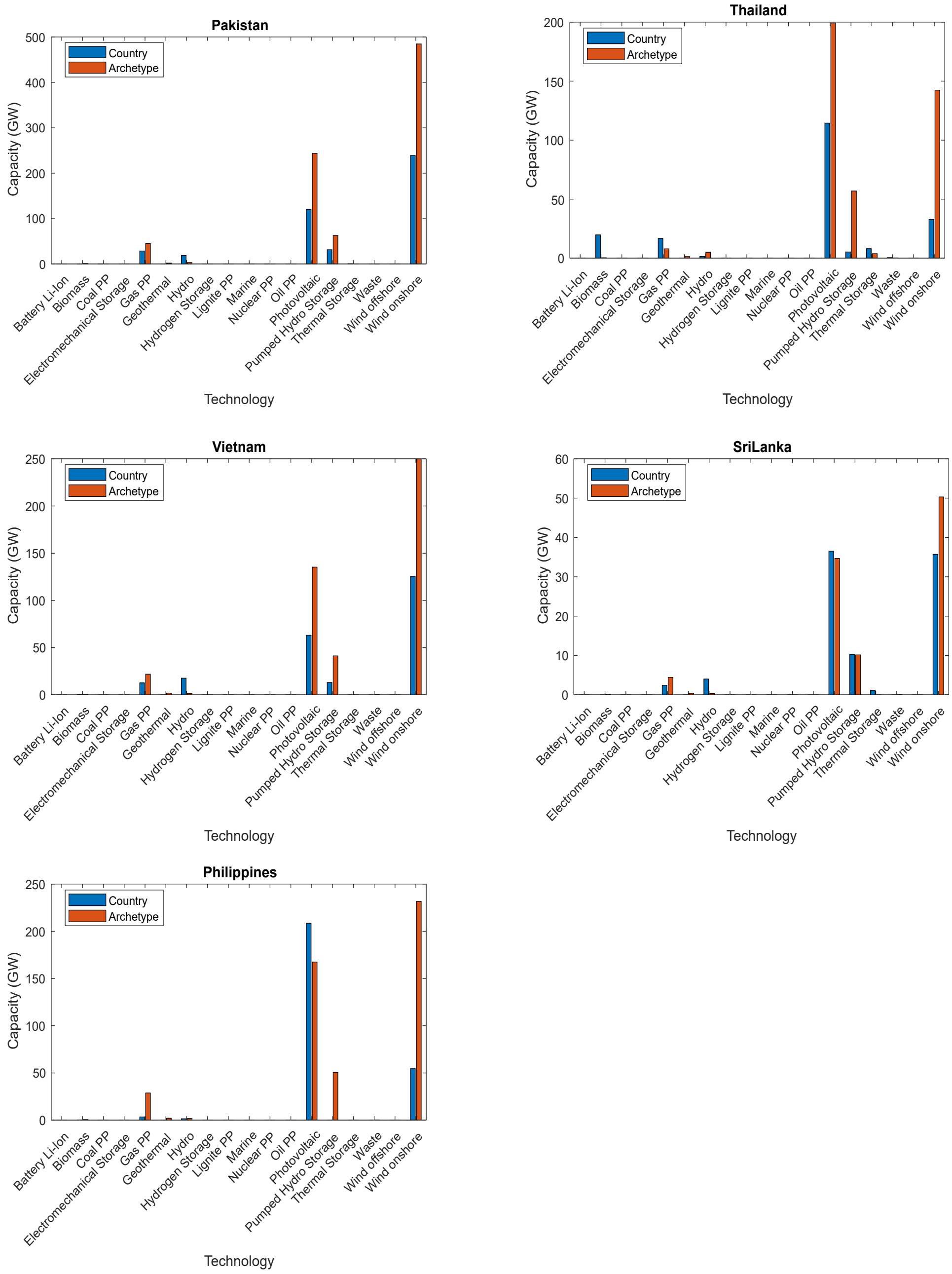
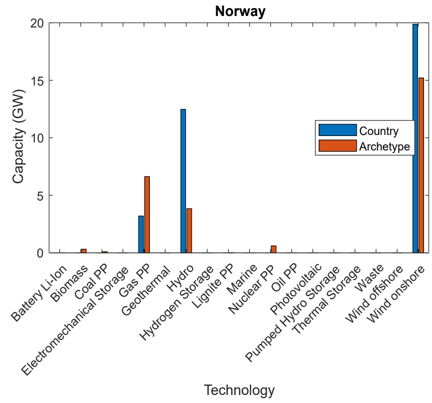
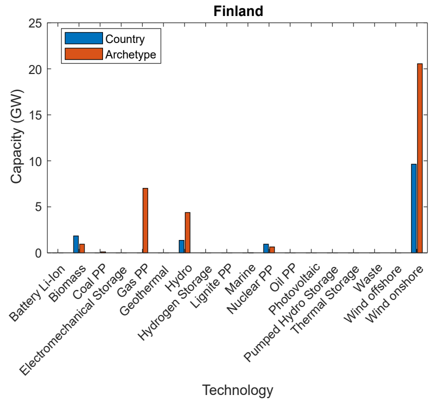
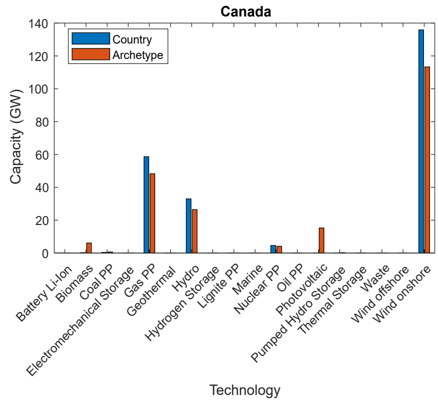


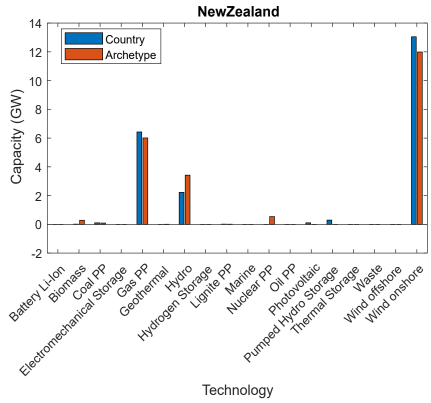
Figure B.2: Installed capacities for cluster 6

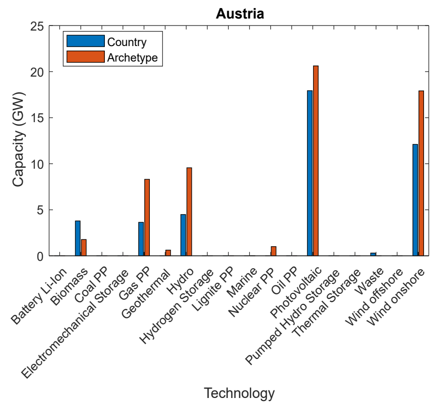
Cluster 14

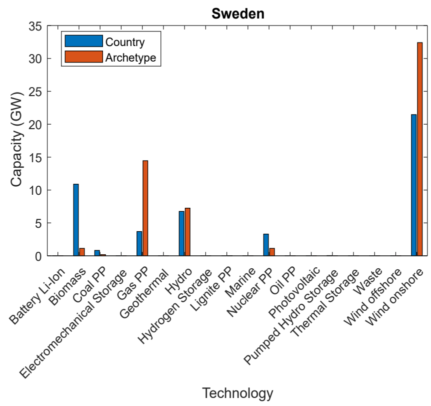

Norway
Country
Archetype
Capacity (GW)
0
5
10
15
20
Battery Li-Ion
Biomass
Coal PP
Electromechanical Storage
Gas PP
Geothermal
Hydro
Hydrogen Storage
Lignite PP
Marine
Nuclear PP
Oil PP
Photovoltaic
Pumped Hydro Storage
Thermal Storage
Waste
Wind offshore
Wind onshore
Technology


Finland
Country
Archetype
Capacity (GW)
0
5
10
15
20
25
Battery Li-Ion
Biomass
Coal PP
Electromechanical Storage
Gas PP
Geothermal
Hydro
Hydrogen Storage
Lignite PP
Marine
Nuclear PP
Oil PP
Photovoltaic
Pumped Hydro Storage
Thermal Storage
Waste
Wind offshore
Wind onshore
Technology


Canada
Country
Archetype
Capacity (GW)
0
20
40
60
80
100
120
140
Battery Li-Ion
Biomass
Coal PP
Electromechanical Storage
Gas PP
Geothermal
Hydro
Hydrogen Storage
Lignite PP
Marine
Nuclear PP
Oil PP
Photovoltaic
Pumped Hydro Storage
Thermal Storage
Waste
Wind offshore
Wind onshore
Technology


NewZealand
Country
Archetype
Capacity (GW)
-2
0
2
4
6
8
10
12
14
Battery Li-Ion
Biomass
Coal PP
Electromechanical Storage
Gas PP
Geothermal
Hydro
Hydrogen Storage
Lignite PP
Marine
Nuclear PP
Oil PP
Photovoltaic
Pumped Hydro Storage
Thermal Storage
Waste
Wind offshore
Wind onshore
Technology


Austria
Country
Archetype
Capacity (GW)
0
5
10
15
20
25
Battery Li-Ion
Biomass
Coal PP
Electromechanical Storage
Gas PP
Geothermal
Hydro
Hydrogen Storage
Lignite PP
Marine
Nuclear PP
Oil PP
Photovoltaic
Pumped Hydro Storage
Thermal Storage
Waste
Wind offshore
Wind onshore
Technology


Sweden
Country
Archetype
Capacity (GW)
0
5
10
15
20
25
30
35
Battery Li-Ion
Biomass
Coal PP
Electromechanical Storage
Gas PP
Geothermal
Hydro
Hydrogen Storage
Lignite PP
Marine
Nuclear PP
Oil PP
Photovoltaic
Pumped Hydro Storage
Thermal Storage
Waste
Wind offshore
Wind onshore
Technology

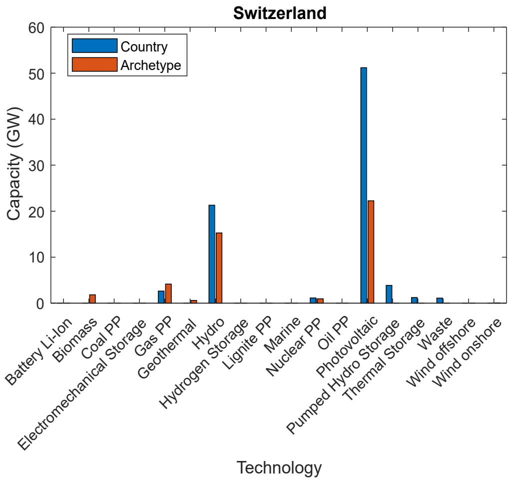


Figure B.3: Installed capacities for cluster 14

Cluster 15

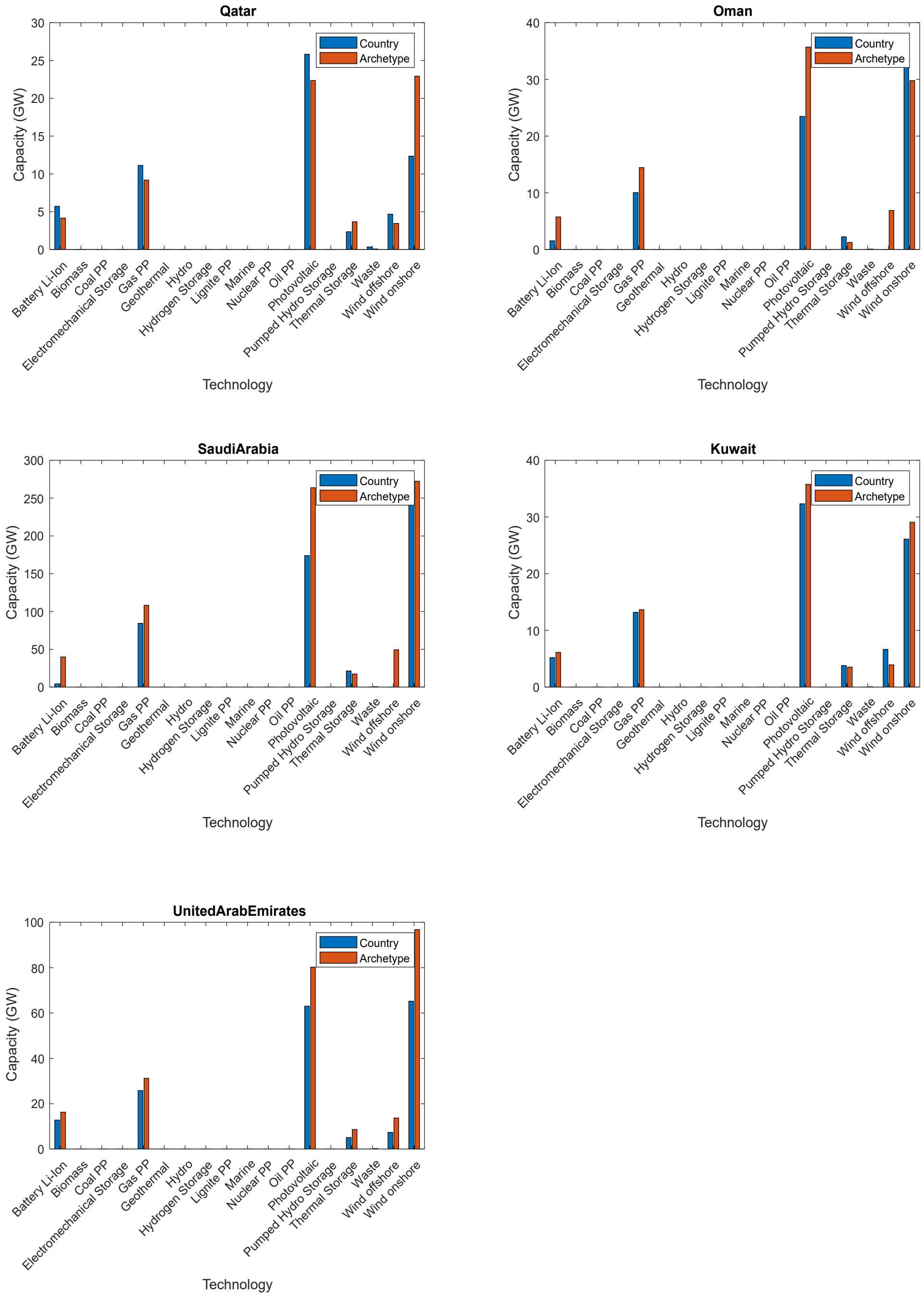


Figure B.4: Installed capacities for cluster 15

B.2 Generation

In this section, the generation for all the analyzed countries in year 2050 are shown for each archetype.

Cluster 13

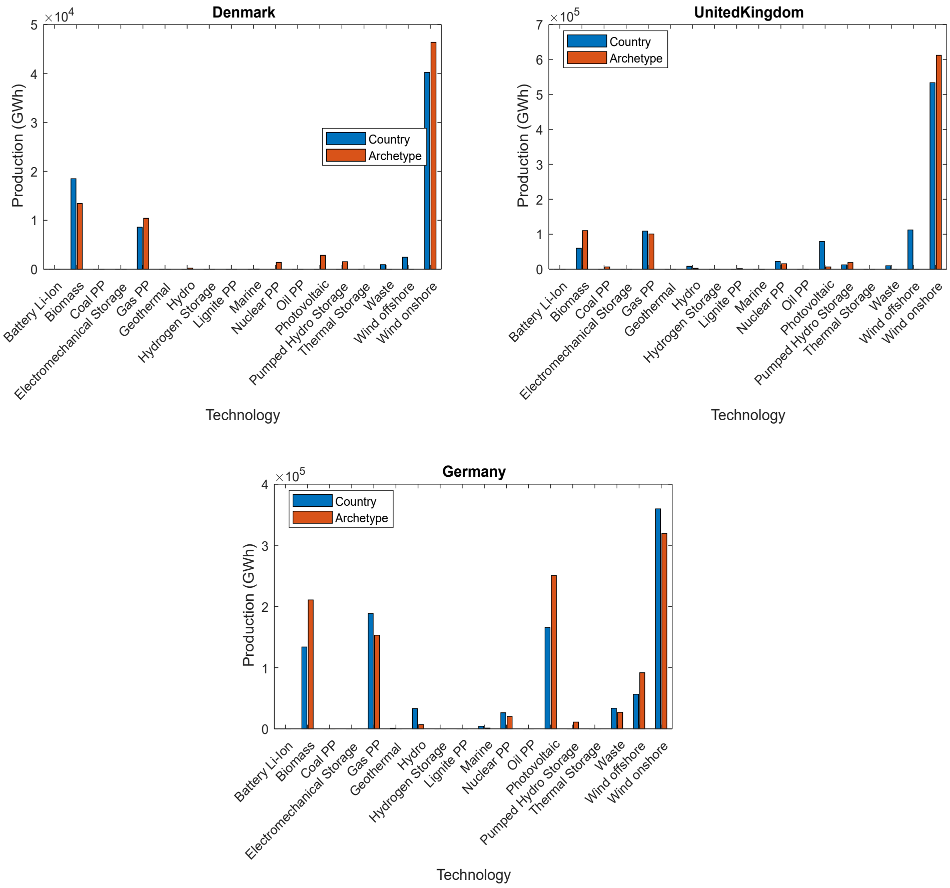
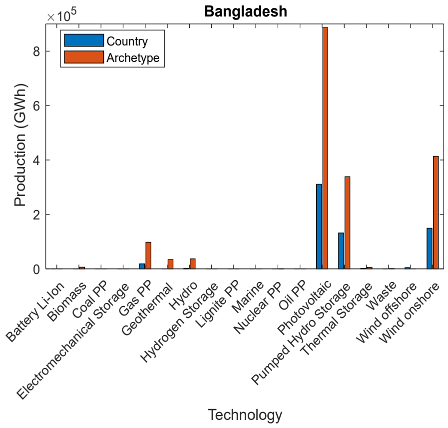
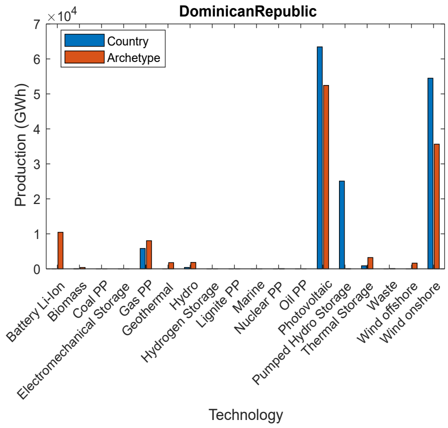
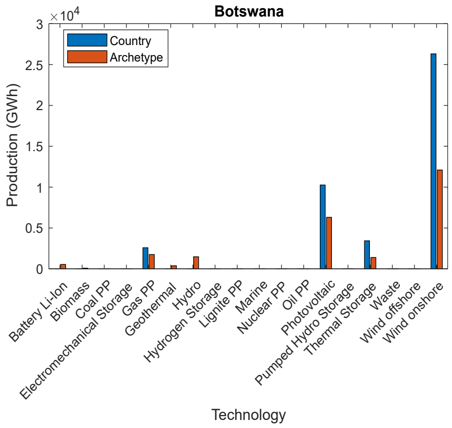


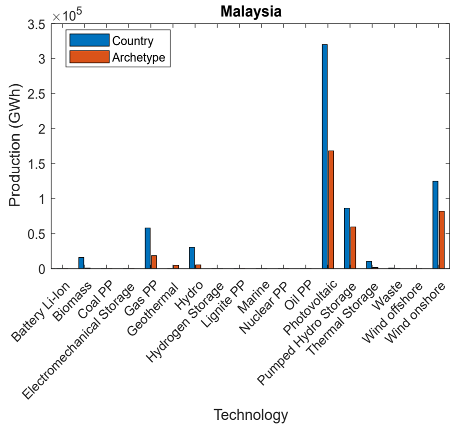
Figure B.5: Generation for cluster 13

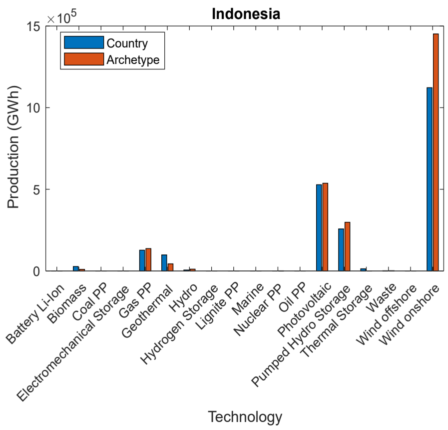
Cluster 6

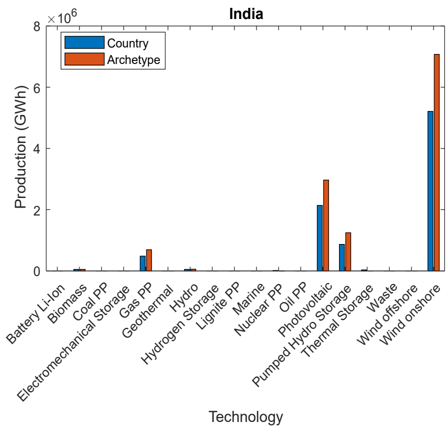

Bangladesh
×10^5
Country
Archetype
Production (GWh)
Technology
Battery Li-Ion
Biomass
Coal PP
Electromechanical Storage
Gas PP
Geothermal
Hydro
Hydrogen Storage
Lignite PP
Marine
Nuclear PP
Oil PP
Photovoltaic
Pumped Hydro Storage
Thermal Storage
Waste
Wind offshore
Wind onshore


DominicanRepublic
×10^4
Country
Archetype
Production (GWh)
Technology


Botswana
×10^4
Country
Archetype
Production (GWh)
Technology


Malaysia
×10^5
Country
Archetype
Production (GWh)
Technology


Indonesia
×10^5
Country
Archetype
Production (GWh)
Technology


India
×10^6
Country
Archetype
Production (GWh)
Technology

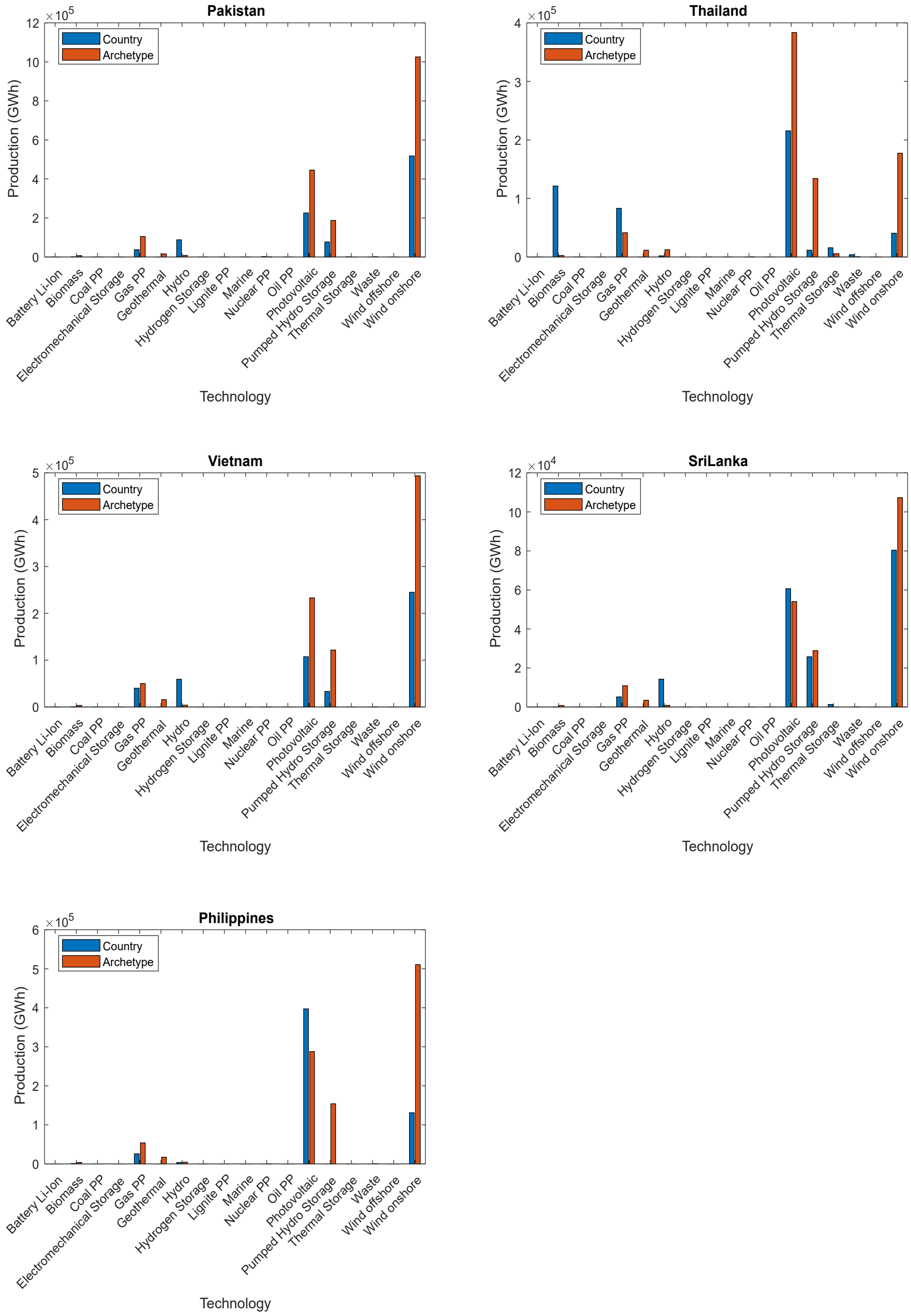
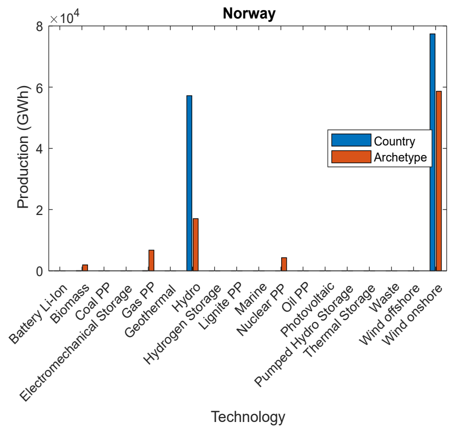
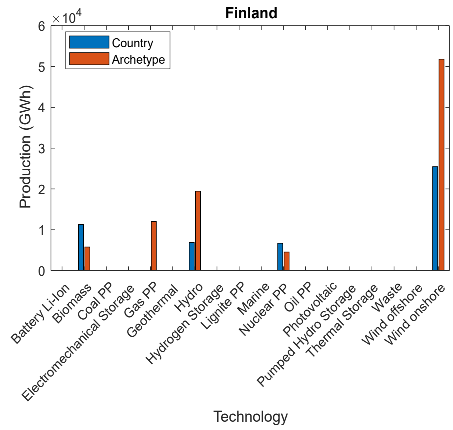
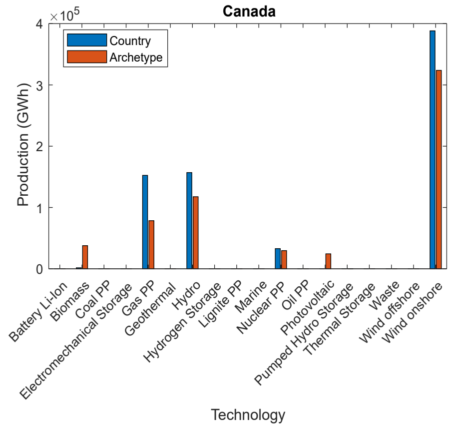


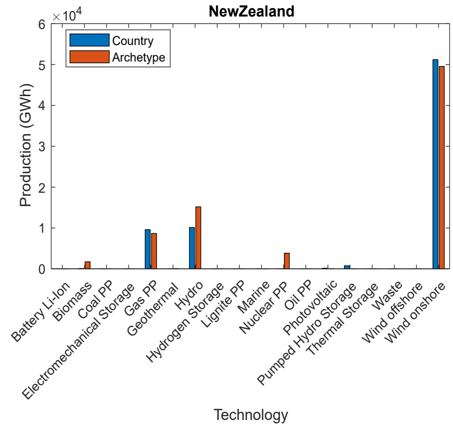
Figure B.6: Generation for cluster 6

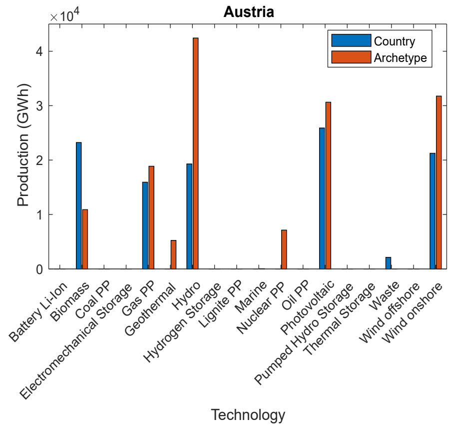
Cluster 14

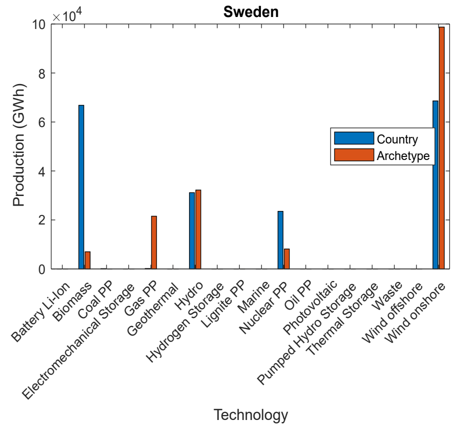

Norway
×10^4
Production (GWh)
Country
Archetype
Battery Li-Ion
Biomass
Coal PP
Electromechanical Storage
Gas PP
Geothermal
Hydro
Hydrogen Storage
Lignite PP
Marine
Nuclear PP
Oil PP
Photovoltaic
Pumped Hydro Storage
Thermal Storage
Waste
Wind offshore
Wind onshore
Technology


Finland
×10^4
Production (GWh)
Country
Archetype
Technology


Canada
×10^5
Production (GWh)
Country
Archetype
Technology


NewZealand
×10^4
Production (GWh)
Country
Archetype
Technology


Austria
×10^4
Production (GWh)
Country
Archetype
Technology


Sweden
×10^4
Production (GWh)
Country
Archetype
Technology

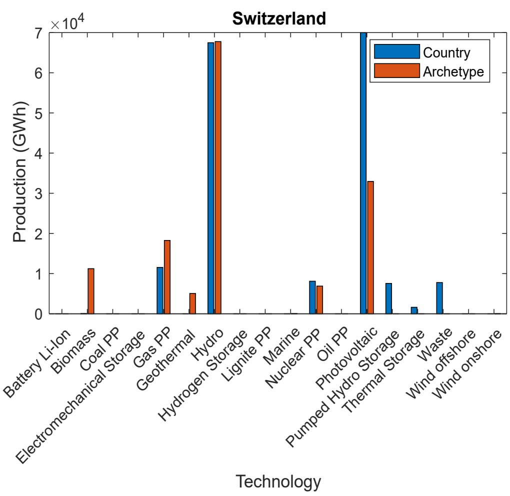


Figure B.7: Generation for cluster 14

Cluster 15

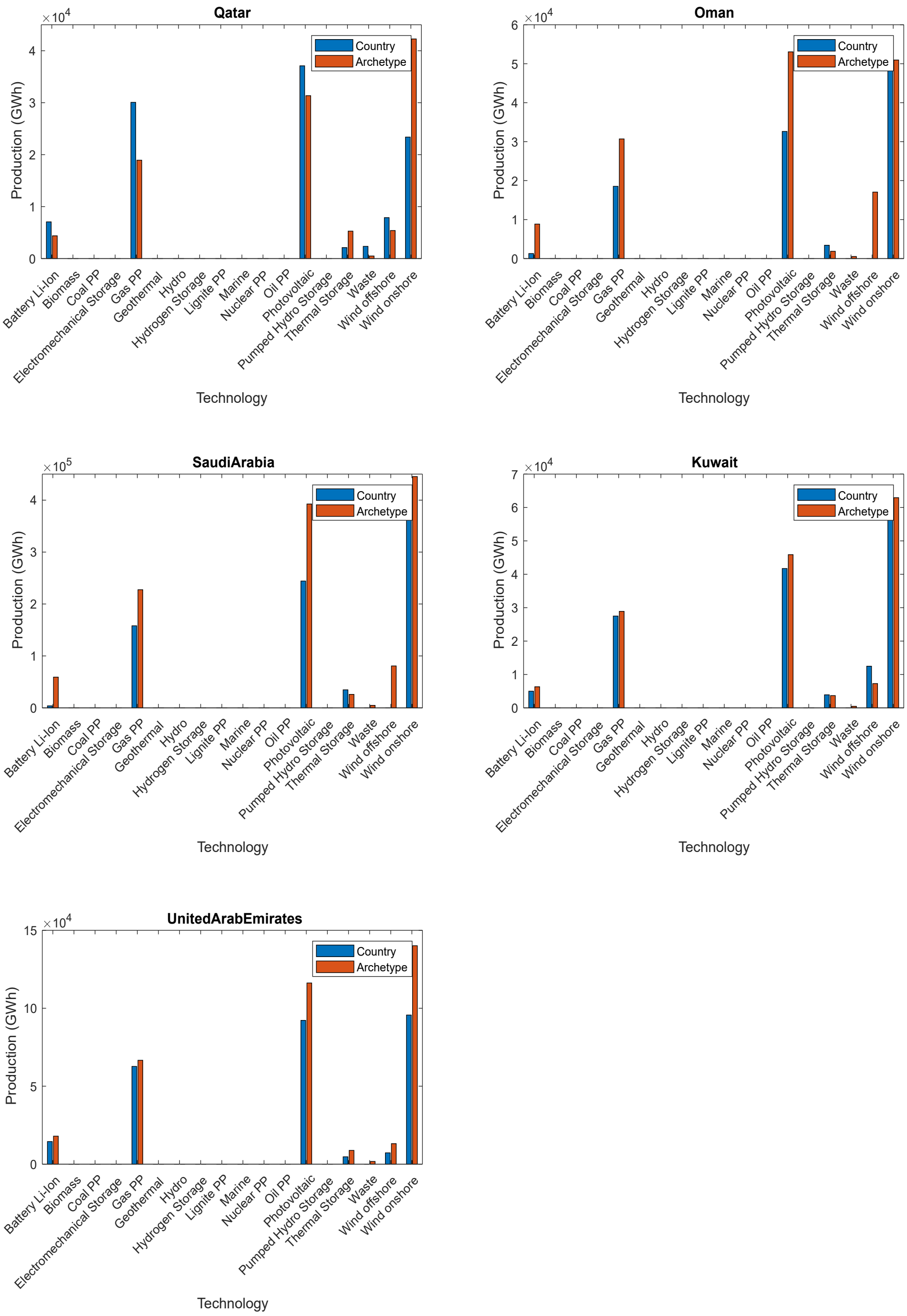


Figure B.8: Generation for cluster 15