OPTIMAL CAPACITY ALLOCATION IN ELECTRICITY INDUSTRY IN
ACCORDANCE WITH RENEWABLE ENERGY SOURCES: THE US CASE

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF APPLIED MATHEMATICS
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

UMUT GÖLBAŞI

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
FINANCIAL MATHEMATICS

MARCH 2021

Approval of the thesis:

OPTIMAL CAPACITY ALLOCATION IN ELECTRICITY INDUSTRY IN ACCORDANCE WITH RENEWABLE ENERGY SOURCES: THE US CASE

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ABSTRACT

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March 2021, 89 pages

Electricity generation cost and environmental effects of electricity generation continue to be among central themes in energy planning. The choice of electricity generation technology and energy source affect the environment through released greenhouse gases and other waste. United States is the world's second-largest CO_2 emitter and electricity consumer. This thesis aims to forecast the optimal capacity expansion of electric power sector in the United States for 2022-2050. We develop a fuzzy multi-objective linear program to minimize cost and environmental effects. In sensitivity analyses, we show how different policies and price evolution may alter the mix. Later on, we examine the effects of the new capacity mix and implied generation on the cost of electricity and emissions. We find that direct modeling of capacity factors give meaningful results. According to this thesis, renewable energy is expected to reach more than 1100 GW installed capacity by 2050. This reduces average cost of electricity generation by more than 70 percent and reduces CO_2 emissions by more than 80 percent compared to expected end-2021 levels.

Keywords: Electricity system, Fuzzy sets, Multi-objective programming, Capacity expansion, Variable renewable energy

ÖZ

YENİLENEBİLİR ENERJİ KAYNAKLARINA GÖRE ELEKTRİK ENDÜSTRİSİNDE OPTİMUM KAPASİTE TAHSİSİ: ABD ÖRNEĞİ

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Elektrik üretim maliyeti ve elektrik üretiminin çevresel etkileri, enerji planlamasında ana temalar arasında yer almaya devam etmektedir. Elektrik üretim teknolojisi ve enerji kaynağı seçimi, salınan sera gazları ve diğer atıklar yoluyla çevreyi etkiler. Amerika Birleşik Devletleri, dünyanın ikinci en büyük CO_2 yayıcısı ve elektrik tüketicisidir. Bu tez, Amerika Birleşik Devletleri'ndeki elektrik enerjisi sektörünün 2022-2050 için optimal kapasite genişlemesini tahmin etmeyi amaçlamaktadır. Maliyet ve çevresel etkileri en aza indirmek için bulanık, çok amaçlı bir doğrusal program geliştirilmiştir. Duyarlılık analizlerinde, farklı politikaların ve fiyat evriminin optimal bileşimi nasıl değiştirebileceği gösterilmektedir. Daha sonra, yeni kapasite bileşiminin ve zımni üretimin elektrik ve emisyon maliyetleri üzerindeki etkileri incelenmektedir. Kapasite faktörlerinin doğrudan modellenmesinin anlamlı sonuçlar verdiği görülmüştür. Bu teze göre, yenilenebilir enerjinin 2050 yılına kadar 1100 GW'ın üzerinde kurulu kapasiteye ulaşması beklenmektedir. Bu, ortalama elektrik üretim maliyetini yüzde 70'in üzerinde düşürmekte ve beklenen 2021 sonu seviyelerine kıyasla CO_2 emisyonlarını yüzde 80'den fazla azaltmaktadır.

Anahtar Kelimeler: Elektrik sistemi, Bulanık setler, Çok hedefli programlama, Kapasite genişlemesi, Değişken yenilenebilir enerji

ACKNOWLEDGMENTS

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

xix

LIST OF ABBREVIATIONS

AHP	Analytic hierarchy process
BA	Balancing authority
CO_2	Carbon dioxide
EIA	Energy Information Agency
EPA	Environment Protection Agency
ES	Exponential smoothing
GHG	Greenhouse gas
kWh	Kilowatt hours
LCOE	Levelized cost of energy
MCDA	Multi-criteria decision-analysis
MCDM	Multi-criteria decision making
MOLP	Multi-objective linear program
MWh	Megawatt hours
NO_x	Nitrogen oxides
PV	Photovoltaics
RES	Renewable energy systems
SARIMA	seasonal autoregressive integrated moving average
SO_2	Sulfur dioxide
TOPSIS	The Technique for order of preference by similarity to ideal
UNFCCC	United Nations Framework Convention on Climate Change
US	United States
VRE	Variable renewable energy

CHAPTER 1

INTRODUCTION

Electricity generation cost and environmental effects of electricity generation continue to be among central themes in energy planning, policy and energy management. As the human population rises and development accelerates, demand for electricity increases. Thus, the importance of electricity system planning is increasing. An electric power system is defined as a network of components used to supply, transmit, and consume electric power [40]. Nearly all components of the electric power system bear upon the environment: The choice of electricity generation technology, energy source, and electricity transmission affect the environment in various ways. We can name some of the effects as follows:

i) Burning hydrocarbon fuels releases greenhouse gases, air pollutants, and other wastes. Solid and hazardous wastes are also side products of the system.

ii) Producing required steam in electricity generation and providing cooling to generators requires using water resources.

iii) Discharge of wastes into the water and returning heated water to the originally cooler water body affects the water ecosystem.

iv) Land use for fuel production, power generation, and transmission and distribution lines is another effect [55].

As of 2019, 38% of utility-scale electricity generation in the US is from natural gas, 24% from coal, 20% from nuclear, and 17% from renewable energy sources [61]. It adds up to 62% of generation from fossil resources. Energy-related carbon dioxide accounts for 81.5% of greenhouse gases (GHG) in the US, and 27% of GHG

emissions is a result of electricity generation [64]. High GHG emissions stem from burning fossil resources affect nature adversely. As an obviation, most of the US states have either goals or mandates to achieve clean or renewable energy generation ultimately [53]. For instance, legislation in California mandates authorities to achieve 100% clean energy by 2045, whereas in Washington DC, the mandate is to accomplish 100% electricity generation from renewable sources in 2032. Moreover, some states encourage renewable energy deployment through policy mechanisms like tax credit and feed-in tariffs, which accelerate investment in renewable energy systems and technologies. Feed-in tariffs achieve this by offering long-term contracts to renewable energy producers that guarantee a purchase of electricity produced by wind and solar farms [13].

In addition to carbon dioxide, there are other hazardous wastes, some of them produced by burning fossil resources. The Clean Energy Act of the US and its 1990 amendments require Energy Protection Agency (EPA) to set standards for six common air pollutants: nitrogen oxides, sulfur dioxide, lead, carbon monoxide, particulate matter and ground-level ozone [4]. Nitrogen oxides are a family of poisonous, highly reactive gases. Among many other threats, they are critical components of photochemical smog and produce the smog's yellowish-brown color. Nitrogen oxides interact with water, oxygen and other chemicals and form acid rains, and they pollute nutrients in coastal waters [57]. Sulfur dioxide has a sharp, irritating odor, affects the respiratory system, particularly lung function, and can irritate the eyes. Sulfur oxides react with other compounds in the atmosphere to form small particles, contributing to particulate matter pollution. When sulfur dioxide reacts with water and other chemicals, it forms sulfuric acid, which is the main ingredient of acid rains [41]. The EPA established the Acid Rain Program under the 1990 Clean Air Act Amendments. The Acid Rain Program requires major emission reductions of sulfur dioxide (SO_2) and nitrogen oxides (NO_x), from the power sector. The program is phased in an allowance trading market, where sulfur dioxide allowances can be bought and sold.

Besides economic and environmental characteristics of different sources of electricity generation, variability in renewable energy brings some complexity into energy planning [9]. Renewable energy sources such as wind and solar are volatile compared to fossil energy sources. While power systems have been designed to handle the vari-

able nature of loads (demand), the additional supply-side variability and uncertainty can pose other challenges for utilities and system operators. System operators need to ensure that they have sufficient resources to accommodate up or down ramps in wind generation to maintain system balance. Another challenge occurs when wind or solar generation is available during low load levels: In some cases, conventional generators may need to turn down to their minimum generation levels. In cases of solar, the variability of solar irradiation, which stems from the movement of the sun, usually coincides with the load. Other sources of variability in solar energy are cloud cover, including the amount of water or ice in clouds and aerosols. This variability is obviated by distributing solar panels across the land so that clouds cannot cover solar energy generation farms altogether. Sky imagers and satellite imagers are also helpful to assess the direction and speed of approaching clouds [9, 69].

The predictability of wind speed and direction is less than solar irradiation. Sometimes variability of the supply of wind energy is larger than the variability of the load. Therefore, even when changes in wind energy production matches electricity demand, management of high penetration of wind energy into the grid may require greater flexibility or better supply planning [9].

Electricity generation that relies on wind turbines and solar irradiation has intermittent characteristics affected by meteorological variables' randomness. Variable and partially unpredictable wind and solar power penetration into the electricity grid have two main aspects to consider: "increasing uncertainty" and "non-dispatchable generation". Increasing uncertainty requires more reserve capacity, mainly in the form of fast-starting combustion turbines. High penetration resulting from favorable wind and sun conditions reduces electricity prices and utilization rates of other plants. Lower electricity prices reduce profitability, and lower utilization rates lessen the efficiency of other power plants. This effect is fostered when there is a purchase guarantee for electricity production from renewable resources [20]. Since generation from wind turbines and solar photovoltaics are non-dispatchable, that is, the operators cannot adjust output on demand; other dispatchable power sources need to adapt their production [20]. As the states switch to more renewables to alleviate the environment's burden, electricity penetration from renewables increased. Consequently, variability in renewables has to be considered in optimal capacity expansion planning processes.

1.1 Gap in the Literature and the Aim of the Thesis

As we present in Section 1, three aspects are prominent in large-scale electricity generation capacity planning: i) cost, ii) environmental effects, and iii) variability in renewable energy sources. In these three aspects, the cost and environmental effects may be considered as competing objectives. Researches address such capacity expansion problems mainly with multi-objective linear programming (MOLP) models and multi-criteria decision-making (MCDM) methods. The latter set of methods are generally used to rank the power plant alternatives. In both sets of methods, energy planning experts decide the weights of the competing objectives, the cost and environmental effects. This thesis presents a new fuzzy multi-objective linear programming (MOLP) model to find the optimal capacity expansion and electricity generation mix in terms of cost and environmental effects. Fuzzy modeling is generally useful when objectives and constraints are vague. This vagueness may appear when objectives are identified not precisely. In our case, future electricity generation has uncertainties and depends on various factors. Fuzzy modeling is connected to fuzzy set theory and allows such uncertainties exist, given an estimate is available.

The literature concerning the US nationwide is scarce. Instead of smaller regions, our study comprises the US nationwide in the long term. Instead of micro-level economic capacity expansion studies or somewhat more technical studies incorporating transmission line expansion, our motivation has a macro perspective. The thesis results show what optimally arranged least costly and least CO_2 emitting capacity expansion mix might be. Moreover, through sensitivity analyses, we show how different policies could alter the capacity mix and consequently cost and CO_2, SO_2 and NO_x emissions.

This thesis is expected to assist the policy-makers by showing how CO_2 emissions from electricity generation may evolve and how different scenarios may alter economic and environmental objectives. We specifically study on the US market due to

   i) Developed regulations in renewables and investment environment,

   ii) US being the world's second-largest electricity consumer and CO_2 emitter,

iii) Recent political influences on the energy markets,

iv) Widespread data availability both in fossil fuel plants, renewables and environmental indicators,

v) Policy targets on reduction of energy cost, dependence on fossil sources and outside suppliers.

This study incorporates installation and retirement decisions of power plants of 7 primary electricity sources: nuclear, hydroelectric power, solar photovoltaics, onshore wind, coal, natural gas-fired combined cycle, and combustion turbine. Moreover, we also analyze new carbon capture technologies in coal-fired and natural gas-fired power plants. Capacity factor is a unitless metric that measures in what proportion the installed capacity of a power plant or fleet of plants is utilized (Section 3.1). Apart from the literature, we propose a plain model to accomplish complex work. We directly model capacity factors of power generating technologies. In fact, it is also possible to obtain capacity factors as a side-product of a dispatch model with higher time resolution (and, in some instances, highly complex). However, we assume that in a large-scale capacity expansion and generation mix optimization problem (the whole US in our case), historical time series of capacity factors inherit relevant information about their past to model them accurately. As these capacity factor observations are fed by all the power plants across the nation, we can get meaningful results without more complex, higher-resolution models. These models would also bring a significant computational burden to draw optimal views for the year 2050 under different scenarios. We also incorporate integration costs/total system costs into the thesis, which researchers mostly ignore. The literature on the costs of VRE integration to the system is not coherent. Therefore, in this thesis, we compute these costs again.

1.2 Organization of the Thesis

This thesis is comprised of five chapters. In Chapter 1, we introduce the capacity expansion problem of the electric power sector. The selection of the best power generation option involves economic and environmental aspects. Investment costs, fuel costs, variable and fixed operational costs and transmission costs are among economic

aspects. Harmful substances are side-products of electric power generation: CO_2 is the most important greenhouse gas, and SO_2 and NO_x are important air-pollutants. Transition to clean energy is the solution to environmental necessities in the electric power sector. In the literature, electricity generation mix and capacity expansion problems are addressed with multi-objective programming, multi-criteria decision making, portfolio theory, and game theory. We addressed the problem with a fuzzy multi-objective linear program. In the literature, papers generally concern a limited number of energy sources, and the studied area is spatially limited. In multi-objective programming models, the optimal mix is usually found via a dispatch model. A model gives hourly or sub-hourly dispatch decisions, and at the end, the optimal generation mix is an output of the model. Seeking optimal mix via dispatch models with hourly or sub-hourly resolutions is demanding in computational resources. This thesis shows that directly modeling capacity factor series and using them as inputs in the optimization model gives meaningful results. The capacity factor is the periodic generation of a power plant divided by the product of the capacity and the number of hours over a given period. We exploit the fuzzy set theory in constructing the multi-objective linear program.

Production of wind, solar and hydropower depends on nature. Among them, wind and solar power are not dispatchable, which means operators cannot adjust production according to demand. Thus, the rest of the grid providers with the ability to respond have to adjust their production levels. In case of a demand and supply mismatch, balancing authorities intervene with the reserve capacities. This regulation intervention may be within seconds or in a longer time horizon. All electricity generated by non-dispatchable renewable sources feeds the grid. Sometimes, the level of generation is high and reduces the utilization of other plants. These attributes of variable renewable energy (VRE) suggest there are additional costs associated with VRE. These costs are called the integration or system costs of VRE, and they are omitted in some optimal mix studies. There is no consensus in the literature about VRE system costs; therefore, we introduce the concepts and then calculate the costs with the recent data.

Chapter 2 briefly refers to the electricity markets and the electric power sector in the US. The US is the second-largest electricity consumer and CO_2 emitter of the

world [62]. Most American states aim to reach carbon-neutrality by the mid-21st century. Competitive markets supply two-thirds of Americans' electricity, and state-regulated companies supply one-third. The US's electricity system comprises 71 balancing authorities and 3 interconnections that also cover parts of Canada and Mexico. Regional Transmission Organizations monitor and coordinate multi-state grids. In this chapter, we also presented and analyzed the data sets.

In Chapter 3, we forecast the capacity factors of power plants. We test various time series models. Seasonal ARIMA models give better validation set errors than exponential smoothing models. Later, we calculate VRE system integration costs, which we find as low as $3/MWh. In addition to the data we present in Chapter 2, capacity factor series and VRE integration costs are inputs for the fuzzy multi-objective optimization model.

Chapter 4 presents the main model, a base case, and four additional cases: high renewable cost, high fuel prices, 75% clean energy limit, and 90% clean energy limit case. We draw new merit-order dispatch curves and show how electricity cost may evolve. In the base case, we predict capacity mix would be as in Figure 4.4, implied generation mix would be as in Figure 4.5 and new merit-order curve be as in Figure 4.6. As this thesis covers the whole United States in the long-term, it may provide valuable inputs for policy-makers. Additionally, electricity price studies mostly cover short and partially medium-term [67]. This thesis also contributes to the literature with electricity price predictions in the much longer term.

Chapter 5 gives some concluding comments about our findings.

CHAPTER 2

PRELIMINARIES AND LITERATURE SURVEY

This chapter is dedicated to giving details of the US electricity market and a literature review on the optimal electricity generation mix and capacity expansion problem. The literature's prevalent methods can be clustered into four branches: multi-objective linear programming (MOLP), multi-criteria decision making (MCDM), portfolio theory, and game theory. Additionally, in the current chapter, we provide a review of the literature assessing the cost of renewable energy variability.

2.1 US Electricity Market

The US electricity generation system is very complex, made up of over 7,300 power plants, nearly 160,000 miles of high-voltage power lines and millions of miles of low-voltage power lines and distribution transformers, connecting 145 million customers [66]. In a typical electricity grid, electric power is generated by centralized power plants and decentralized units. It is transported and transformed through a system of substations, transformers and transmission lines.

Electricity is delivered in two major models. In the first one, there are state-regulated, vertically connected electricity producers. Second is the competitive model, in which power producers participate in wholesale electricity auctions. Competitive markets reduced entering barriers for new producers and improved efficiency. Two-thirds of consumers are served in this model [18]. In wholesale markets, power producers submit their bids in typically five-minute-long scheduling intervals. The bids include the asking price and capacity offered. Market participants first submit their bids in

day-ahead markets (one day before delivery). Then, they update their forecasts in each of the following bidding intervals. At the real-time market, grid operators dispatch the lowest to highest cost resources until the load is met. The most expensive resource sets the market-clearing price. Grid operators signal generators with directions about their production levels to ensure supply and demand match. If generators do not follow these signals, the producers may be charged with a penalty.

We illustrate a hypothetical merit-order curve in Figure 2.1. Here, we assume that the capacities are proportional to the existing capacities of the US as of September 2020. The marginal cost of the solar power is the lowest, while the marginal cost of oil is the highest. The figure also reveals that the renewable energy sources' marginal cost is lower than the fossil energy sources. From the figure, it is clear that the average cost of generation exceeds \$0.58/kWh (the blue line) when all capacity is used. Hence, we may conclude that in the long run, an increasing share of variable renewable energy may force non-renewables out of business since operational costs of VRE are close to zero. Capacity markets are established to incentivize non-variable energy producers to maintain a certain generating capacity.
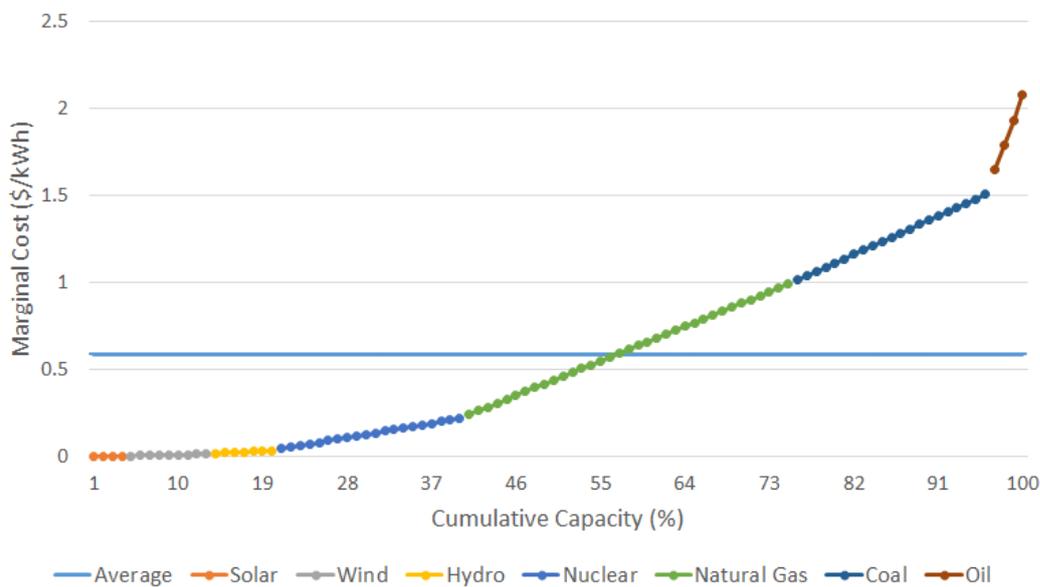
Figure 2.1: Economic dispatch with renewables. *In the market, the electricity load is first met with lowest-cost power sources. Namely, solar, wind and conventional hydro power in our case. As the demand increases, more expensive and relatively more flexible solutions are deployed.*

The electricity system that serves the US is divided into three interconnections, which also cover parts of Canada and Mexico. These are the Western Interconnection, the Eastern Interconnection and the Electric Reliability Council of Texas (ERCOT) Interconnection [66]. They operate largely independently from each other with a limited electricity transfer to each other. Electricity supply and demand on each interconnection are balanced within smaller geographical areas called control areas or balancing authorities (BAs). BAs are responsible for balancing electricity generation to load in real-time [18]. BAs also provide ancillary services to support the transmission of electricity. The services include operating reserves, voltage support services and black start [15].

Electricity in the US is generated using a variety of resources and technologies. We graph electricity generation by its source in Figure 2.2 for the period 1971-2020. The figure illustrates that the majority of the electricity is produced using conventional sources such as natural gas, oil, coal and nuclear power plants. The figure also illustrates that the electricity demand is used to be met mostly by coal before 2000. Since the early 2000s, while the share of coal has decreased, the share of natural gas, wind and solar have increased.
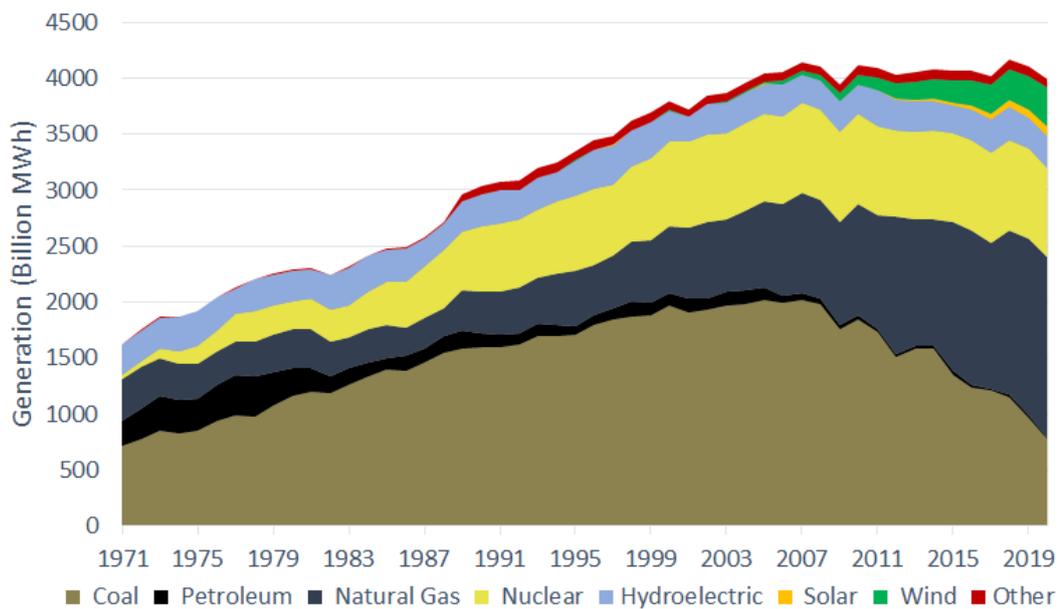
Figure 2.2: Electricity generation in the US by source for the period 1971-2020.

According to the reference case of Annual Energy Outlook from Energy Information Administration, electricity generation from renewables is expected to reach 42% in

2050 from 21% in 2020. Generation from natural gas is expected to be flat about 36%. On the other hand, the generation from nuclear drops to 11% from 19%, generation from coal drops from 19% to 11% [59]. These ratios imply more than 200 gCO_2 *per kWh* by 2050, which is not enough to reach the Paris Climate Agreement's emission targets of roughly 50 gCO_2 *per kWh*.

2.2   Literature on Electricity Generation Mix and Capacity Expansion

Moura and de Almeida [37] analyze three methodologies to compensate for the effects of the variability and randomness of the renewable energy availability in Portugal, which are the use of complementarity between renewable sources, demand-side management, and demand-side response. They propose an MOLP to limit the spread between average electricity generation of renewable sources and average generation from all sources in each period. They find relatively high complementarity between solar energy and wind power/hydroelectric power pair for Portugal with a climate model. Solar energy, then, can be used to face the seasonal variations of wind power. Such a conclusion may also be used for the US since Figure 2.3 clearly shows the negative correlation among the capacity factors of solar PV plants and wind power plants. On the other hand, hydroelectric power is not complementary to wind power. However, hydropower has storage benefits, dispatchable power, and dynamic response capabilities. Thus, it is ideal for storing the excess wind energy to cope with the intermittence. Figure 2.3 also presents the complementarity between solar and wind power. However, as emphasized by [10], the challenge VRE present is not in seasonal variations, but in much shorter time frames.

Yu et al. [70] develop a fuzzy multi-objective optimization model to find an optimal mix of four renewable energy systems (RES), namely hydro, wind, solar PV, and biomass for China's electricity market. The optimal blend of accumulated installed capacity of renewable energy in China from 2017 to 2022 is found to be hydropower as the first, wind as the second, followed by solar PV and biomass; with a target of solar PV will become the first between 2023 and 2030. However, hydro remains the largest RES in terms of on-grid generation. According to their findings, these four kinds of renewable power generation may eliminate 34.9-37.5 billion tonnes of CO_2
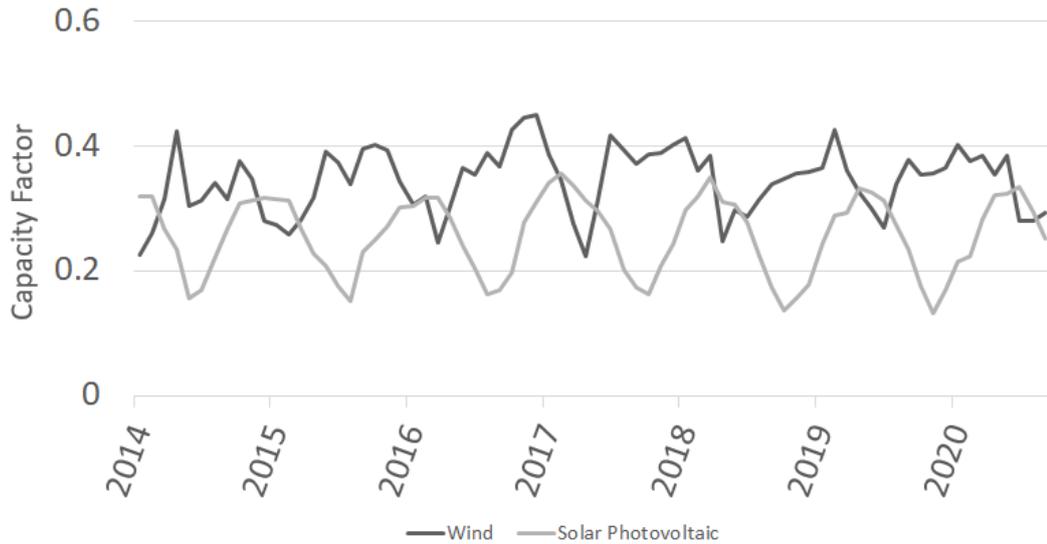
Figure 2.3: Complementarity between solar PV and wind power.

emissions.

Incekara and Ogulata [25] develop a multi-objective mixed-integer linear programming model under the goals/objectives of the Ministry of Energy of Turkey's goals/objectives, UNFCCC and Kyoto Agreement responsibilities of Turkey. Low and high demand scenarios are considered in their study. They optimized the shares of hydro, wind, biomass, geothermal, solar, coal, lignite, asphaltite, natural gas, and nuclear energy. Experts assign objective weights. Solar, wind, and hydropower plants rank in the top three positions in both scenarios. This study takes renewable energy generation objectives and capacity objectives of other power technologies from the Ministry of Energy as constraints and finds generations of different energy sources in 2023 and 2030.

Mavrotas et al. [32] introduce a mixed binary multi-objective program to plan expansion in the Greek electricity power sector to meet the future electricity demand in Greece. They modify the branch and bound algorithm to minimize the cost and SO_2 emission. They analyze coal, oil, and natural gas-fired power plants.

Arnette and Zobel [7] build a MOLP with objectives to minimize generation costs and emissions. The study focuses on energy planning at the regional level in the US. Coal, nuclear, oil, natural gas, wind, hydro, biomass, and solar energy are included in the analysis.

With a linear investment and production optimization model, Aboumahboub [5] studies a prospective globally interconnected electricity system, which integrates a high share of solar and wind energy. This model optimizes the capacities of power generation and storage systems as well as inter-zonal energy transport capacities using a time frame to 2100.

Antunes et al. [6] propose a multi-objective mixed-integer linear program, in which a decision-maker directs the program by deciding on non-dominated solutions. Demand-side management is allowed as an option to trim peak demand when used.

San Cristobal [44] tackles the problem of optimal capacity expansion with a goal programming model, based on a multi-source multi-sink network, in order to locate five renewable energy plants for electric generation in five places situated in the north of Spain.

Brand et al. [12] adopt a two-step approach. They first build an electricity model, then conduct an MCDM analysis using "The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)" methodology. The simulation model forecasts the configuration of the Tunisian power system until 2030 in 5-year periods. Each forecast period consists of 32 typical days, representing different electricity load profiles (working days and weekend days) and hourly wind speed and solar radiation patterns for four seasons. Then, five power mix scenarios are evaluated using an MCDM analysis regarding power generation costs, energy security, environmental impact, and social welfare effects. They use MCDM analysis in conjunction with an electricity generation system model to calculate and evaluate different Tunisian power system scenarios. Criteria valuations are obtained through consultations with Tunisian stakeholders. The Tunisian power sector's key stakeholders defined five different scenarios for the Tunisian electricity mix until 2030. These scenarios are tested against 13 criteria. They report that the best-ranking electricity mix by 2030 consists of 15% wind, 15% solar, 70% natural gas-generated electricity.

Haddad et al. [21] combine an analytic hierarchy process (AHP) and experts' feedback to evaluate different renewable energy options. The performance of varying RES options is assessed against 13 sub-criteria reflecting social, environmental, economic and technical concerns. The results highlighted the importance of social and ecolog-

14

ical criteria as the main drivers for the final ranking, with three of these sub-criteria weighting 35% in the decision process. Solar power is particularly well suited for Algeria, outperforming most of the other renewable options. Wind power is found to be second, followed by biomass, geothermal and lastly by hydropower. Wind and solar power together achieve a total score of more than 0.5 out of 1.

Milstein and Tishler [35] apply game theory (Cournot conjecture) with two types of power generation method: combined cycle gas turbine and solar photovoltaics. There are two stages, and electricity demand throughout the year is met cumulatively, instead of matching production and demand. The authors claim that the results are equally applicable to other power plant types. Parameters in the price-demand equation are assumed to be known. They state solar PV increases volatility and electricity prices. However, they disregard hydropower as a dispatchable renewable energy technology, which could compensate for the volatility stem from solar PV. The decline in solar PV investment costs leads to more solar power investment and more volatility.

Zhang et al. [71] tackle the problem of optimal power generation mix of China with Markowitz Portfolio Theory (mean-variance). The study considers technological developments and governments' non-fossil and non-hydro renewables generation policies in four different cases. A constraint is added to ensure the goals of each case.

Lorca and Prina solve power portfolio optimization problems from a power producer's view using Markowitz Portfolio Theory. They find that the power producer holding thermal generating units in more than one location may maximize expected profit while keeping the risk limited [28].

Peter [29] compare two alternative electricity system design strategies, one based on the climate change anticipation and one not for the period covering 2015-2120. They found a system design with climate change anticipation increases the share of VRE based on additional wind offshore capacity in 2100, at a reduction in nuclear, wind onshore and solar photovoltaic capacity. They modeled an investment and dispatch model based on a cost-minimizing optimization problem. They interpret the problem as a social planner with perfect foresight minimizes total system costs.

In this section, we review model types in power generation optimization. Among

them, the portfolio theory models consider financial cost and risk perspectives mainly from the view of electricity producers. However, these models do not focus on environmental concerns. MCDM models incorporate multiple objectives, but they are mainly used to rank power generation alternatives rather than give detailed plant installation and retirement road-map and a consequent optimal mix. Multi-objective optimization models consider economic and environmental objectives, and fuzzy multi-objective models deal with the vagueness associated with uncertainty in power plant generations and incomparable objective functions. However, studies concern mostly spatially limited areas and solely from the perspective of power producers.

2.3   Literature on Cost of Variability of Renewable Energy

Levelized cost of energy (LCOE) is a widely adopted metric that shows net present costs of a power generating technology per generation unit such as MWh, enabling comparison of different technologies. As an addition, system LCOE also incorporates integrating that particular power generating technology into the electricity system.

The presence of variable renewable energy on the electricity grid causes coal and natural gas-fired plants to turn on and off more frequently to modify the output. Such cycling reduces efficiency because of running the plant at part load and increases wear-and-tear of the equipment, particularly because of thermal changes. In general, such costs are the highest in coal-fired thermal units and considerable in natural gas-fired combined cycles and combustion turbines unless it is specifically designed for flexible generation [10]. In Western Wind and Solar Integration Study, Lew et al. state that, at the high wind and solar penetrations, cycling costs are from \$0.47/MWh to \$1.28/MWh on average [27].

Although there is no consensus [22], according to some researchers (such as [16, 48]), system costs might include adequacy costs, balancing costs and grid-related costs. Adequacy costs are the costs to back the system up against demand and supply mismatches, arise in generation shortages or outages, or unexpected increase in load. Balancing costs incur to balance the required voltage in the grids in cases of deviations from committed generation. Lastly, grid-related costs arise when additional in-

16

vestments are needed in transmission infrastructure to ensure a particular power plant is connected to the grid. Some RE resources are widely distributed geographically. Others, such as large-scale hydropower, can be more centralized but have integration options constrained by geographic location.

In the case of VRE, Ueckerdt et al. [54] proposes an economic formulation to the System LCOE of VRE. VRE integration costs are additions to LCOE of VRE plants and composed of three parts, which are profile costs, balancing and grid costs. At which profile costs are decomposed into three components: overproduction, full-load hour reduction and backup costs. Overproduction costs occur when, in extreme cases, VRE generation exceeds demand. Full-load hour reduction cost occurs when VRE reduces the full-load hours of dispatchable power plants, mostly for intermediate and baseload plants. Then the annual and life-cycle generation per capacity of those plants is reduced. Lower capacity utilization leads to a higher average cost of generation for dispatchable power plants. The authors Ueckerdt et al. calculate the system-wide integration costs of VRE with screening curves and load duration curves. (discussed in Section 2.3) Balancing and grids costs are parameterized from literature estimates. They find that integration costs can be in the same range as generation costs of wind power and conventional plants at high wind shares.

Hirth et al. make a similar decomposition of integration costs as in [54] and declare that the calculation of profile costs is quite sensitive to assumed fixed and variable costs of fossil-fuel power plants, which will be analyzed further in this study. They find that wind integration costs are about \$25-35/MWh at 30-40 % penetration.

Screening curves lend assistance to determine the annual revenue required to cover the cost of electricity generation. In these curves, annualized capital costs, annual fixed and variable costs are graphed against load factor or operating hours per year (Figure 2.4). In addition to the standard screening curves, Batlle and Rodilla [8] propose a heuristic optimization algorithm to incorporate start-up costs of conventional fossil-fuel plants. In a study by Nuclear Energy Agency, a simulation model with hourly dispatch is used. They conclude that integration costs of VRE at 50% penetration level are \$25-35/MWh. They argue that a cost-effective, low carbon system should consist of a sizeable share of VRE and at least an equally sizeable share of dis-

patchable zero-carbon technologies such as nuclear energy and hydroelectricity [2].
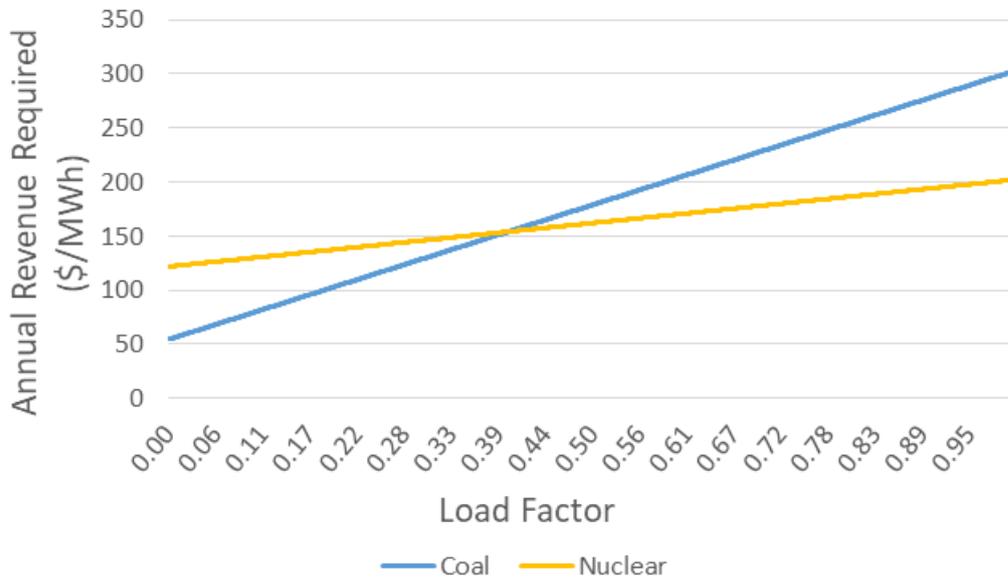
Figure 2.4: A screening curve example. *At the lowest load levels fixed costs of nuclear energy plants exceed costs of coal-fired thermal power plants. As plants run at higher load levels throughout the year, operating a nuclear power plant becomes more economical than coal.*

There are also studies in which integration costs of VRE are found modest. For instance, Frade et al. [19] measure wind balancing costs for Portugal. In Portugal, wind generation has a high fraction of demand. Using real market data, they state that wind balancing costs are $2/MWh thanks to advanced transmission grids across Portugal and Spain.

Fast dispatch serves reducing regulation reserves. Five-minute dispatch is currently adopted in Independent System Operators (ISO) throughout the US. A study conducted by Western Governors' Association covering the US's western part shows that the integration costs have ranged from $0/MWh to $4.40/MWh in areas with five-minute dispatch, compared to $7/MWh to 8/MWh in areas with hourly dispatch [69]. Interestingly, GE Energy argues that hourly scheduling had a greater impact on regulation requirements than the variability introduced by wind and solar power in the scenarios studied. Although some researchers ([16, 48, 54]) consider adequacy (backup) costs in VRE integration costs, Eastern Wind Integration and Transmission Study prepared by EnerNex argues that wind power generation can contribute to the system

adequacy, and additional transmission can enhance that contribution [1].

Katzenstein and Apt [26] develop a metric to quantify the sub-hourly variability cost of individual wind power plants. They separate wind energy generation into three parts: load-following, hourly energy component and regulation component. They find a constant hourly energy component for each hour and match the load-following component to demand changes. The remaining regulation component is multiplied by up-and-down regulation prices of the Energy Reliability Council of Texas (ERCOT). They find twenty interconnected wind plants had a variability cost of $4.35 per MWh in 2008.

Swinand and Godel [51] study the impact of wind generation on system balancing costs of the UK market and systems operator for every period from November 2008 to November 2011. An econometric cost function approach is used, where the total cost of balancing is regressed against wind generation and other explanatory variables. They estimate the average marginal impact of wind generation on system balancing costs to be about € 0.513/MWh.

Since operational costs of VRE are close to zero, and most of the generation costs are associated with capital expenses, the LCOE of VRE is likely to decrease with increased penetration. Strbac and Aunedi [48] analyze additional VRE integration costs against a benchmark technology (nuclear in that case). They evaluate the integration costs based on the whole-system modeling approach (WeSIM model), with the ability to simultaneously make investment and operation decisions with hourly time resolution. They state that at low VRE penetrations, energy-related operation costs of VRE are high, whereas reserve and response costs constitute 1-2% of operating costs. As wind penetration increases four-fold, the energy-associated operation cost decreases 50%, and reserve and response cost increases to 25% (Figure 2.5). Overall, they argue that additional integration costs are £5-9/MWh for Great Britain.
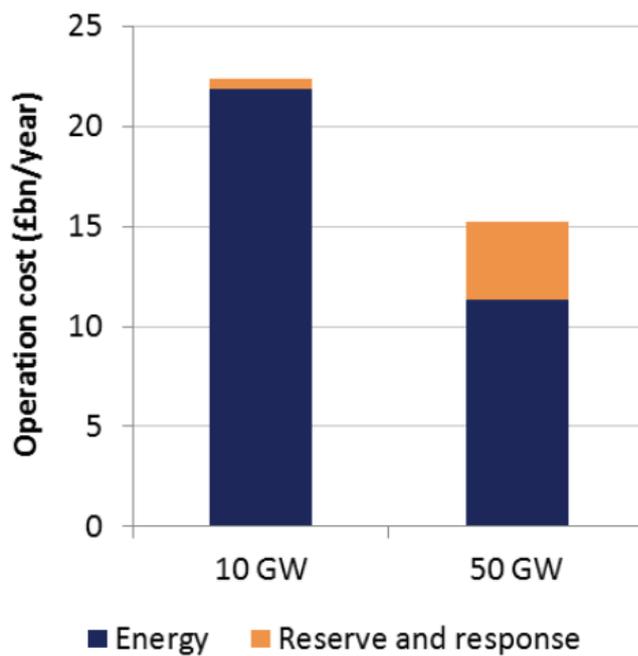
Figure 2.5: Operating cost associated with energy, reserve and response services for different wind penetration levels [48]. *As the share of wind power increases, reserve requirements of balancing authorities increase because of the volatility associated with wind power. On the other hand, since renewable energy sources have near-zero marginal costs, increasing wind energy production decreases operational costs, surpassing economic losses from reserve requirements.*

CHAPTER 3

CAPACITY FACTORS FORECASTING AND THE ESTIMATION OF THE INTEGRATION COST OF VARIABLE RENEWABLE ENERGY

In this chapter, we start with processing the data used in this thesis, then forecast the capacity factors, which are a crucial input for the optimization model. We also calculate system integration costs of variable renewable energy, usually omitted in capacity mix and generation mix optimization problems. A simple flowchart of the proposed methodology is given in Figure 3.1. In our modeling, first, we forecast the electricity generation capacity factor using the seasonal autoregressive moving average (SARIMA) models and estimate the system integration costs for the variable renewable energy. Then, using these outputs, we optimize the capacity expansion.
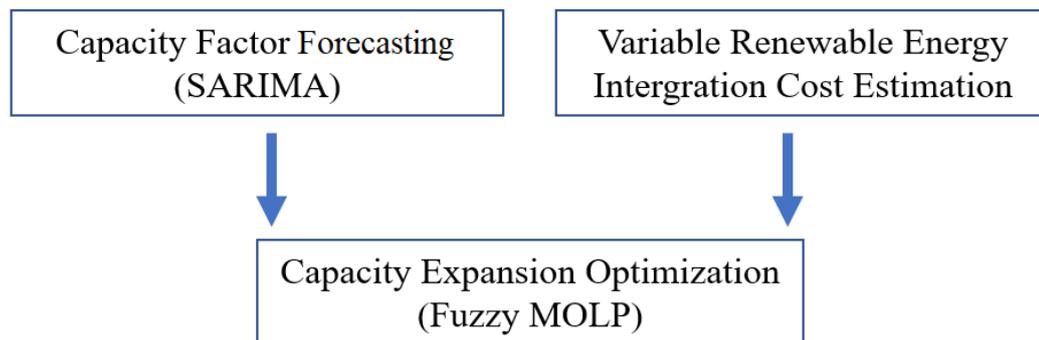
Figure 3.1: Flowchart of the proposed methodology.

3.1 Data Processing

The data of this thesis consist of the following categories, which are gathered from the corresponding sources.

i) Capacity factors, existing capacities, planned new installations and retirements, and electricity generations of utility scale generators across the US [59, 61, 64].

ii) CO_2, SO_2 and NO_x emissions, net nominal capacities, net nominal heat rates, capital costs, variable and fixed operation and maintenance costs, transmission costs of various generating technologies [3, 63].

iii) Hourly total electricity generation by source [39].

iv) Average fuel costs of power generation (coal, natural gas, oil and nuclear) [59, 65].

v) SO_2 allowance prices and SO_2 emission cap [4, 56].[1]

vi) Average operating heat rates (actual averages for VRE system cost calculations) [60].

The data are publicly available in given citations. We present the data in the second and fourth bullets in Table 3.1. The first row gives the heat rates of various power plants. Heat rate measures an electricity generator's efficiency and denotes how much energy is used per kW of electricity produced. Since renewable energy does not burn fuel to produce heat and electricity, this metric is not applicable for hydro, wind and solar power. The next four rows give the capital costs, fixed operation and maintenance costs, fuel costs and operation and maintenance costs of power plants. The last three rows give emission rates of power plants.

The capacity factor is a unitless metric that measures in what proportion the installed capacity of a power plant or fleet of plants is utilized. It can be defined as the periodic generation of a power plant divided by the product of the capacity and the number of hours over a given period [38]. In other words, it is the actual electricity generation

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[1] We assume SO_2 price throughout the analysis will be equal to 7-year advance allowance auction held in 2020 and NO_x price is equal to SO_2 price.

Table 3.1: EIA-defined assumptions on the variables

		Nuclear	Hydro	Wind	Solar	Coal	NG CC	NG CT	Coal 90% CCS	CC 90% CCS
Heat Rate	Btu/kWh	10461	-	-	-	8638	6431	9124	12507	7124
Cap. Cost	$/kW	6317	2752	1319	1331	3661	1079	1170	5997	2569
Fixed OM	$/kw-year	121.13	41.63	26.22	15.19	40.41	14.04	16.23	59.29	27.48
Fuel Cost	$/MMBtu	0.00681	0	0	0	2.16	3.12	3.12	2.16	3.12
Var. OM	$/MWh	2.36	1.39	3	0	4.48	2.54	4.68	10.93	5.82
CO2	lb/MMBtu	0	0	0	0	206	117	117	20.6	11.7
NOx	lb/MMBtu	0	0	0	0	0.06	0.0075	0.09	0.06	0.0075
SO2	lb/MMBtu	0	0	0	0	0.09	0	0	0.09	0

NGCC: Natural gas-fired combined cycle, NGCT: Natural gas-fired combustion turbine, CCS: Carbon Capture and Sequestration

(power $\times$ hours) divided by installed capacity times hours available in the year. The denominator shows the potential of generation without any interruption.

Figure 3.2 shows the capacity factors of various power sources between January 2012 and September 2020 [64]. Except for solar power, all of the series start in January 2012. Series for solar power starts in August 2014. Compared to the forecast horizon, the extent of the train set is short. Forecasting longer horizons with limited historical data is not desirable in time-series modeling. However, the data we employed is aggregate of all power plants in the US, and therefore its variability is minimized.

From the graphs of the series, we observe strong seasonality. Obviously, the capacity utilization of solar power plants increases in summer. On the contrary, wind power dips in the summer season. Since these two produce energy when the wind blows, and the sun shines, these deductions are self-evident. Hydropower reaches the highest capacity utilization during spring when streams are most powerful. Speaking of non-renewable resources, they show strong seasonalities as well. Nuclear power, coal and combined cycles have strong correlations with each other. Their capacity factor is higher in summer and winter than in spring and fall since seasonal electricity demand is greater in the first pair than the latter. Except for NGCT, the seasonality component is more apparent in series than the trend component.

At the day level, electricity demand is higher during the daytime than at night. Intermediate capacity runs during the day and is turned down or off at night (Figure 3.3). Renewables and nuclear constitute the base-load; combined cycle and coal are in the intermediate zone, and combustion turbines are peakers.

(a) Nuclear Power

(b) Hydro Power

(c) Wind Power

(d) Solar Power

(e) Coal-fired

(f) Natural Gas-fired Combined Cycle

(g) Natural Gas-fired Combustion Turbine
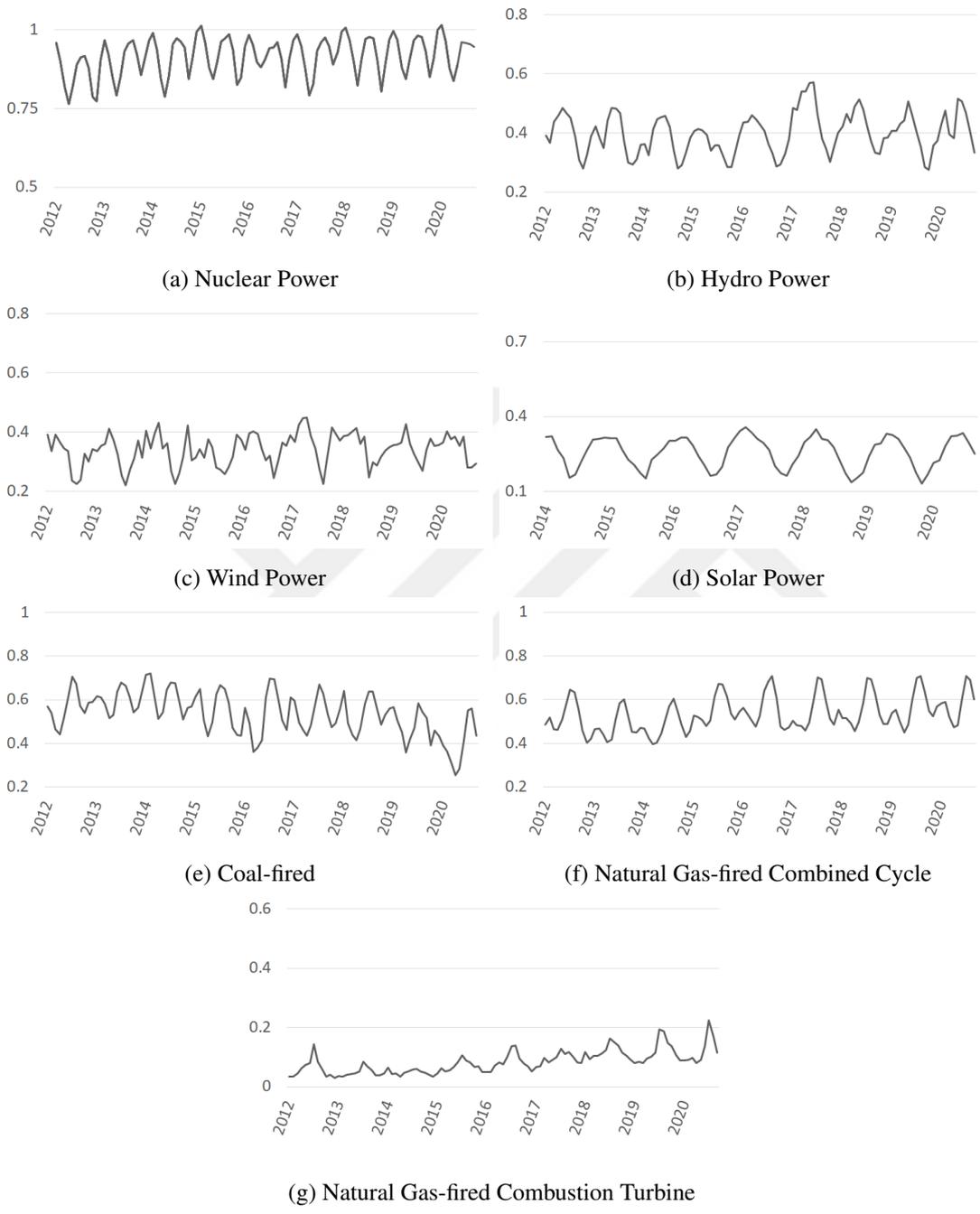
Figure 3.2: Original observations of capacity factors in the US electric power plants.
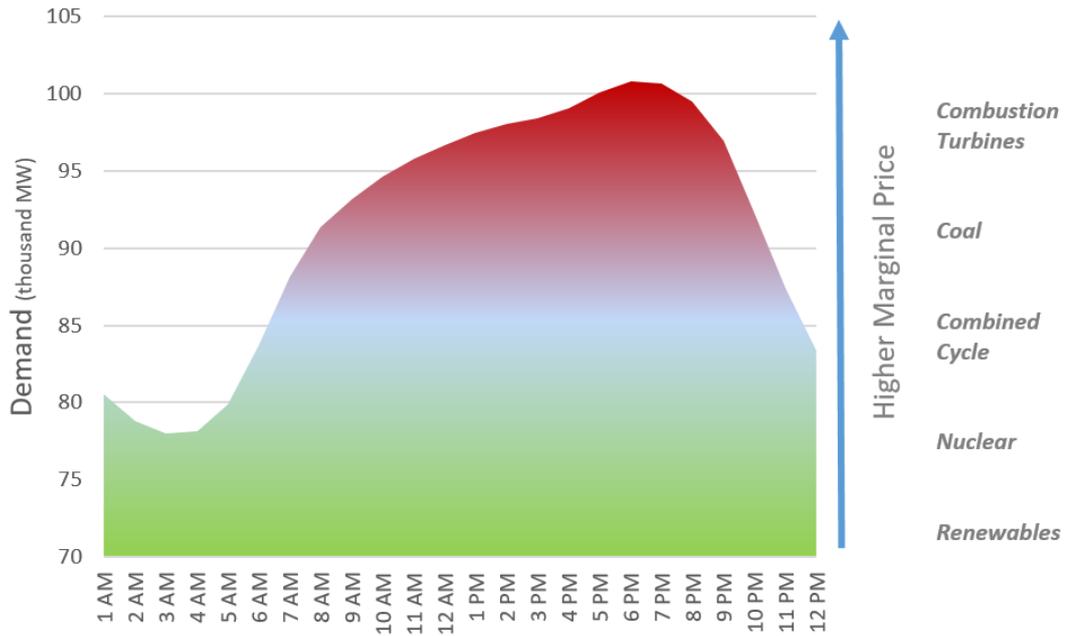
Figure 3.3: Load curve of a typical day [39]. *Renewable and nuclear energy operate mostly every hour of the day. Combined cycle power plants and coal-fired plants constitute mid-level sources, adjusting production to usual up-and-downs in demand. Combustion turbines are the most flexible plants and operate only a few hours a day when the demand surges.*

Table 3.2: Descriptive statistics of capacity factor time series.

	Nuclear power	Hydro power	Wind power	Solar power	Coal-fired	NGCC	NGCT
Mean	0.915	0.397	0.342	0.255	0.538	0.531	0.081
Std. Error	0.006	0.007	0.005	0.007	0.010	0.008	0.004
Median	0.922	0.394	0.348	0.267	0.545	0.513	0.080
Mode	0.967	0.407	0.345	0.312	0.612	0.465	0.080
Std. Dev.	0.062	0.070	0.054	0.063	0.100	0.079	0.035
Kurtosis	-0.594	-0.510	-0.402	-1.172	-0.201	-0.361	0.464
Skewness	-0.558	0.202	-0.424	-0.360	-0.406	0.606	0.798
Range	0.253	0.296	0.229	0.226	0.465	0.313	0.164
Minimum	0.764	0.275	0.220	0.131	0.255	0.395	0.029
Maximum	1.017	0.571	0.449	0.357	0.720	0.708	0.193
JB Test	6.786	1.931	3.790	5.550	2.982	6.753	11.143
p-value	0.034	0.295	0.095	0.046	0.147	0.034	0.013

Descriptive statistics (Table 3.2) show that nuclear power has the highest mean, while the highest variance is observed in coal-fired power plants. The distribution of observations has negative kurtosis except for natural gas-fired combustion turbine and

biomass. Hydroelectric power and natural gas-fired are right-skewed. According to the Jarque-Bera (JB) test for normality for nuclear power, solar power, biomass, natural gas-fired combined cycle and combustion turbine, we reject the null hypothesis that these series come from normal distributions at a significance level of 0.05. We applied Box-Cox transformation [11] to the first five series and Yeo-Johnson transformation [24] to the last three series To achieve better normal distribution characteristics. Applying mathematical transformations to the initial data may help to have normally distributed residuals with constant variance. These properties ease the calculation of prediction intervals [42].

The one-parameter Box-Cox transformations [11] are defined as

$$y_i^{(\lambda)} = \begin{cases} \log(y_t) & \text{if } \lambda = 0; \\ (y_t^\lambda - 1)/\lambda & \text{otherwise,} \end{cases}$$

where, y_t are observations and λ is a parameter, selected to obtain best normal approximation, where $\lambda \in [-5, 5]$. When λ is zero, simple log transform is applied, otherwise a power transformation is used. As λ increase in magnitude, exponentiation effect and denominator increases in different scales. The Yeo-Johnson transformation allows $\lambda \in \mathbb{R}$ and negative values in the series as follows [24].

$$y_i^{(\lambda)} = \begin{cases} ((y_i + 1)^\lambda - 1)/\lambda & \text{if } \lambda \neq 0, \ y \geq 0 \\ \log(y_i + 1) & \text{if } \lambda = 0, \ y \geq 0 \\ -[(-y_i + 1)^{(2-\lambda)} - 1]/(2 - \lambda) & \text{if } \lambda \neq 2, \ y < 0 \\ -\log(-y_i + 1) & \text{if } \lambda = 2, \ y < 0. \end{cases}$$

Histograms of the original series and transformed series are appended in Appendix A. After transformations, the series get normal distribution characteristics to varying extent, except for solar power.

3.2 Capacity Factor Forecasting

In classical regression analysis, the dependent variable is only allowed to be explained by present independent variables. However, sometimes, such an assumption may

not be sufficient to model time series data, only with current independent variables. In these cases, it is desirable to predict dependent variable with past and present observations of independent variables, as well as past observations of the dependent variable [43].

We model capacity factors with SARIMA and exponential smoothing state space (ES) models in our work. Best fitting models are selected according to the root-mean-squared-error (RMSE) values of the test set. The last 12 months of the observations are spared as test sets and the earlier ones as training sets. We model the series both with and without normality transformations to observe normality transformation effects on test set errors. In non-transformed data, each best fitting (seasonal) ARIMA models have lower error measures than best fitting ES models. In the transformed data, except for two series (nuclear and coal), where the ES model is slightly better, ARIMA models have lower error measures. Therefore, we forecast the capacity factors using the best fitting SARIMA models.

Autoregressive moving average models (ARMA) describe a stationary process with two components. The AR part models past lagged values of the variable to be described, MA part models past observed error terms. The generalized ARMA(p, q) model can be defined as follows:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t.$$

Unlike MA models, AR models are not always stationary. Autoregressive integrated moving average models combine the ARMA model and differencing of lagged values to make series stationary. Seasonal ARIMA models are formed by including three new terms to specify seasonal AR, I and MA components of the time series [42].

We model nuclear power series with SARIMA$(1,0,3)(0,1,1)_{12}$ model. The first three digits define the trend component of the model, the second three digits define seasonal components, and the last number denotes the seasonality of the series. The series exhibits regular fluctuations every 12 months. The value at time t can be explained by functions of the past values of time $t-1$, error term of time $t-3$ and error term of time $t-12$. One differencing is needed to remove seasonality. We used `forecast` package in R statistical software [68, 23]. We tested each model with AR and MA lags from 0 to 3. Interested readers may find a detailed list of tested ARIMA and ES

models in Appendix B. Plots of predictions and test set, and plots of predictions in 5-year horizon are illustrated in Figures 3.4 and 3.5.

Residuals diagnostics are given in the Appendix C. Residuals of a good forecast should satisfy two criteria [42]. Firstly, residuals should center around zero; this is essential to claim that the models are unbiased. Graphs of the residuals and histograms of residuals show this property is satisfied. Secondly, no correlation should exist between lagged residuals. Otherwise, there would be information left to be used in the forecast. Autocorrelation function (ACF) graphs of residuals indicate that no lagged values have a correlation outside of the bounds (-0.2,0.2) (except for three high lags).

These capacity factor forecasts are inputs of the Fuzzy MOLP model. Capacity factors are affected by factors that affect electricity generation. These include the availability of a source of energy (such as wind or sun), initiatives to promote specific sources like natural gas, nuclear and renewable energy, air pollution regulations, price developments for coal and natural gas, changes in generation technology, and power dispatch decisions made by utility or power grid operators [46]. Dispatch decisions are given continuously according to some economic, environmental or operational considerations. Economic dispatch decisions aim to maximize welfare; environmental decisions aim to minimize detrimental effects on the environment. Operational considerations may include ramp rates or minimum running hour requirements [14, 36]. In our work, we simulate capacity factors using SARIMA models. Then include them in the proposed optimization model. Thereby, we can incorporate all the factors that affect capacity factor, then seek an answer to the electricity generation mix problem to minimize cost and environmental effects.

(a) Nuclear Power, SARIMA$(1,0,3)(0,1,1)_{12}$

(b) Hydro Power, SARIMA$(0,0,3)(2,1,3)_{12}$

(c) Wind Power, SARIMA$(1,0,3)(1,1,0)_{12}$

(d) Solar Power, SARIMA$(3,0,3)(2,1,2)_{12}$

(e) Coal, SARIMA$(3,1,3)(3,1,0)_{12}$

(f) NGCC, SARIMA$(0,0,0)(2,1,2)_{12}$

(g) NGCT, SARIMA$(0,0,0)(3,1,3)_{12}$
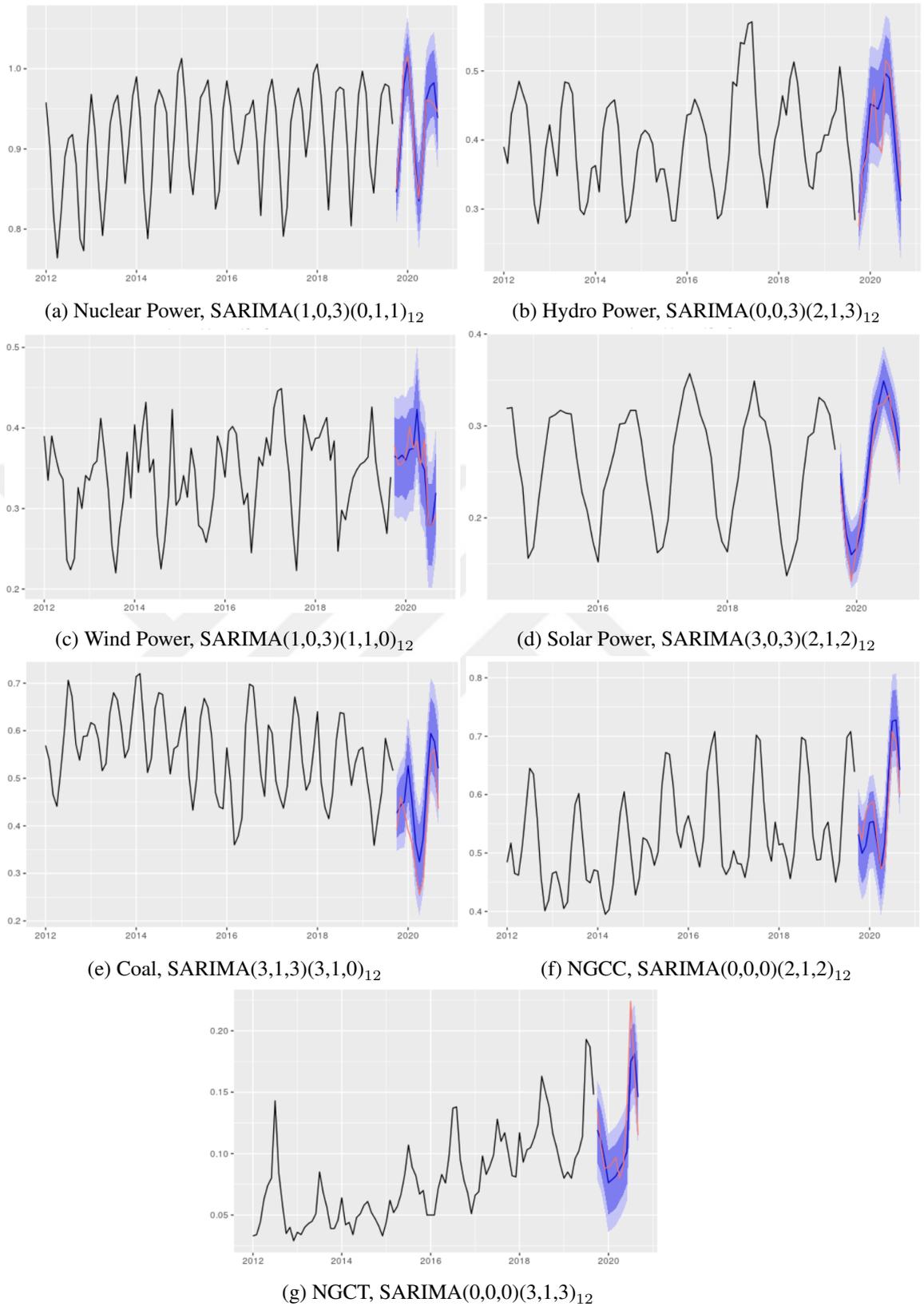
Figure 3.4: Train set forecasts and test set patterns of capacity factors (Orange lines are test sets).

(a) Nuclear Power, SARIMA$(1,0,3)(0,1,1)_{12}$

(b) Hydro Power, SARIMA$(0,0,3)(2,1,3)_{12}$

(c) Wind Power, SARIMA$(1,0,3)(1,1,0)_{12}$

(d) Solar Power, SARIMA$(3,0,3)(2,1,2)_{12}$

(e) Coal, SARIMA$(3,1,3)(3,1,0)_{12}$

(f) NGCC, SARIMA$(0,0,0)(2,1,2)_{12}$

(g) NGCT, SARIMA$(0,0,0)(3,1,3)_{12}$
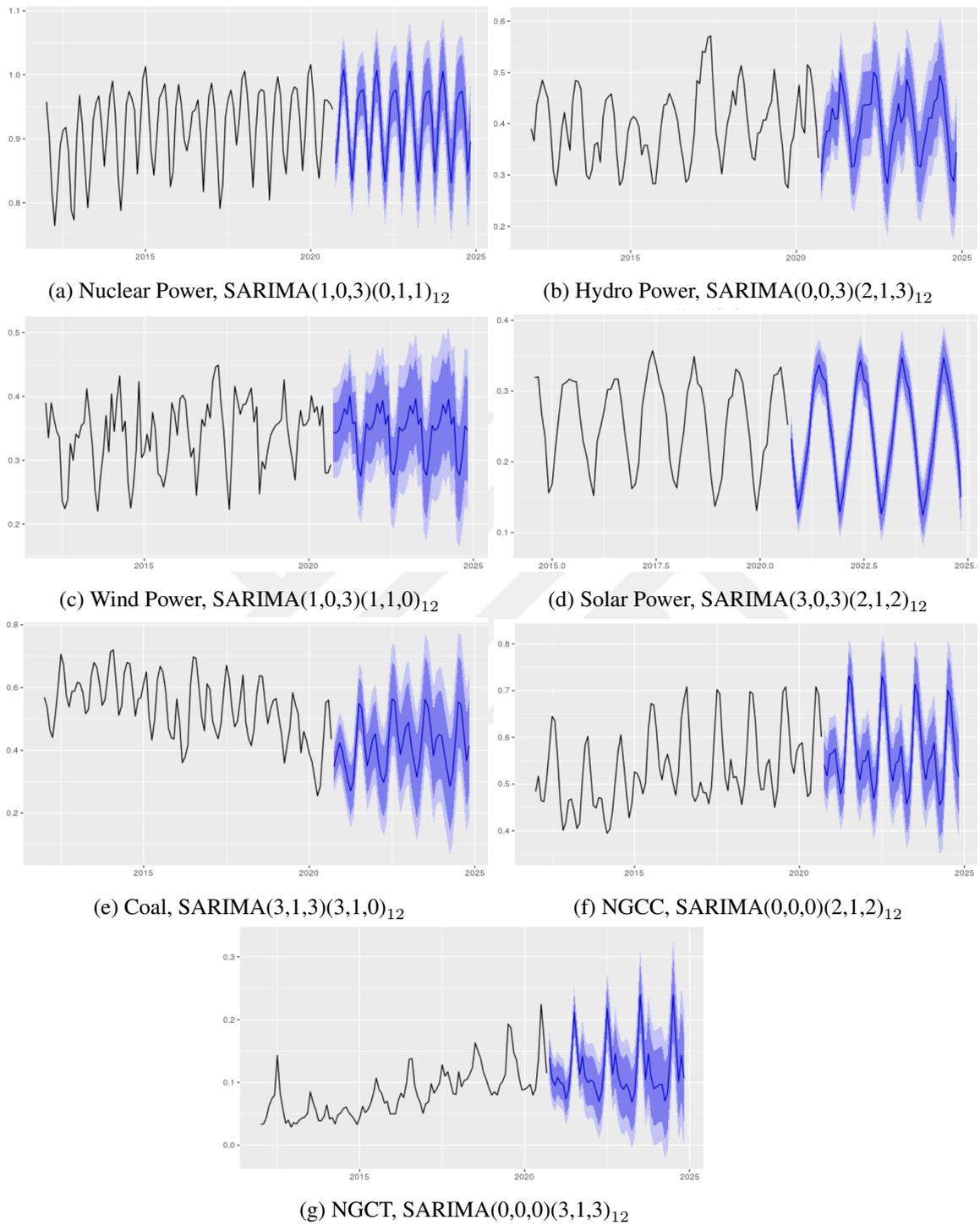
Figure 3.5: Best fitting forecasts of capacity factors.

30

3.3 Cost of Variable Renewable Energy Integration

As we present in Section 2.3, there is no consensus on power units' system costs. Common approaches to estimate system costs are economic theory, statistical learning, historic prices-based, and dispatch models. The lack of a consensus is understandable since system costs (energy-related and integration-related costs) may depend on the existing structure of the electric power sector, capital and variable costs of technologies and geographical conditions. Therefore, in this section, we estimate VRE integration's cost to the system for this thesis. We mainly follow methods in Power System Economics [47].

The integration costs are defined as:

$$C_{integration} := C_{profile} + C_{balancing} + C_{grid}, \tag{3.1}$$

$Gen_{residual}$ denotes amount of non-VRE generation and it is given as

$$Gen_{residual} = Gen_{total} - Gen_{VRE}. \tag{3.2}$$

Let $C_{total}(0)$ denotes total system cost when there is no generation from VRE and $C_{residual}(Gen_{VRE})$ denotes total costs of the conventional part of a power system with VRE. Then, the profile costs are defined as:

$$C_{profile} := C_{residual}(Gen_{VRE}) - C_{total}(0) \times \frac{Gen_{residual}}{Gen_{total}}. \tag{3.3}$$

Since the remaining units in the system undertake integration costs, we can define profile costs as in the Equation (3.3). The first term can also be stated as the total system cost minus generation costs of VRE. The second term excludes VRE from the system. Excluding near-zero marginal cost generation from the system increases the total cost. Therefore, we multiply it with the share of the remaining generation.

To estimate $C_{total}(0)$, we draw a load-duration curve with the data of PJM Interconnection in 2019 and a screening curve with the capital and variable cost data we gave in Section 3.1. We illustrate the load-duration curve in Figure 3.6. In Figure 3.6, the blue curve shows net generation as a function of hours per year, i.e., for how many hours that generation level was seen, and the orange curve shows generation by the residual system without VRE.
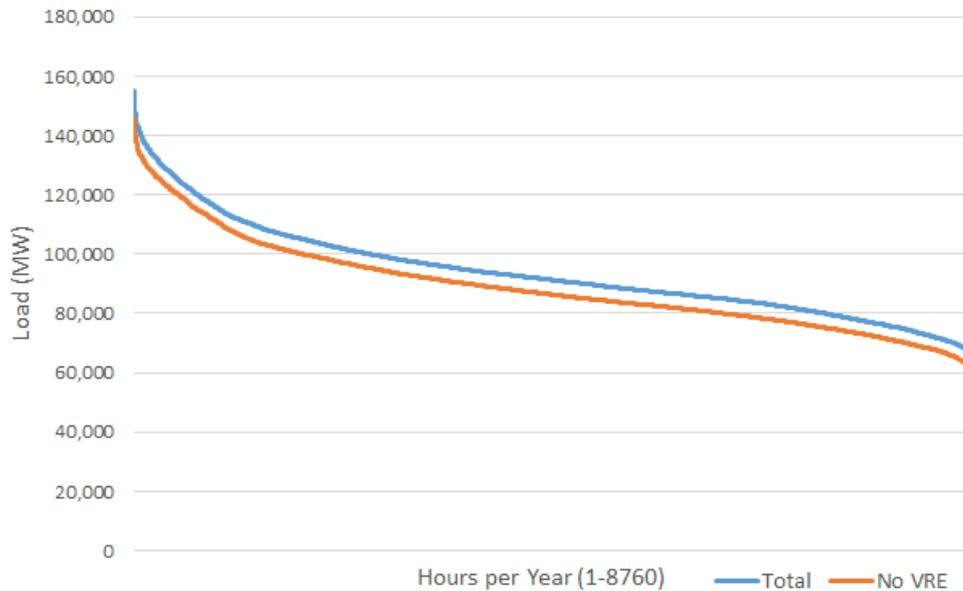
Figure 3.6: Load-duration curve. *Electricity load is graphed against the number of hours per year. For very few hours in a year, electricity demand exceeded 140 GW. On the other hand, there was at least 60 GW electricity load in every hour of the year. The orange curve represents the load-duration curve when the load met by VRE is subtracted.*

Figure 3.8 gives the total costs of fossil-fueled power plants as a function of time. Only fossil-fueled plants are given because they are not subject to natural variability as VRE are. So that we can calculate hypothetical cost figures if we were to meet all demand with the lowest-cost fossil-fuel plants. This figure shows that oil-fired combustion turbines have the lowest capital and fixed annual costs and highest variable costs. The natural-gas combined cycle has slightly higher capital costs and lower variable costs. An interesting point to note that coal and nuclear are not economically efficient. This is mostly due to natural gas's downward price movements compared to pre-2009 levels (Figure 3.7) and partly due to changes in fixed costs and thermal efficiency of plants. Figure 3.8 suggests that running oil-fired combustion turbines are economically efficient only if they run for 182 hours. This makes them eligible as peaker units, which run only when the load surges. Assuming we are able to expand the capacity as much as required, the rest of the load should be met by natural gas-fired combined cycles. Higher natural gas prices imply a screening curve, as in Figure 3.9. This curve also implies nuclear energy becomes economically efficient after running for most of the hours in a year. Therefore, under the conditions of

32

Figure 3.9, nuclear energy would constitute the baseload and run throughout the year.

$$Total\ Cost(t) = \quad Annualized\ Capital\ Cost\ +\ Fixed\ Annual\ Costs$$
$$+\quad Variable\ Costs(t). \tag{3.4}$$

Figure 3.7: Henry Hub natural gas prices.
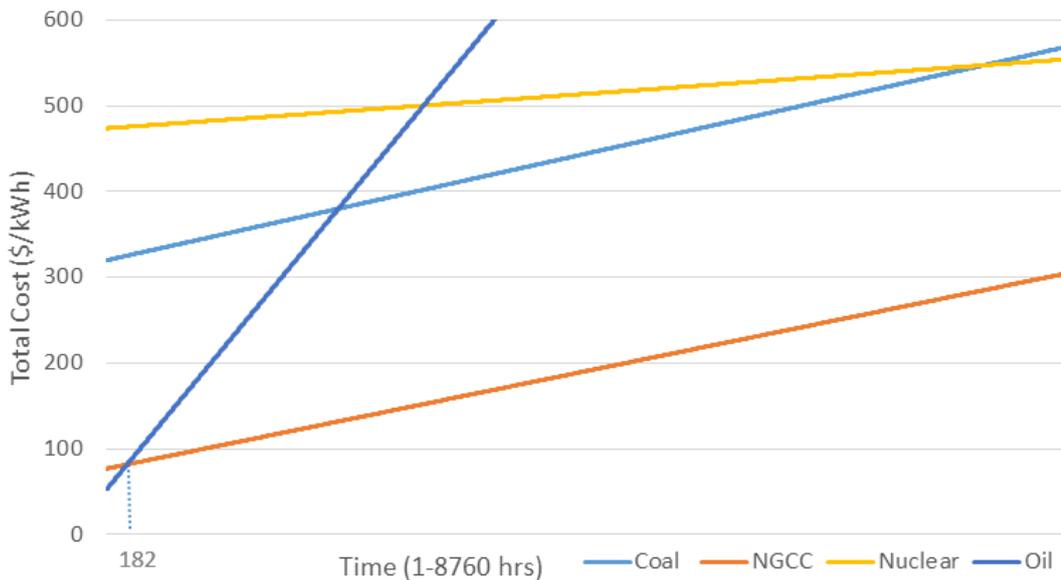
Figure 3.8: A screening curve. *Running oil-fired combustion turbines are economically efficient only if they are run for 182 hours. This makes them eligible as peaker units, which run only when the load surges. Coal and nuclear are not economically efficient. This is mostly due to natural gas's downward price movements.*

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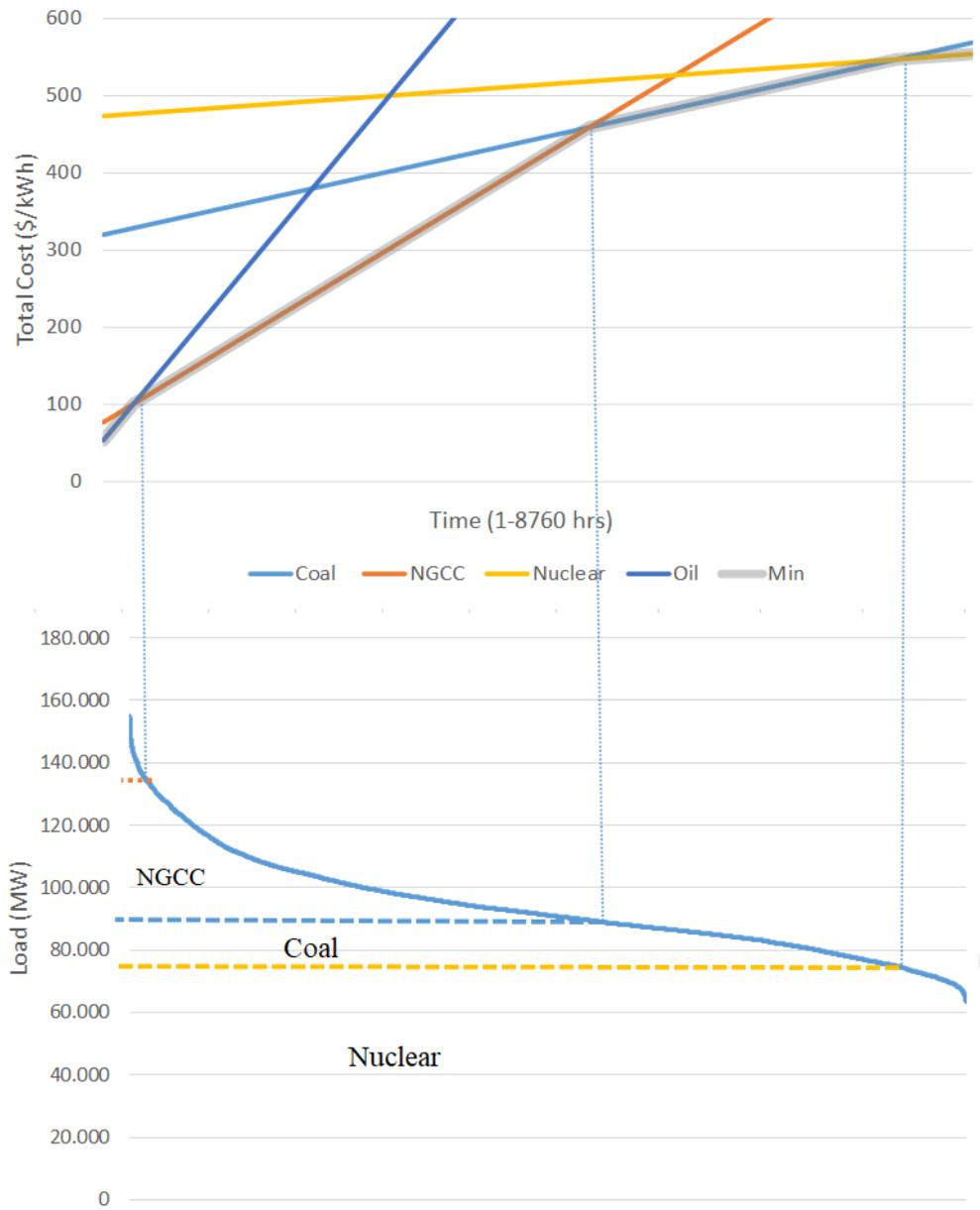
Figure 3.9: Screening curve and load-duration curve with higher NGCC variable costs. *In the case of higher natural-gas-fired combined-cycle variable costs, screening curves and load duration curve are drawn as above. Oil-fired plants have the lowest fixed costs, and nuclear power plants have the highest fixed costs. Thus, oil-fired plants are economically efficient only if they run for very limited hours in a year.*

The total cost can be formulated as a function of time as in Equation 3.4. An alternative formulation of the total cost is obtained by inverting the load-duration curve. In Equation 3.5, we multiply the inverse load-duration curve with the minimum cost values in the screening curve and integrate over peak load level.

34

Let ll denote load level (MW), ll_{max} denote the peak load, $B(ll)$ denote inverse of load-duration curve $A(t)$ and $E_{min}(ll)$ denote minimum cost of energy (nuclear, coal, natural gas-fired combined cycle and oil-fired combustion turbines) in that load level ll.

$$C_{total}(0) = \int_0^{ll_{max}} B(ll) \times E_{min}(ll)\, d(ll). \tag{3.5}$$

Integrating over $[0, ll_{max}]$ gives total cost in case no VRE. To obtain total cost with VRE penetration $C_{residual}(Gen_{VRE})$, we need to integrate the expression over residual load level, i.e., peak load - load served by VRE. Then, we solve Equation (3.3) with these values. We can interpret Equation (3.3) as follows: VRE penetration shifts the load-duration curve to the left (Figure 3.6), making fossil-fuels above baseload operate less than they actually could generate efficiently. Therefore, these fossil-fuel generators operate in suboptimal load levels.

We calculate profile cost \$0.2/MWh for 20% VRE penetration. We take balancing costs exogenously from literature estimates and transmission cost from EIA estimates, [27, 63] as these are not the main focus of the research. We assume \$3/MWh VRE integration costs in total. So far, we have forecast and estimated two inputs of the multi-objective optimization model: capacity factors and VRE integration costs.

CHAPTER 4

CAPACITY EXPANSION PREDICTION USING FUZZY OPTIMIZATION

4.1 Problem Statement

Our goal in capacity expansion optimization is to draw a viable, economical and environment-friendly path to construction and retirement decisions of electricity generation capacity. Electricity capacity expansion should satisfy the electricity demand of the upcoming periods and should be technically feasible. The problem of determining optimal power plant construction and retirement decisions includes uncertainties. The fuzzy model we propose here allows uncertainties to exist, such as cost function. The cost function includes fuel cost, capital costs and other variable costs which cannot be determined with certainty. Given an estimate is available, the fuzzy theory allows any value to be set to a level within a range. Then the decision-maker chooses the most desired solution given the constraints [70].

4.2 Fuzzy Multi-Objective Models

Fuzzy multi-objective programming is based on fuzzy sets in Mathematics. To define fuzzy sets, we first define crisp sets. A classical (crisp or hard) set is a collection of distinct objects, defined in such a manner as to separate the elements of a given universe of discourse into two groups: those that belong (members) and those that do not belong (non-members). The transition of an element between membership and non-membership in a given set in the universe is abrupt and well defined [45]. A fuzzy

set is a generalization of an ordinary set in that it allows the degree of membership for each element to a range over the unit interval $[0, 1]$ [17]. The membership in a crisp subset of X is often viewed as a characteristic function μ_A from x to $\{0, 1\}$ such that

$$\mu_A(x) = \begin{cases} 1, & \text{if and only if } x \in A \\ 0, & \text{otherwise,} \end{cases}$$

where $\{0, 1\}$ is called a valuation set. Whereas, $\tilde{A}$ is a set of ordered pairs, where $\mu_A(x)$ is called the membership function (or characteristic function) of x and $\mu_A(x)$ is the grade of membership of x in $\tilde{A}$ [17].

$$\tilde{A} = \{(x, \mu_A(x)) | x \in U\},$$

where the set U denotes universal set. On the other hand, the multi-objective optimization problems can be formulated as follows:

$$\underset{x \in X}{\text{minimize}} \quad F(x) = [f_1(x), f_2(x), ..., f_i(x)], \tag{4.1}$$

where $X \in \mathbb{R}$ is an arbitrary set, and $i \in I$, where I is the set of objective functions.

For a nontrivial multi-objective optimization problem, no single solution exists, but a set of alternatives represents Pareto optimal front. The Pareto front is defined as a set of non-inferior or non-dominated solutions in the objective space defining a frontier, beyond which none of the objectives can be improved without making at least one of the other objectives worse [34]. If objective functions are not improved simultaneously, or they are conflicting, Pareto frontier(s) exists.

Without additional subjective preference information, all Pareto optimal solutions are considered equally good [33]. The solution approaches to multi-objective problems can roughly be grouped into two categories. In the first group, neutral Pareto optimal sets are found, and the trade-offs in satisfying the conflicting objectives are quantified. This group includes the so-called "no preference" methods, at which there is no need for an expert to assign preferences to different objectives. In the second group, a single solution is found by combining different objectives via an expert's preferences on each of them. Preferences of an expert are involved in the process in so-called "a priori, a posteriori or interactive" methods [34].

In a priori methods, preference information is first asked from an expert/decision-maker and then a solution best satisfying these preferences is found. In a posteriori

method, a decision-maker chooses from a representative set of Pareto optimal solutions. In interactive methods, a decision-maker is shown a non-dominated set of solutions and steers the search in what direction the solutions could be improved [34].

In our fuzzy multi-objective model, we follow the methods presented in [30] and [70]. Majidi et. al. [30] propose a multi-objective model for optimal operation of various energy systems using weighted sum technique and fuzzy satisfying approach. Yu et al. [70] develop a fuzzy multi-objective optimization model to find an optimal mix of four renewable energy systems (RES) hydro, wind, solar PV, and biomass for China's electricity market. They aim to minimize capital costs, maximize utilization hours and maximize carbon reduction. These objectives subject to power demand, renewable power exploiting potentiality, range of cumulative installed capacity and non-water renewable power consumption target constraints.

We express each objective as a convex combination of 0 and 1 through membership functions. This transformation enables commensurability among different ranges and units. The new range of values between 0 and 1 shows goal achievement for that individual objective [70]. A linear membership function μ_{f_i} of the objective function i, can be defined as follows. A linear membership function of a minimization problem is shown in Figure 4.1.

$$\tilde{A} = \{(f_i(x), \mu_A(x)) | x \in U\}$$

where

$$\mu_{f_i} = \begin{cases} 1, & \text{for } f_i \leq f_{i,min} \\ \dfrac{f_{i,max} - f_i}{f_{i,max} - f_{i,min}}, & \text{for } f_i \leq f_{i,max} \text{ and } f_i \geq f_{i,min} \\ 0, & \text{for } f_i \geq f_{i,max}. \end{cases}$$

In two-objective function model, $f_{1,min}$ is obtained when objective function f_1 is optimized in a single objective function model separately. $f_{1,max}$ is obtained when objective function f_2 is solved separately. These are maximum and minimum possible values of objective function f_i.

After transforming objective functions using membership functions, the optimization

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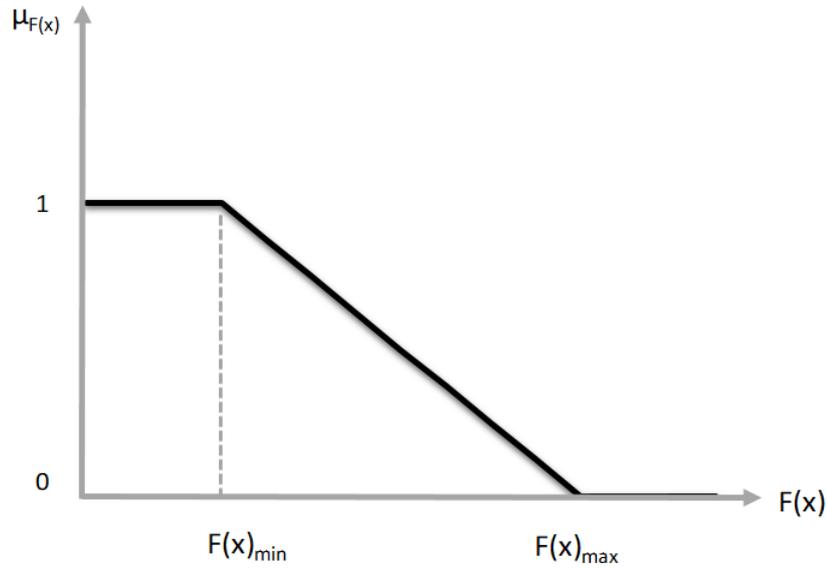
Figure 4.1: Linear membership function.

problem given in Equation 4.1 becomes:

$$\underset{x \in X}{\text{maximize}} \ \lambda(x) = w_1 \times \mu_{f_1}(x) + w_2 \times \mu_{f_2}(x),$$

$$s.t. \ \lambda(x) \leq \mu_{f_1}(x) + d_1^+ + d_1^-,$$

$$\lambda(x) \leq \mu_{f_2}(x) + d_2^+ + d_2^-,$$ \hfill (4.2)

$$w_1 + w_2 = 1,$$

where w_1 and w_2 represent weights of the objective functions given by the decision-maker, d_i^+ and d_i^- denote the deviational variables in positive and negative directions as in [49, 50]. We test the model using different weight parameters ranging from 0 to 1 with increments of 0.01. We present the flowchart of the proposed model in Figure 4.2.
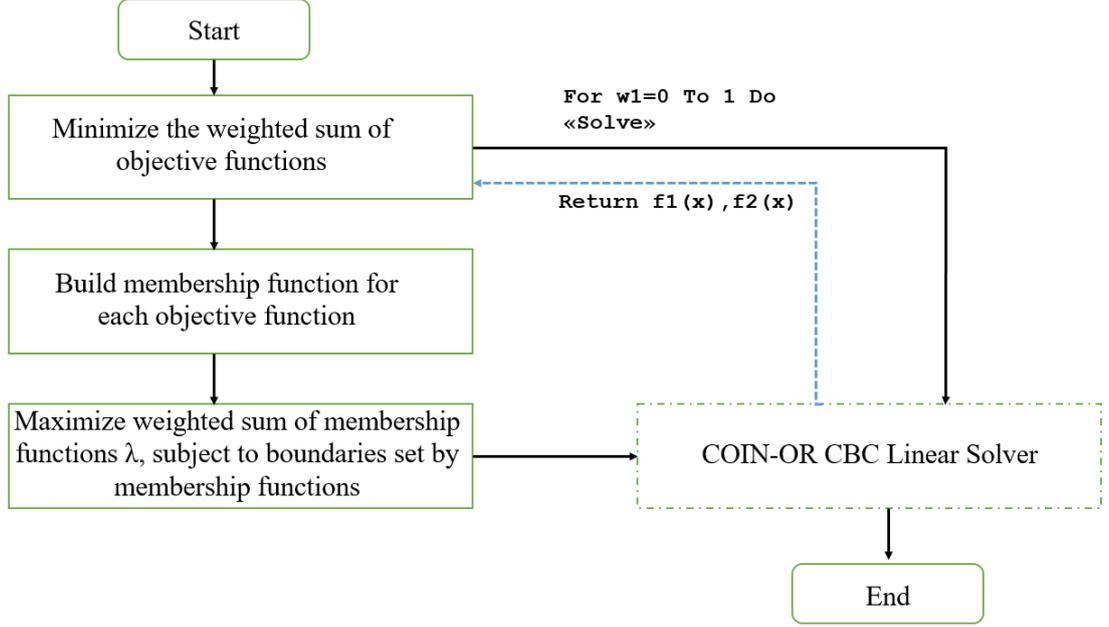
Figure 4.2: Flowchart of the proposed Fuzzy MOLP.

4.3 Multi-Objective Linear Model

In this model, we assume that capital investments are made once for a plant, the whole transmission grid is interconnected, geothermal and biomass capacities do not change and planned power plants (under construction) and planned retirements are going to take place in 2021.

Decision variables are the number of installed power plant p, in period t, $X_{p,t}$ and the number of retired power plant p, in period t, $Z_{p,t}$. $p \in P$ and the set P consists of 9 types of power plants, namely hydro, nuclear, wind, solar, coal, NGCC, NGCT, coal with 90% carbon capture and NGCC with 90% carbon capture technologies. $t \in T$ and the set T covers 2021 Q4-2050.

Control variables are given in Table 4.1 which are going to be inserted in the model. Some of them are defined in Section 3.1. We present the summary of the optimization model in Section **??**.

Two objective functions are set for each of the targets. The first one f_1 aims to minimize total costs (investment costs, fixed annual costs, operations and maintenance costs, fuel costs of electricity generation, and sulfur dioxide and nitrogen oxide al-

41

Table 4.1: Control Variables

Abbr.	Variable	Unit
CC_p	Capital cost of a power plant p.	*$/MW*
FA_p	Fixed annual costs of power plant p.	*$/MW*
OM_p	Operations and maintenance costs of power plant p.	*$/MW*
$Fuel_p$	Fuel costs of power plant p.	*$/Btu*
$CO2_p$	Carbon dioxide emission of a plant p.	*lb/MMBtu*
$SO2_p$	Sulfur dioxide emission of a plant p.	*lb/MMBtu*
NOx_p	Nitrogen oxides emission of a plant p.	*lb/MMBtu*
HR_p	Heat rate of a plant p. How much heat is produced per MWh electricity generated. The higher the heat rate, the lower the thermal efficiency of a plant.	*Btu/MkWh*
$CF_{p,t}$	Capacity factor of a plant p in period t.	
$UnitCap_p$	Nominal unit capacity of power plant p.	*kW*
h_t	Utilization hours in period t. Number of days in the month times 24.	*hours*
$PRNW$	Renewable energy sources.	
$PCLN$	Clean energy sources (renewable energy sources and nuclear energy).	
AC	Allowance costs of SO_2 and NO_x	*$*
Cap_{SO2}	Total emission cap of SO_2 emitted by electricity generating units.	*lb*
w_i	Weights of objective functions 1 and 2 in fuzzy optimization setting	
$Cln_{p,t}$	Electricity generation from renewable and nuclear energy in period t	*MWh*
Inv_t	Capital available to invest for period t	*$*
$q_{p,1}$	Maximum aggregate power of retired plants in period t.	*MW*
$q_{p,2}$	Maximum aggregate power of new plants in period t.	*MW*

lowance costs) and it is given as follows.

$$
\begin{aligned}
\underset{X,Z}{\text{minimize}}\ \ f_1 = \sum_{p=1}^{P}\sum_{t=1}^{T}\ \Bigg[& X_{p,t} \times CC_p \\
& + (X_{p,t} + Z_{p,t} - [X_{p,t-1} + Z_{p,t-1}]) \times UnitCap_p \\
& \times \Big[FA_p + (CF_{p,t} \times h_t) \\
& \quad \times \big[(OM_p + Fuel_p \times HR_p) \\
& \quad + AC \times (SO_{2p} \times HR_p + NO_{Xp} \times HR_p) \big] \Big] \Bigg].
\end{aligned}
$$

subject to:

$$
\sum_{p=1}^{P}(X_{p,t} + Z_{p,t} - [X_{p,t-1} + Z_{p,t-1}]) \times UnitCap_p \times CF_{p,t} \times h_t = D_t \quad \forall t.
$$

$$
q_{p,1} \le Z_{p,t} \le 0, \quad 0 \le X_{p,t} \le q_{p,2} \quad \forall t,\ \forall p.
$$

$$
\begin{aligned}
& (X_{ct,t} + Z_{ct,t} - [X_{ct,t-1} + Z_{ct,t-1}]) \times UnitCap_{ct} \times CF_{ct,t} \times h_t \\
& \ge 0.05 \times \sum_{p=1}^{P}(X_{p,t} + Z_{p,t} - [X_{p,t-1} + Z_{p,t-1}]) \times UnitCap_p \times CF_{p,t} \times h_t, \quad \forall t.
\end{aligned}
$$

$$
\begin{aligned}
& (X_{hyd,t} + Z_{hyd,t} - [X_{hyd,t-1} + Z_{hyd,t-1}]) \times UnitCap_{hyd} \times CF_{hyd,t} \times h_t \\
& \ge 0.05 \times \sum_{p=1}^{P}(X_{p,t} + Z_{p,t} - [X_{p,t-1} + Z_{p,t-1}]) \times UnitCap_p \times CF_{p,t} \times h_t, \quad \forall t.
\end{aligned}
$$

$$
\sum_{p=1}^{P} X_{p,t} \times UnitCap_p \times CC_p \le Inv_t.
$$

$$
\sum_{p=1}^{P}\sum_{t=1}^{T}(X_{p,t}+Z_{p,t}-[X_{p,t-1}+Z_{p,t-1}]) \times UnitCap_p \times CF_{p,t} \times h_t \times SO_{2p} \times HR_p \le Cap_{SO2}.
$$

$$
(X_{p,t} + Z_{p,t} - [X_{p,t-1} + Z_{p,t-1}]) \times UnitCap_p \ge 0, \quad \forall t,\ \forall p.
$$

We can reformulate f_1 by introducing $Gen_{p,t}$ and $Y_{p,t}$. $Gen_{p,t}$ denotes electricity generation of a power plant p, in period t. It can be expressed as: $Gen_{p,t} = Y_{p,t} \times CF_{p,t} \times h_t$. $Y_{p,t}$ denotes cumulative installed capacity of a power plant p, in period t.

It can be expressed as: $Y_{p,t} = (X_{p,t} + Z_{p,t}) \times UnitCap_p + Y_{p,t-1}$. By placing these two variables into the f_1, we can rewrite the same function as:

$$\underset{X,Z}{\text{minimize}} \; f_1 = \sum_{p=1}^{P} \sum_{t=1}^{T} \big[X_{p,t} \times CC_p + Y_{p,t} \times FA_p$$
$$+ Gen_{p,t} \times (OM_p + Fuel_p \times HR_p)$$
$$+ Gen_{p,t} \times AC \times (SO_{2p} \times HR_p + NO_{Xp} \times HR_p) \big],$$

with the constraints given above. The term $X_{p,t} \times CC_p$ gives one-time capital investment per MW of new capacity constructed. The term $Y_{p,t} \times FA_p$ denotes cumulative aggregate capacity times fixed annual costs, the annual fixed costs such as rental lease payments. The term $Gen_{p,t} \times (OM_p + Fuel_p \times HR_p)$ denotes operations and maintenance costs and fuel costs per MWh of electricity generated. The term $Gen_{p,t} \times (OM_p + Fuel_p \times HR_p)$ gives allowance costs of sulphur dioxide and nitrogen oxides per MWh of electricity generated.

The second objective function f_2 is set to minimize CO_2 emissions and given as follows.

$$\underset{X,Z}{\text{min}} \; f_2 = \sum_{p=1}^{P} \sum_{t=1}^{T} (X_{p,t} + Z_{p,t} - [X_{p,t-1} + Z_{p,t-1}]) \times UnitCap_p \times CF_{p,t} \times h_t \times CO_{2p} \times HR_p.$$

subject to:

$$\sum_{p=1}^{P} (X_{p,t} + Z_{p,t} - [X_{p,t-1} + Z_{p,t-1}]) \times UnitCap_p \times CF_{p,t} \times h_t = D_t \quad \forall t.$$

$$q_{p,1} \leq Z_{p,t} \leq 0, \quad 0 \leq X_{p,t} \leq q_{p,2} \quad \forall t, \; \forall p.$$

$$(X_{ct,t} + Z_{ct,t} - [X_{ct,t-1} + Z_{ct,t-1}]) \times UnitCap_{ct} \times CF_{ct,t} \times h_t$$
$$\geq 0.05 \times \sum_{p=1}^{P} (X_{p,t} + Z_{p,t} - [X_{p,t-1} + Z_{p,t-1}]) \times UnitCap_p \times CF_{p,t} \times h_t, \quad \forall t.$$

$$(X_{hyd,t} + Z_{hyd,t} - [X_{hyd,t-1} + Z_{hyd,t-1}]) \times UnitCap_{hyd} \times CF_{hyd,t} \times h_t$$
$$\geq 0.05 \times \sum_{p=1}^{P} (X_{p,t} + Z_{p,t} - [X_{p,t-1} + Z_{p,t-1}]) \times UnitCap_p \times CF_{p,t} \times h_t, \quad \forall t.$$

$$\sum_{p=1}^{P} X_{p,t} \times UnitCap_p \times CC_p \leq Inv_t.$$

$$\sum_{p=1}^{P}\sum_{t=1}^{T}(X_{p,t}+Z_{p,t}-[X_{p,t-1}+Z_{p,t-1}])\times UnitCap_p \times CF_{p,t}\times h_t\times SO_{2p}\times HR_p \leq Cap_{SO2}.$$

$$(X_{p,t}+Z_{p,t}-[X_{p,t-1}+Z_{p,t-1}])\times UnitCap_p \geq 0, \quad \forall t,\ \forall p.$$

Please note that the term $(X_{p,t}+Z_{p,t}-[X_{p,t-1}+Z_{p,t-1}])\times UnitCap_p \times CF_{p,t}\times h_t$ gives electricity generation of plant p, in period t, and we can rewrite the function as follows.

$$\underset{X,Z}{\text{minimize }} f_2 = \sum_{p=1}^{P}\sum_{t=1}^{T} Gen_{p,t}\times CO_{2p}\times HR_p.$$

with the same constraints given earlier. In more detail, constraints are explained as follows. The first constraint is set to meet electricity demand and given as

$$\sum_{p=1}^{P}(X_{p,t}+Z_{p,t}-[X_{p,t-1}+Z_{p,t-1}])\times UnitCap_p \times CF_{p,t}\times h_t = D_t, \quad \forall t.$$

The second constraint sets a condition to the range of new installations and retirements of power plants:

$$q_{p,1}\leq Z_{p,t}\leq 0, \quad 0\leq X_{p,t}\leq q_{p,2} \quad \forall t,\ \forall p.$$

Here, $q_{p,1}$ corresponds to maximum aggregate power (number of plants $\times$ unit capacity of a plant) of retired plants in period t and $q_{p,2}$ corresponds to the maximum aggregate power of new plants.

Flexible and fast technologies must exist against load surges in the system. Therefore, the third constraint sets the minimum share of combustion turbines (ct), which is set to be 5%.

$$(X_{ct,t}+Z_{ct,t}-[X_{ct,t-1}+Z_{ct,t-1}])\times UnitCap_{ct}\times CF_{ct,t}\times h_t$$
$$\geq 0.05\times \sum_{p=1}^{P}(X_{p,t}+Z_{p,t}-[X_{p,t-1}+Z_{p,t-1}])\times UnitCap_p\times CF_{p,t}\times h_t, \quad \forall t.$$

The fourth constraint sets a minimum share of generation from hydropower units (hyd). Since hydroelectric power has other benefits such as flood control, irrigation, and water supply, and considering natural endowments, it should have a lower bound,

which is set to be 5%.

$$(X_{hyd,t} + Z_{hyd,t} - [X_{hyd,t-1} + Z_{hyd,t-1}]) \times UnitCap_{hyd} \times CF_{hyd,t} \times h_t$$
$$\geq 0.05 \times \sum_{p=1}^{P}(X_{p,t} + Z_{p,t} - [X_{p,t-1} + Z_{p,t-1}]) \times UnitCap_p \times CF_{p,t} \times h_t, \quad \forall t.$$

The fifth constraint limits the capital available to invest.

$$\sum_{p=1}^{P} X_{p,t} \times UnitCap_p \times CC_p \leq Inv_t.$$

The sixth constraint corresponds to the SO_2 emissions cap.

$$\sum_{p=1}^{P}\sum_{t=1}^{T}(X_{p,t}+Z_{p,t}-[X_{p,t-1}+Z_{p,t-1}])\times UnitCap_p\times CF_{p,t}\times h_t\times SO_{2p}\times HR_p \leq Cap_{SO2}.$$

The seventh constraint in the base case ensures the non-negativity of cumulative capacity.

$$(X_{p,t} + Z_{p,t} - [X_{p,t-1} + Z_{p,t-1}]) \times UnitCap_p \geq 0, \quad \forall t, \ \forall p.$$

There are also two constraints additional to base case. The first one sets minimum share of clean energy generation in the cases Clean Standards 75% and 90%.

$$\sum_{p=1}^{PCLN} (X_{p,t} + Z_{p,t} - [X_{p,t-1} + Z_{p,t-1}]) \times UnitCap_p \times CF_{p,t} \times h_t \geq Cln_t, \quad \forall t,$$

where Cln_t is the lower generation limit of renewables and nuclear energy. The second additional constraint sets minimum share of renewable energy generation in the cases Clean Standards 75% and 90%.

$$\sum_{p=1}^{PRNW} (X_{p,t} + Z_{p,t} - [X_{p,t-1} + Z_{p,t-1}]) \times UnitCap_p \times CF_{p,t} \times h_t \geq Ren_t, \quad \forall t,$$

where Ren_t is the lower generation limit of renewables.

We implement the optimization problem using OpenSolver [31].

4.4 Results and Discussion

Findings are presented in two parts, the base case and sensitivity analyses, which include four additional cases built according to extremes in renewable energy costs, fuel costs and minimum clean energy standards.

4.4.1 Base Case Results

In this section, we examine global optimal solutions corresponding to the fuzzy multi objective programming algorithm. First, we calculate possible minimum and maximum values of objective functions (f_1 and f_2). Then, construct membership functions, and maximize the new objective function given in Equation 4.2, $\lambda(x) = w_1 \times \mu_1(x) + w_2 \times \mu_2(x)$ by using a variety of weight parameters.

As the weight parameters of an objective function vary from 1 to 0, the corresponding membership function goes from 1 to 0 with a different rate. Here, the functions $\mu_1(x)$ and $\mu_2(x)$ denote the membership functions of the first and second objectives, minimize cost and minimize CO_2 emissions, respectively. Evolution of the membership functions are summarized with details in Table 4.3 and Figure 4.3. Optimal weights and the solution are presented in bold. The granularity of weight parameters is 1 percent. Orange and grey curves represent the membership functions of the first and second objectives, respectively. The horizontal axis shows the given weight to the first membership function in Equation 4.2. The weight of the second membership function is not shown in the graph. The vertical axis shows the level of membership for both objectives.

According to the algorithm we provide in Section 4.2 we pick solution number 10 as the global optimal solution. If we choose the weight of the objective function "minimize total cost" 91% and the weight of the objective function "minimize total emissions" 9%, the functions are optimal over 90%. As w_2 increases from 0% to 1%, in other words, minimization of CO_2 emissions is now a concern for the model, total CO_2 emission improves significantly. The optimality degree of f_2 jumps from 0% to 44%, whereas optimality degree of f_1 decreases only by 0.7% to 99.3%.

Table 4.2: Minimum and maximum possible values of objective functions

$f_{1,min}$	$f_{1,max}$	$f_{2,min}$	$f_{2,max}$
2950	7506	48909	71350

Visualisation of optimal installed capacity of power plants and implied electricity generations are illustrated in Figures 4.4, and 4.5. Overall comparison of all scenarios are given in Section 4.6.

Table 4.3: Fuzzy MOLP solutions for base case

Solution No.	Weights		Billion $	Billion lbs		Mem. Fn.		
	w_1	w_2	f_1	f_2	λ	μ_1	μ_2	min (μ_1, μ_2)
1	100%	0%	2950	71350	100,0%	100,0%	0,0%	0,0%
2	99%	1%	2983	61477	99,3%	99,3%	44,0%	44,0%
3	98%	2%	3011	59451	98,7%	98,7%	53,0%	53,0%
4	97%	3%	3086	56577	96,1%	97,0%	65,8%	65,8%
5	96%	4%	3148	54866	94,8%	95,7%	73,5%	73,5%
6	95%	5%	3209	53560	93,6%	94,3%	79,3%	79,3%
7	94%	6%	3259	52683	92,6%	93,2%	83,2%	83,2%
8	93%	7%	3309	51953	91,7%	92,1%	86,4%	86,4%
9	92%	8%	3359	51345	90,9%	91,0%	89,1%	89,1%
10	**91%**	**9%**	**3391**	**50891**	**90,4%**	**90,3%**	**91,2%**	**90,3%**
11	90%	10%	3425	50660	89,8%	89,6%	92,2%	89,6%
12	89%	11%	3453	50420	89,4%	89,0%	93,3%	89,0%
13	88%	12%	3464	50335	89,3%	88,7%	93,6%	88,7%
14	87%	13%	3492	50135	88,9%	88,1%	94,5%	88,1%
15	86%	14%	3510	50024	88,7%	87,7%	95,0%	87,7%
16	85%	15%	3519	49966	88,7%	87,5%	95,3%	87,5%
17	84%	16%	3540	49855	88,4%	87,0%	95,8%	87,0%
18	83%	17%	3555	49782	88,3%	86,7%	96,1%	86,7%
19	82%	18%	3559	49760	88,3%	86,6%	96,2%	86,6%
20	81%	19%	3571	49709	88,3%	86,4%	96,4%	86,4%
21	80%	20%	3581	49668	88,2%	86,1%	96,6%	86,1%
22	70%	30%	3637	49500	88,7%	84,9%	97,4%	84,9%
23	60%	40%	3675	49427	89,5%	84,1%	97,7%	84,1%
24	50%	50%	3733	49355	90,4%	82,8%	98,0%	82,8%
25	40%	60%	3767	49324	91,7%	82,1%	98,1%	82,1%
26	30%	70%	3815	49301	93,1%	81,0%	98,3%	81,0%
27	20%	80%	4443	49121	92,7%	67,2%	99,1%	67,2%
28	10%	90%	5518	48934	94,3%	43,6%	99,9%	43,6%
29	0%	100%	7506	48909	100,0%	0,0%	100,0%	0,0%

In the reference scenario, installed capacities of nuclear energy are predicted stable. Nuclear increases to 107 GW capacity from 102 GW capacity in the last quarter of 2021. Hydropower increases from 88 GW to 129 GW. Wind power enjoys the strongest increase: from 88 GW to 666 GW. Solar power is predicted to reach 326 GW from 92 GW. Natural gas-fired capacities are predicted to shrink to 262 GW from 452 GW. Coal almost phases out: predicted capacity in 2050 is 28 GW, compared to 2021 Q4 levels 239 GW. By 2039, natural gas-fired combined cycles with 90% carbon capture and sequestration technologies enter into optimal solution (graphed in "other"). It reaches 25 GW capacity by 2050.

The base case implies a model merit-order dispatch curve given in Figure 4.5. The marginal cost of the last generating unit determines the market-clearing price. If all
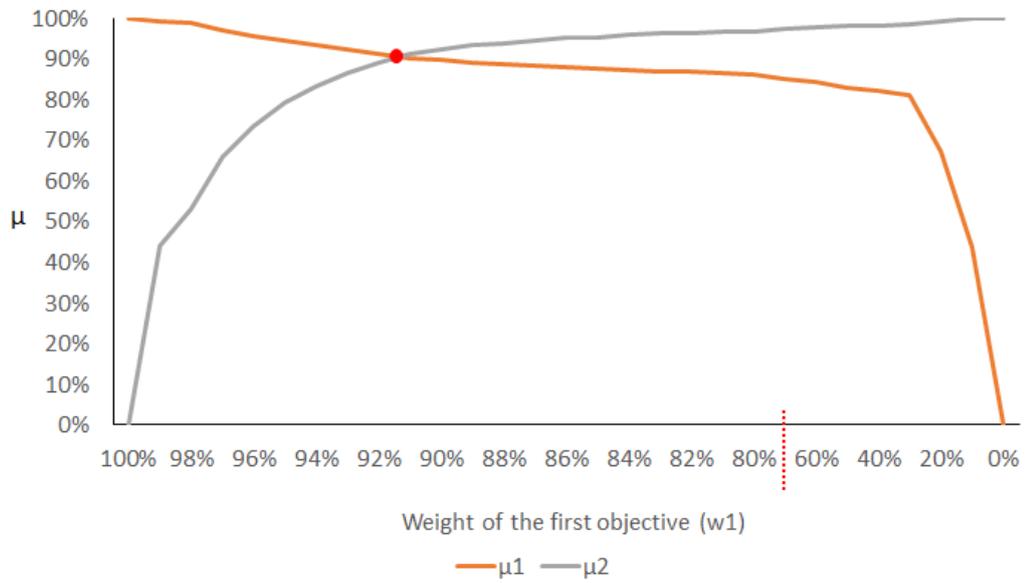
Figure 4.3: Membership functions.
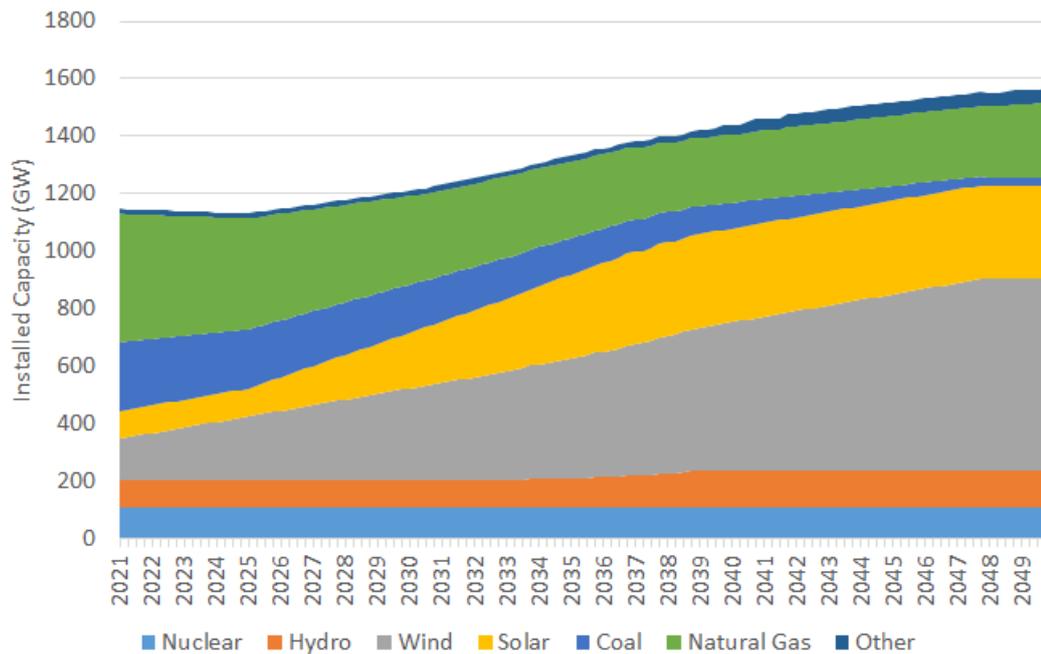
Figure 4.4: Capacity expansion in reference scenario between 2021 Q4 - 2050.

the available capacity is used, marginal cost is expected to be \$1/kWh. The average cost is expected to be \$0.16/kWh, down from \$0.58/kWh, which we found in the hypothetical dispatch curve of September 2020. Therefore, the base case implies a 55 % reduction in the marginal cost of electricity generation. Cost reduction is
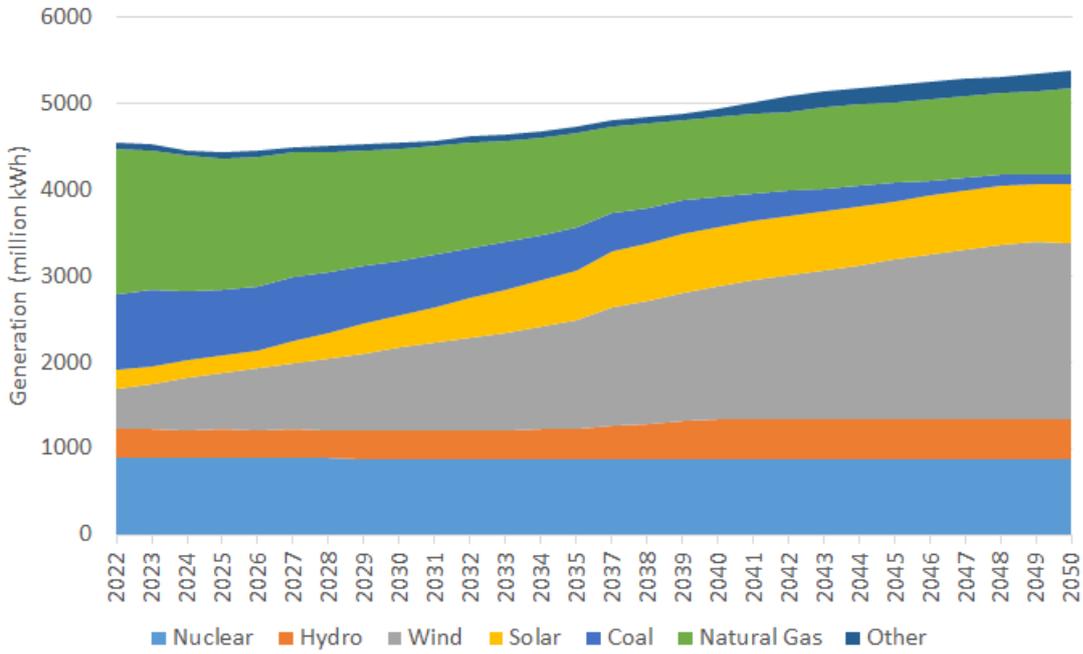
Figure 4.5: Electricity generation in reference scenario between 2022 - 2050.

accomplished by high fuel savings thanks to the renewable energy units.
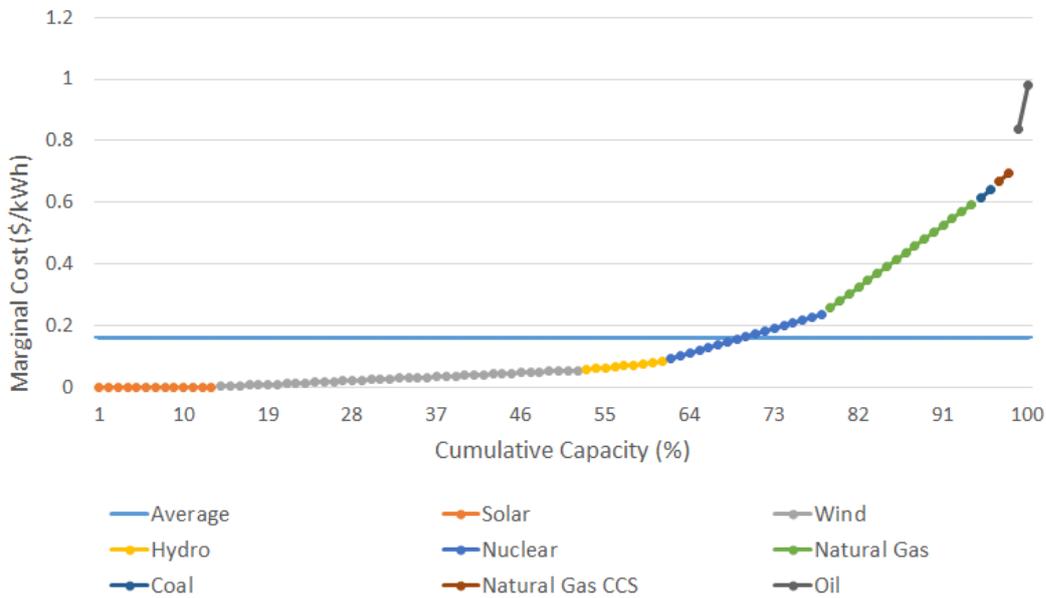
Figure 4.6: Predicted economic dispatch of power plants in 2050 (base case).

4.5 Sensitivity Analyses

Apart from the base case, we examine four additional scenarios: High renewable cost, high fuel prices, clean standards 75%, and clean standards 90%.

4.5.1 High Renewable Cost

In this scenario, we multiply fixed and variable VRE costs by two and increase integration costs to \$30/MWh from \$3/MWh. This time, the fuzzy multi-objective algorithm's optimal solution is obtained when w_1 is equal to 94%, and w_2 is 6%. Compared to the reference scenario, high renewable costs increase nuclear and natural gas shares significantly and keep VRE constant. Until 2034, nuclear energy substitutes diminishing coal. After 2034, natural gas plants' capacities increase significantly, substitute coal and meet increasing demand. Until 2034 net installations of natural gas and coal power plants are negative, this gap is procured by high capacity factor nuclear power. By 2033, natural gas-fired combined cycles with 90% carbon capture and sequestration technologies enter the optimal solution.
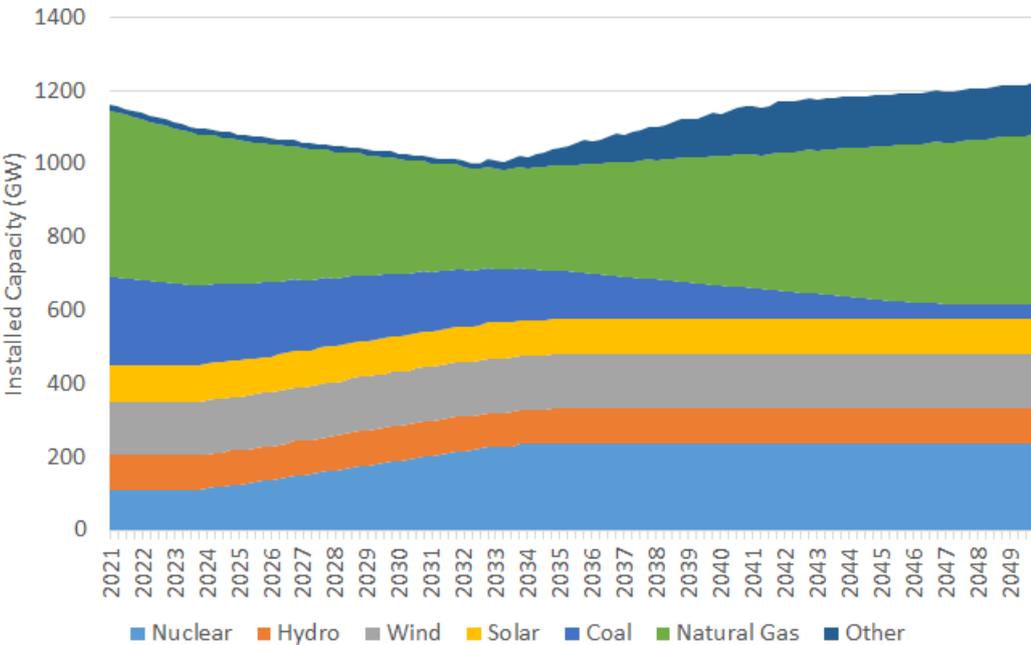
Figure 4.7: Capacity expansion in the high renewable cost scenario.

4.5.2 High Fuel Prices

In this scenario, we multiply fossil-fuel costs by 3. With the help of a higher cost advantage, the capacities of wind and hydropower increase dramatically. The optimal solution of the fuzzy multi-objective algorithm is obtained when w_1 is equal to 67%, and w_2 is 33%.
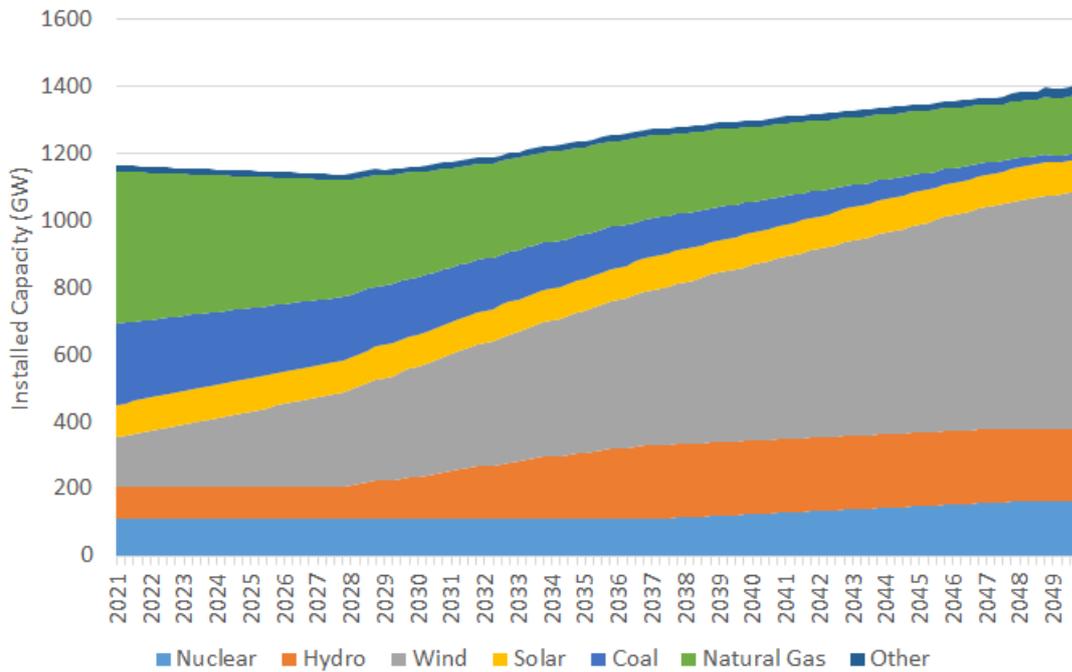
Figure 4.8: Capacity expansion in the high fuel cost scenario.

4.5.3 Clean Standards 75%

In this scenario, we set a lower limit for the shares of clean energy plants. This scenario favors nuclear and wind power. Nuclear increases to 211 GW capacity from 102 GW capacity in the last quarter of 2021. Hydropower increases from 88 GW to 94 GW. Wind power enjoys the strongest increase: from 88 GW to 716 GW. Solar power is predicted to reach 98 GW from 92 GW. Natural gas-fired capacities are predicted to shrink to 164 GW from 452 GW. Coal almost phases out: predicted capacity in 2050 is 14 GW, compared to 2021 Q4 levels 239 GW. The Merit-order dispatch curve implied by this case is given in Figure 4.10. The marginal cost of the last generating unit determines the market-clearing price. If all the available capacity is used, marginal cost is expected to be \$0.8/kWh, and the average cost is expected to be \$0.17/kWh.
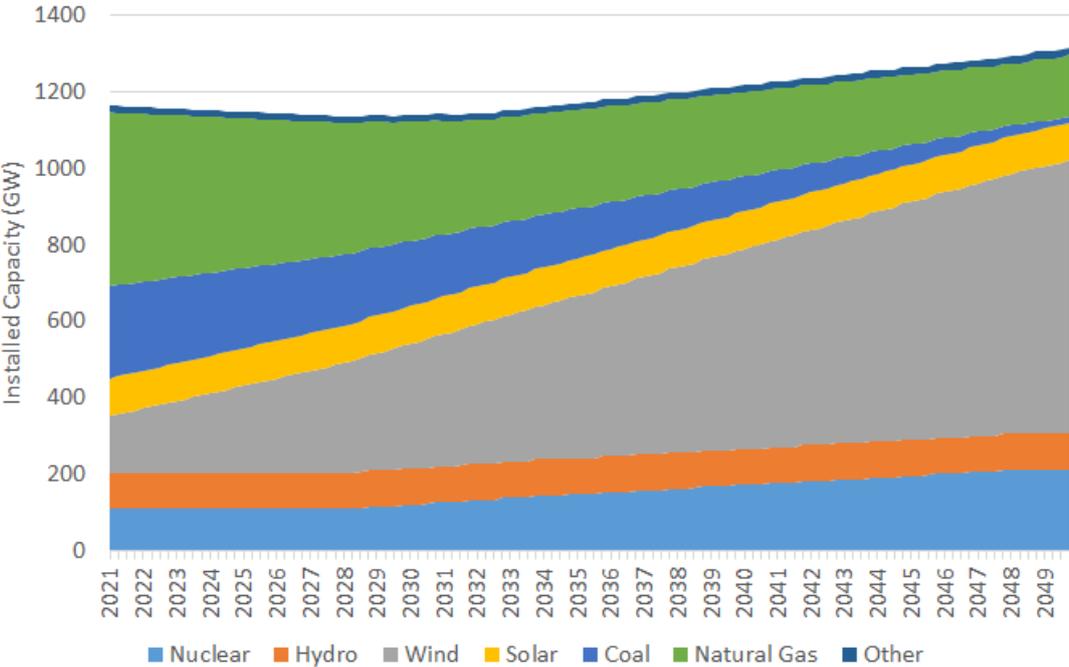
Figure 4.9: Capacity expansion in the 75% clean energy scenario.
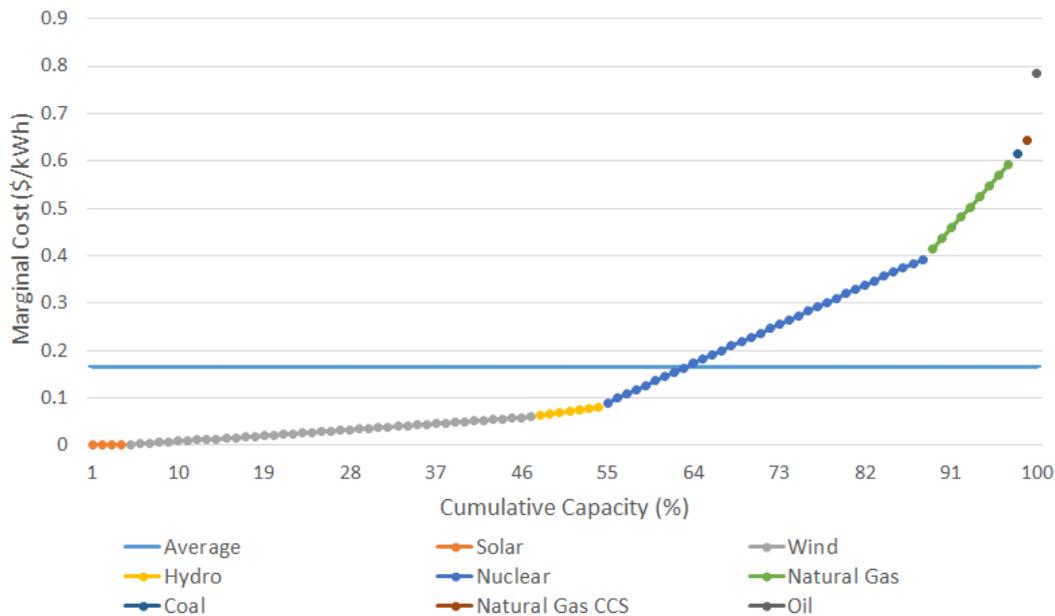
Figure 4.10: Predicted economic dispatch of power plants in 2050 (75% clean energy case).

4.5.4 Clean Standards 90%

In this scenario, we set a stricter lower limit for the shares of clean energy plants. We include coal and natural gas plants with 90% carbon capture and sequestration technologies into the clean energy group. Coal is almost phased out. By 2047, natural gas-fired combined cycles with 90% carbon capture and sequestration technologies enter into the optimal solution. This scenario strongly favors nuclear, wind and solar power. In comparison to the previous scenario, nuclear power and solar power is more prominent. This prominence is mostly due to the second constraint, the range of new installations and retirements. If this range is relaxed, nuclear power may lose share.

In 2050 of this scenario, 31% of total capacity is wind power, 27% of it is nuclear, 16% is solar, 14% is natural gas, and 6% is hydropower. These capacities imply 53% of the production comes from nuclear power plants, 23% from wind farms, 8% from solar farms, 7% from natural gas-fired plants and 5% from hydropower plants. This scenario achieves 39 grams of CO_2 emissions per kWh electricity produced, which is below the Paris Agreement's 50 g/kWh target.
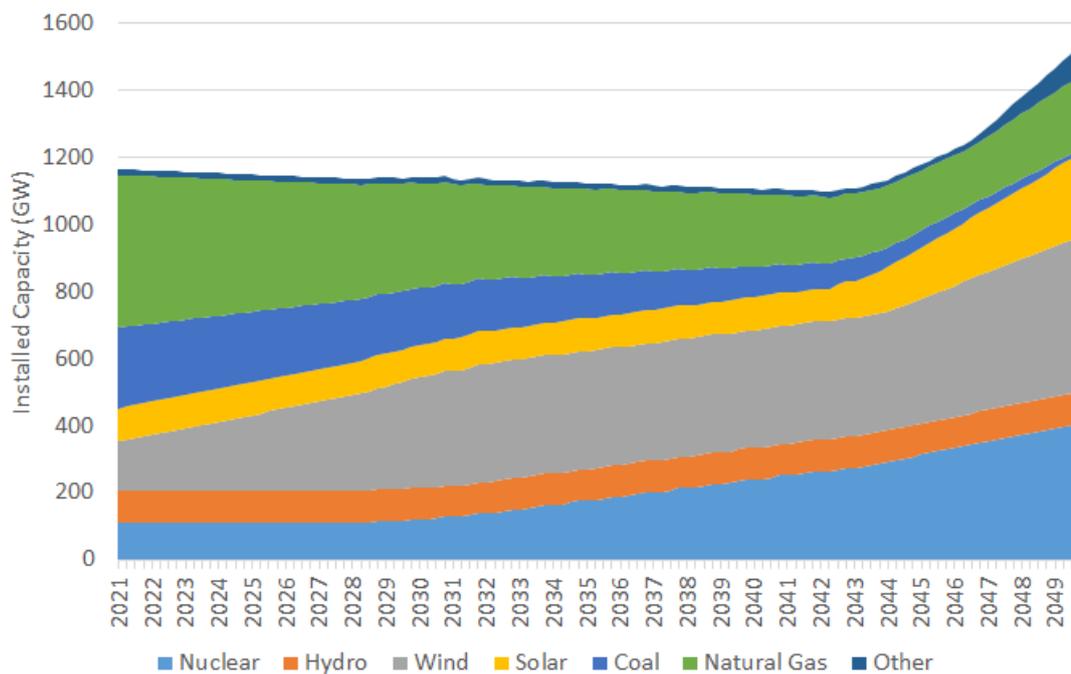
Figure 4.11: Capacity expansion in the 90% clean energy scenario.

4.6 Environmental and Economic Implications

In this section, we present how total CO_2, SO_2 and NO_x emissions evolve in five different scenarios. In scenarios "high fuel cost, 75% clean energy and 90% clean energy CO_2 emission levels (Figure 4.12) are very close to each other and about 20% of end 2021 levels. In the base case scenario, total CO_2 emissions reduce to 31% of end 2021 levels. Since these are total emission levels, emissions per electricity generated are much lower. For example, we expect CO_2 emissions per MWh electricity generated to be 176 lbs compared to 662 lbs/MWh by the end 2021.

SO_2 emissions (Figure 4.13) do not exhibit significant deviations across scenarios. In the base case scenario total SO_2 emissions are about 15% of end 2021 levels. Except for "high renewable cost" scenario, NO_x emissions (Figure 4.14) are close to each other in four scenarios. In the base case scenario total NO_x emissions are about 25% of end 2021 levels. Regarding cost, the third and fifth scenarios require above \$ 100 billion yearly average investment. The highest investment is needed in the "high fuel cost" scenario (Figure 4.15) because of early investments in renewable energy. "90% clean energy scenario" with high nuclear power share requires second highest capital
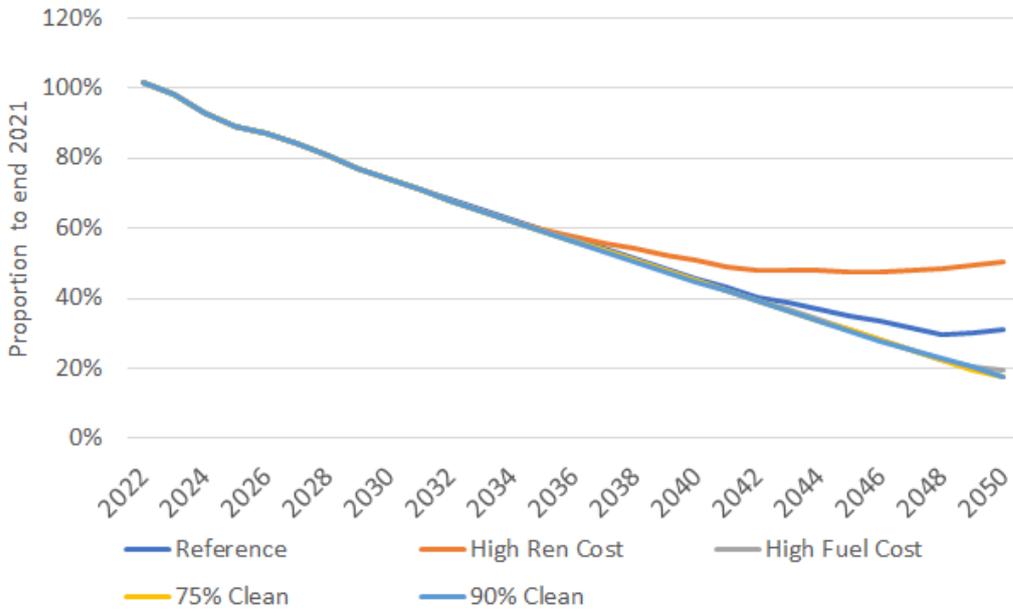
Figure 4.12: Changes in CO_2 emission in proportion to base year 2021.
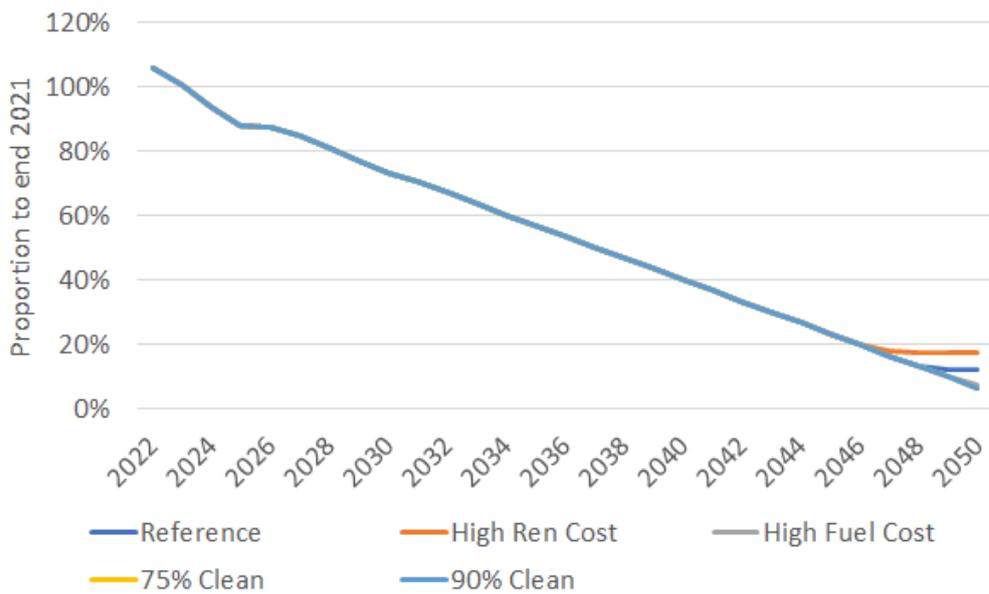
Figure 4.13: Changes in SO_2 emission in proportion to base year 2021.

investment. In the base case, the average yearly investment is about $68 billion.
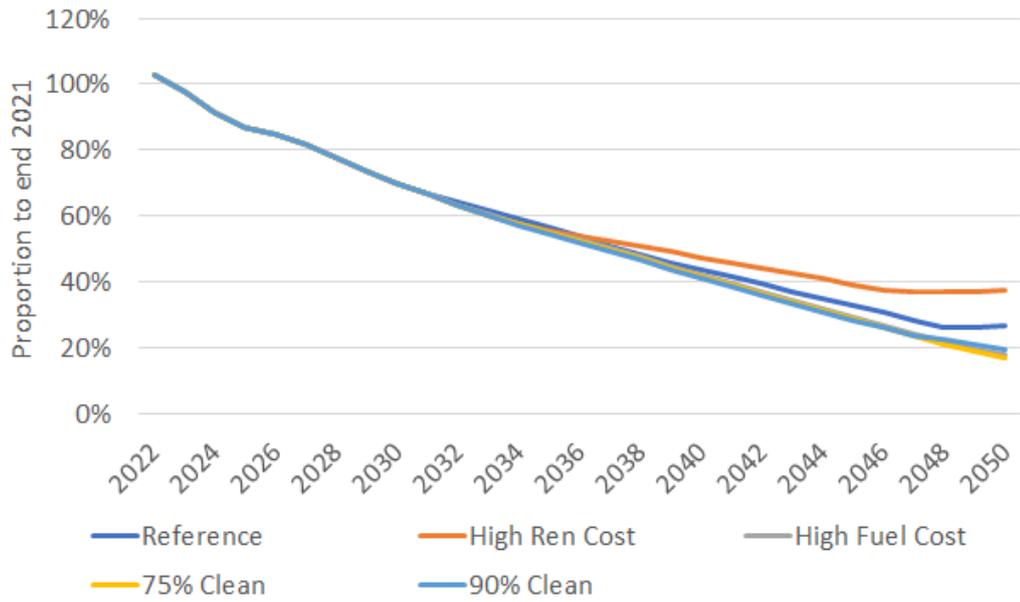
Figure 4.14: Changes in NO_x emission in proportion to base year 2021.
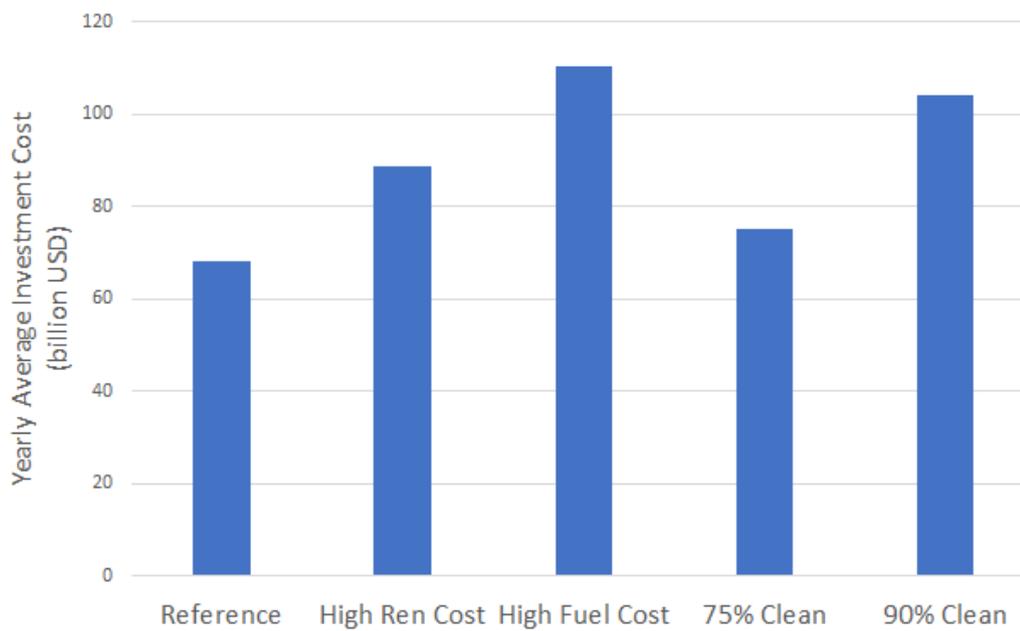
Figure 4.15: Yearly average investment costs.
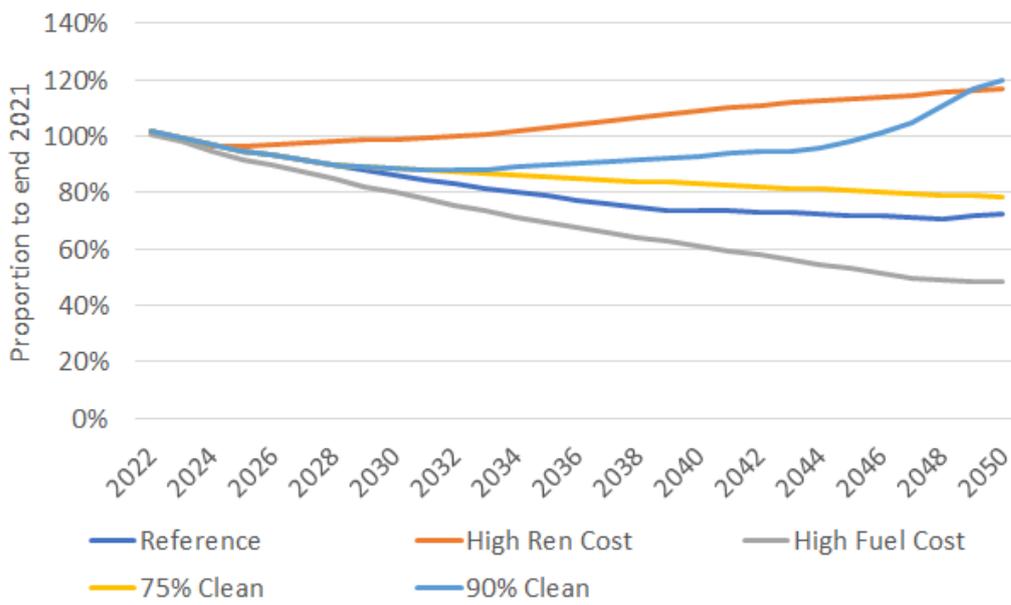
Figure 4.16: Changes in variable costs in proportion to base year 2021.

CHAPTER 5

CONCLUSIONS AND POLICY RECOMMENDATIONS

This thesis works on the US's electric power sector's capacity expansion problem, the second-largest CO_2 emitter in the world. The selection of the best power generation option involves economic and environmental aspects. Switching to clean energy is the solution to environmental aspects, but there are challenges that the variable nature of renewable energy poses. We deal with the capacity expansion problem by proposing a fuzzy multi-objective linear programming model (MOLP). This model allows uncertainties to exist and does not require making a priori decisions regarding incomparable objectives such as economic and environmental. Optimal capacity expansion problems in the literature generally focus on spatially limited areas and shorter time horizons. This thesis shows that directly modeling capacity factor series and using them as inputs in the longer-term optimization model gives meaningful results. To achieve this, we employ consecutive series of modeling, which are time series, to capture the behavior of each electric power plant's capacity factors. These constitute the input for the MOLP. On average, the time series models predict capacity factors for 2050 as follows. 92% for nuclear, 40% for conventional hydropower, 35% for wind, 24% for solar, 41% for coal, 57% for NGCC and 12% for NGCT.

We calculated system integration costs of variable renewable energy (VRE) and used it as an input to the fuzzy MOLP. We find these costs of VRE quite modest: $3/MWh. This very low system integration costs and high fuel savings potential favors VRE significantly. The fuzzy MOLP model predicts the highest increase in installed capacity for wind power. The plants with the highest increase in aggregated installed capacity can be listed as wind > solar > hydropower > nuclear. And the plants with

the highest decrease in capacity can be ranked as coal > natural gas. Wind power is expected to reach 666 GW in 2050 from 88 GW in the last quarter of 2021. Solar power is predicted to reach 326 GW from 92 GW, and conventional hydropower increases from 88 GW to 129 GW. Lastly, nuclear increases to 107 GW capacity from 102 GW. On the other hand, natural gas-fired capacities are predicted to shrink to 262 GW from 452 GW. Coal almost phases out: predicted capacity in 2050 is 28 GW, compared to 2021 Q4 levels of 239 GW.

In the base case, the aggregate installed capacity of renewable units reach 74% of all generating capacity. This shows renewable units turn out already efficient, without having to set lower bounds on renewable capacity. By 2050, nuclear energy capacity is predicted to reach 7% of all generating capacity, down from 9% in the last quarter of 2021. Share of coal-fired units in aggregate capacity shrinks to 2%, conventional NGCC to 11% and NGCT to 5%. NGCC with carbon capture and sequestration (CCS) units are predicted to have 1.6% capacity share by end-2050.

In sensitivity analyses, we present how different policies and price evolutions may alter the optimal mix. In the high renewable cost scenario, we doubled the capital costs of renewable units and multiplied VRE system integration costs by 10. In this extreme case, the aggregate installed capacity of renewable units reach 31% by the end-2050, and nuclear power expands its share to 22%. In this scenario, NGCC reaches 27% and NGCC with CCS reaches 11%.

In the high fuel prices scenario, we increased the fuel prices of fossil power plants by %50. In this case, renewable units cover 74% of all capacity and the share of nuclear power increase to 11%. In total, clean energy increases its share by 4%. Therefore, it can be said that the sensitivity of fossil power plants to fuel costs is low.

As we stated above, in the base case, the clean energy totals 74% and therefore, 75% clean energy standard is not a strictly binding constraint. In the 90% clean energy policy scenario, the share of nuclear energy increases besides VRE.

The capacity growth rate of hydropower plants lags behind wind and solar power plants for the last decade. However, hydropower has important advantages such as storage and dynamic response capabilities. The optimization results support the

idea that hydropower deserves more attention for the upcoming periods. The Department of Energy's Hydropower Vision Framework predicts %50 increase in all US hydropower capacity (conventional and pumped storage) by 2050 [58]. In parallel to that report, our model predicts a %47 capacity increase for hydropower units.

These capacities and implied electricity generation could achieve 80% less CO_2 emission compared to the end-2021. SO_2 and NO_x emissions are also around 20% of their end-2021 levels. This reduction would be substantial, considering increased electricity generation in 2050. Moreover, higher VRE capacities reduce the cost of electricity significantly. If all available capacity is used, the average cost of electricity generation is expected to be $0.16/kWh, down from $0.58/kWh.

Yu et al. [70] find solar PV will be the most cost-effective power plant type for China and they state hydropower will have the highest proportion of renewable power generation by 2030. Comparing to China case, this study highlights wind power as the optimal power plant type for the U.S. and agrees that hydropower will maintain its significance in the following periods.

Based on the optimization results, we can note the following to achieve orderly development of electricity generation capacity in the US.

i) We find that the system integration costs of wind and solar power are quite modest compared to their contribution to fuel savings and carbon-emission reductions. We also find wind power is the most cost-effective power for the US electric power sector.

ii) Power plants with carbon sequestration and capture techniques are promising in curtailing GHG emissions, but their share in the optimal mix is low at the current development level. However, their role will increase in case of more ambitious goals of GHG emission reduction.

iii) By increasing the number of renewable energy plants, the US can have its required energy and retire most of its fossil-based power plants. As a result, it is possible to decrease the damage to nature.

iv) The development in electricity production has a potential effect on the costs. Hence, in the long run, there will be a reduction in electricity prices.

v) Following President Biden's executive order to rejoin Paris Climate Agreement on January 2021, investments in clean energy may be intensified to reach ambitious emission targets [52].

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APPENDIX A

HISTOGRAMS

In Figure A.1 we provide histograms of capacity factor series for original and transformed data. Except for solar power, transformations let the series get normal distribution characteristics in varying extent.
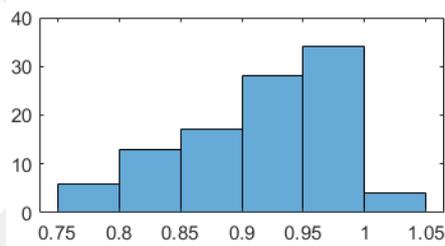
(a) Nuclear Power 1
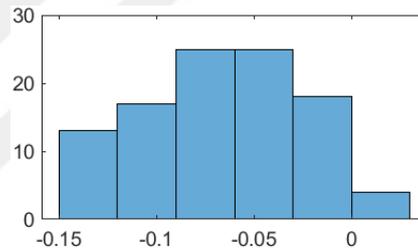
(b) Nuclear Power 2
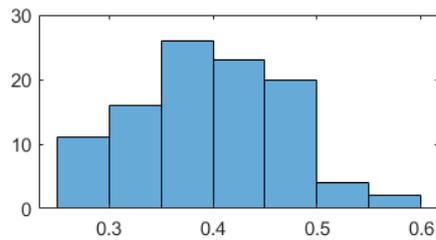
(c) Hydro Power 1
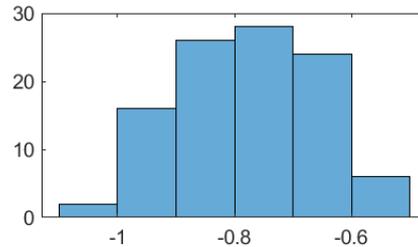
(d) Hydro Power 2
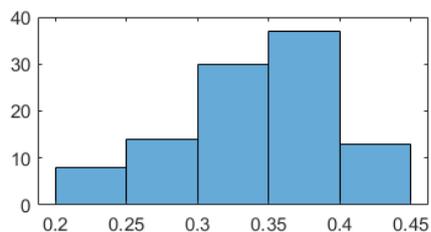
(e) Wind Power 1
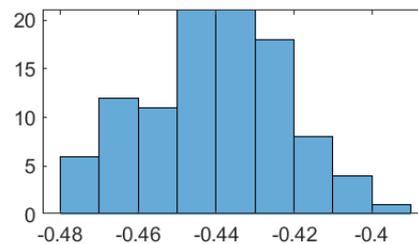
(f) Wind Power 2
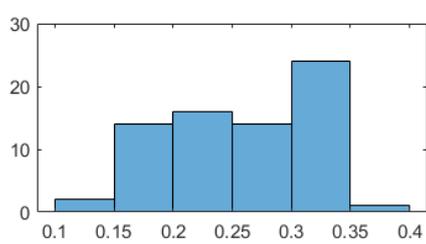
(g) Solar Power 1
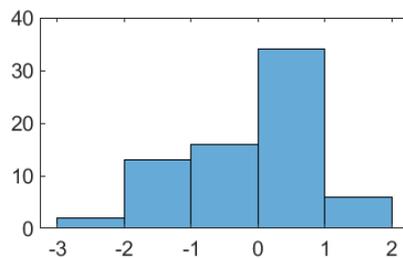
(h) Solar Power 2
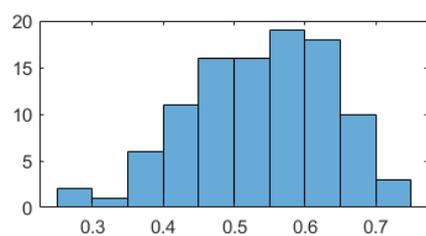
(i) Coal 1
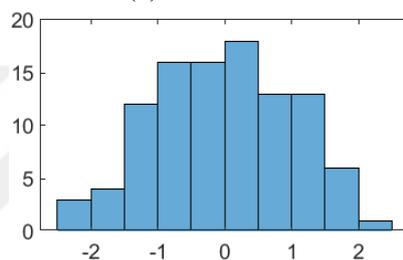
(j) Coal 2
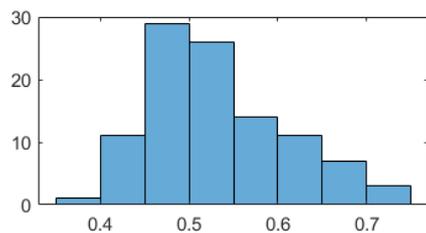
(k) Combined Cycle 1
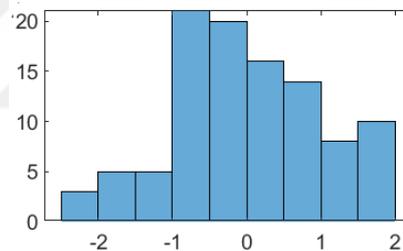
(l) Combined Cycle 2
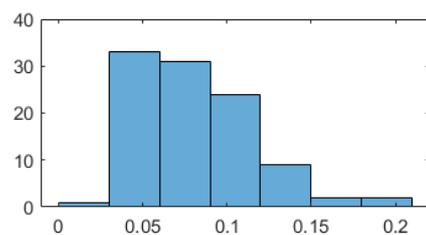
(m) Combustion Turbine 1
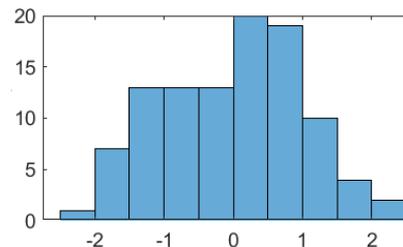
(n) Combustion Turbine 2

Figure A.1: Histograms of capacity factors

APPENDIX B

MODEL SELECTION

In Table B.1 we present root-mean-square errors of test sets in tested seasonal ARIMA models. tAR, tMA, sAR and sMA denotes trend and seasonal autoregressive and moving average parts.

Table B.1: Root-mean-square error of tested ARIMA models

NUCLEAR					HYDRO					SOLAR				
RMSE	tAR	tMA	sAR	sMA	RMSE	tAR	tMA	sAR	sMA	RMSE	tAR	tMA	sAR	sMA
0,00612	1	3	0	1	0,02481	0	3	2	3	0,01235	3	3	2	2
0,00634	2	2	0	1	0,02500	2	1	3	3	0,01253	1	1	3	0
0,00653	3	3	0	1	0,02502	1	0	1	0	0,01255	2	3	3	0
0,00680	3	2	0	1	0,02503	1	1	3	2	0,01259	1	3	3	0
0,00738	1	3	1	1	0,02530	1	1	2	3	0,01260	3	2	1	2
0,00756	1	2	1	1	0,02531	1	3	3	2	0,01261	2	2	3	0
0,00762	2	2	0	2	0,02532	1	2	3	3	0,01265	1	2	3	0
0,00771	3	3	0	2	0,02534	1	2	3	2	0,01267	3	0	3	1
0,00773	2	3	0	2	0,02535	1	1	3	3	0,01271	3	1	1	3
0,00782	3	2	0	2	0,02538	1	1	1	0	0,01271	1	1	1	3
0,00791	1	0	1	0	0,02546	2	3	3	2	0,01271	3	3	2	1
0,00798	1	2	1	0	0,02548	2	0	1	0	0,01274	1	3	1	2
0,00801	1	3	0	2	0,02549	1	3	2	3	0,01276	1	3	1	3
0,00803	3	0	1	0	0,02557	2	3	3	3	0,01278	2	1	3	0
0,00824	1	3	1	0	0,02563	0	3	3	3	0,01279	3	1	1	2
0,00825	2	1	1	0	0,02564	0	0	1	3	0,01279	3	3	3	2
0,00833	1	1	1	0	0,02566	0	0	2	3	0,01280	3	1	3	1
0,00837	1	2	0	2	0,02567	0	0	2	2	0,01280	3	3	1	1
0,00842	2	3	1	0	0,02570	1	3	3	3	0,01283	2	1	3	3
0,00843	3	2	1	0	0,02571	0	1	2	3	0,01286	2	1	2	2
0,00847	2	2	1	0	0,02572	1	2	1	0	0,01287	1	1	1	2

0,00850	3	1	1	0	0,02578	2	1	1	0	0,01290	2	2	1	0
0,00864	2	0	1	0	0,02580	2	2	3	2	0,01290	2	1	1	3
0,00884	2	0	0	2	0,02588	0	3	3	2	0,01290	3	1	0	1
0,00889	0	1	1	0	0,02591	2	2	3	3	0,01291	1	2	1	3
0,00894	1	0	0	2	0,02606	0	0	1	2	0,01291	1	1	1	0
0,00895	1	1	0	2	0,02608	1	0	3	2	0,01291	2	1	1	0
0,00897	0	3	1	0	0,02611	2	3	0	1	0,01291	1	2	1	0
0,00913	2	3	1	1	0,02614	3	2	1	0	0,01292	0	0	0	0
0,00914	2	1	0	2	0,02620	0	0	0	3	0,01294	2	0	2	3
0,00918	0	1	0	2	0,02628	1	0	3	3	0,01294	1	3	0	1
0,00926	3	1	0	2	0,02634	3	2	0	1	0,01294	2	3	0	1
0,00951	0	3	0	2	0,02643	2	3	1	0	0,01296	3	1	3	2
0,00952	3	0	3	2	0,02652	3	0	1	0	0,01297	3	1	1	0
0,00955	3	0	0	2	0,02655	0	1	1	2	0,01298	3	2	1	0
0,00959	0	2	0	2	0,02659	0	1	2	2	0,01299	1	1	0	1
0,00961	3	3	1	0	0,02661	0	1	1	3	0,01299	1	2	3	1
0,00969	0	1	0	3	0,02667	0	1	3	3	0,01299	2	3	1	0
0,00972	0	2	1	0	0,02673	0	3	0	1	0,01300	1	3	1	0
0,00974	1	0	3	2	0,02688	1	3	1	0	0,01300	3	0	2	3
0,00979	0	1	3	3	0,02697	3	3	1	0	0,01300	1	2	1	2
0,00982	3	3	3	3	0,02698	0	0	0	2	0,01303	1	1	3	1
0,00992	3	2	1	2	0,02703	3	3	0	1	0,01303	1	3	1	1
0,00996	3	3	1	1	0,02704	2	1	2	2	0,01304	0	0	0	3
0,00997	1	3	0	3	0,02706	3	2	0	3	0,01306	2	3	1	1
0,01007	1	2	0	3	0,02710	2	1	1	3	0,01306	3	1	1	1
0,01008	3	2	3	3	0,02713	2	1	1	2	0,01307	2	1	2	3
0,01009	3	0	2	3	0,02714	0	3	1	2	0,01308	1	3	2	2
0,01011	1	0	2	3	0,02715	2	3	1	2	0,01308	1	3	2	1
0,01013	3	0	1	3	0,02716	2	1	2	3	0,01308	2	3	1	3
0,01019	1	2	2	2	0,02720	1	3	0	1	0,01308	2	2	3	1
0,01020	1	1	2	3	0,02721	2	2	1	3	0,01309	1	3	0	3
0,01021	1	0	1	3	0,02723	0	3	1	3	0,01310	2	2	0	1
0,01022	0	3	1	2	0,02723	2	1	2	1	0,01310	1	3	0	2
0,01025	1	0	1	1	0,02736	0	3	2	2	0,01311	2	3	0	3
0,01025	1	2	0	1	0,02737	2	3	1	3	0,01311	3	2	3	0
0,01026	1	2	1	3	0,02750	1	1	0	1	0,01311	0	0	1	0
0,01028	3	0	1	1	0,02750	2	0	0	1	0,01311	3	1	0	3
0,01037	2	0	1	1	0,02757	1	0	0	1	0,01312	3	1	0	2

0,01039	1	1	1	1	0,02759	2	3	2	2	0,01312	2	3	0	2
0,01041	3	0	3	3	0,02761	0	1	0	3	0,01313	3	2	0	2
0,01042	0	3	3	2	0,02764	2	1	0	1	0,01314	2	3	2	1
0,01044	3	1	2	3	0,02770	3	0	0	1	0,01314	2	1	1	2
0,01044	2	3	0	3	0,02771	0	2	3	2	0,01315	2	2	1	1
0,01045	2	1	2	3	0,02771	1	2	0	1	0,01316	1	1	1	1
0,01045	1	2	2	3	0,02780	3	1	0	1	0,01319	3	1	3	0
0,01047	0	1	1	1	0,02782	0	2	1	2	0,01319	2	3	2	2
0,01048	2	0	1	3	0,02787	2	2	0	1	0,01321	0	1	0	0
0,01048	2	2	2	3	0,02789	2	1	1	1	0,01321	1	1	0	3
0,01049	1	0	3	3	0,02793	0	1	0	2	0,01322	1	1	0	2
0,01052	2	1	1	1	0,02800	1	3	2	2	0,01325	3	0	3	0
0,01052	3	0	0	3	0,02802	3	1	3	3	0,01326	3	3	0	3
0,01054	3	1	1	1	0,02805	0	0	3	3	0,01327	1	2	2	1
0,01054	2	2	1	1	0,02806	1	3	1	3	0,01328	2	2	0	3
0,01054	1	1	1	2	0,02808	0	1	1	1	0,01328	2	2	1	3
0,01055	2	2	3	3	0,02809	1	3	1	2	0,01329	1	2	0	1
0,01056	1	0	0	3	0,02815	1	1	3	1	0,01329	2	2	0	2
0,01058	0	1	3	2	0,02817	2	3	2	1	0,01329	1	2	2	3
0,01059	2	2	1	3	0,02818	3	0	2	3	0,01330	2	1	0	1
0,01060	1	1	1	3	0,02819	2	3	3	1	0,01330	1	2	1	1
0,01063	2	0	0	3	0,02819	0	1	2	1	0,01332	0	1	0	1
0,01065	1	1	0	3	0,02821	3	3	0	3	0,01332	0	1	1	2
0,01067	0	0	0	1	0,02821	2	1	0	3	0,01334	2	1	1	1
0,01068	3	1	1	3	0,02824	2	0	1	2	0,01335	1	2	0	3
0,01069	0	0	1	0	0,02825	2	0	1	3	0,01335	1	2	2	2
0,01069	0	2	0	3	0,02828	1	1	1	2	0,01336	3	2	2	3
0,01073	2	0	1	2	0,02831	1	3	3	1	0,01337	1	2	0	2
0,01073	0	3	2	3	0,02831	3	0	1	2	0,01337	0	0	1	2
0,01074	2	2	0	3	0,02832	1	1	2	1	0,01338	0	0	0	1
0,01084	0	0	1	1	0,02832	1	1	1	3	0,01338	2	2	1	2
0,01085	3	1	0	3	0,02833	0	2	2	3	0,01339	2	1	0	3
0,01085	2	1	1	3	0,02835	1	2	2	3	0,01340	2	1	0	2
0,01086	0	3	0	3	0,02836	3	0	1	3	0,01341	2	3	2	3
0,01095	2	3	1	3	0,02838	3	1	1	2	0,01341	3	3	1	0
0,01095	2	1	0	3	0,02839	1	1	2	2	0,01343	3	0	0	1
0,01097	2	3	2	3	0,02840	1	2	1	2	0,01343	1	3	2	3
0,01098	0	1	1	2	0,02841	2	0	0	3	0,01344	1	3	2	0

73

0,01102	0	2	1	1	0,02841	2	3	1	1	0,01344	0	1	0	3
0,01112	1	0	1	2	0,02842	3	1	1	3	0,01345	3	2	2	1
0,01113	0	2	1	2	0,02844	1	0	2	3	0,01345	3	1	2	2
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0,01120	3	2	0	3	0,02844	3	0	2	2	0,01347	3	1	2	0
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0,01127	0	1	1	3	0,02845	1	3	2	1	0,01348	2	0	3	2
0,01132	0	3	1	1	0,02845	0	1	3	1	0,01349	2	3	1	2
0,01133	0	1	0	1	0,02846	3	0	3	1	0,01350	1	0	0	1
0,01136	1	3	2	2	0,02847	1	1	0	3	0,01350	3	0	1	0
0,01139	3	1	1	2	0,02847	2	2	2	2	0,01353	3	0	3	2
0,01142	3	3	1	2	0,02847	0	3	1	0	0,01353	1	1	2	0
0,01146	1	3	1	3	0,02850	0	2	1	3	0,01355	2	3	2	0
0,01146	0	0	1	2	0,02852	2	3	0	3	0,01356	3	2	2	2
0,01149	2	3	0	1	0,02853	1	2	1	3	0,01357	3	3	2	0
0,01150	3	3	0	3	0,02856	1	0	3	1	0,01358	0	2	0	1
0,01152	1	0	0	1	0,02858	0	1	0	1	0,01359	3	2	3	2
0,01155	2	2	1	2	0,02859	1	3	0	3	0,01361	0	0	1	1
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0,01173	3	0	1	2	0,02861	3	2	3	3	0,01362	2	2	2	0
0,01185	1	2	2	1	0,02862	3	0	2	1	0,01363	2	1	3	2
0,01187	1	3	1	2	0,02862	2	3	0	2	0,01363	0	2	1	2
0,01188	3	0	0	1	0,02863	1	0	1	2	0,01363	3	2	0	3
0,01190	0	0	0	2	0,02863	2	3	3	0	0,01366	3	0	1	1
0,01193	0	0	0	3	0,02863	1	0	2	1	0,01366	1	1	3	2
0,01203	2	0	0	1	0,02866	0	2	2	2	0,01369	3	0	0	3
0,01204	0	2	3	2	0,02867	3	3	0	2	0,01370	3	0	0	2
0,01204	0	3	1	3	0,02867	2	0	1	1	0,01370	0	1	1	1
0,01209	3	2	1	3	0,02867	0	0	2	1	0,01370	3	0	1	2
0,01210	3	0	3	1	0,02869	1	1	1	1	0,01370	1	2	2	0
0,01213	1	3	2	1	0,02869	1	2	2	2	0,01371	2	0	1	3
0,01213	3	0	2	1	0,02871	0	3	0	3	0,01372	0	1	1	0
0,01217	3	1	0	1	0,02872	2	2	3	1	0,01373	3	2	0	1
0,01222	2	1	0	1	0,02874	1	2	3	1	0,01375	2	0	1	0
0,01222	1	2	1	2	0,02875	3	2	3	2	0,01375	2	2	3	2
0,01236	0	2	0	1	0,02877	1	3	1	1	0,01375	3	2	2	0
0,01238	1	1	0	1	0,02878	3	1	2	1	0,01377	2	0	1	1
0,01238	2	1	3	3	0,02880	3	0	0	3	0,01380	2	0	0	3

0,01241	0	2	3	3	0,02880	1	0	1	3	0,01380	2	0	2	1
0,01250	2	3	1	2	0,02881	1	0	1	1	0,01381	2	0	1	2
0,01252	0	3	0	1	0,02883	1	0	0	3	0,01381	2	0	0	2
0,01258	1	3	2	3	0,02885	1	3	3	0	0,01381	2	2	2	2
0,01262	1	3	3	3	0,02885	1	2	2	1	0,01381	2	0	2	2
0,01265	2	1	3	0	0,02886	0	3	0	2	0,01383	2	3	3	2
0,01272	0	0	1	3	0,02886	3	1	1	0	0,01386	0	1	0	2
0,01279	3	2	2	1	0,02887	0	3	3	0	0,01389	1	0	1	3
0,01285	2	3	3	2	0,02892	2	2	1	0	0,01392	1	0	1	2
0,01287	3	2	3	0	0,02893	3	1	0	3	0,01392	3	3	1	2
0,01289	3	2	3	1	0,02897	1	1	3	0	0,01393	0	2	1	1
0,01291	3	3	3	2	0,02897	3	0	1	1	0,01393	0	0	0	2
0,01294	2	3	3	3	0,02897	0	0	3	1	0,01394	3	3	0	1
0,01299	2	2	3	0	0,02898	1	0	2	2	0,01394	1	0	0	0
0,01302	2	3	3	1	0,02899	1	0	3	0	0,01396	3	3	0	2
0,01303	3	3	1	3	0,02900	2	2	0	3	0,01398	0	2	0	3
0,01304	3	3	3	1	0,02903	2	1	0	2	0,01399	1	0	2	2
0,01306	3	3	2	1	0,02908	1	2	1	1	0,01399	0	3	0	1
0,01307	1	0	3	1	0,02908	1	2	0	3	0,01406	1	0	2	1
0,01308	1	0	2	1	0,02911	0	2	3	3	0,01407	0	2	0	2
0,01309	3	3	3	0	0,02914	3	1	1	1	0,01407	3	0	2	0
0,01315	2	3	2	1	0,02919	3	3	3	0	0,01410	1	0	2	3
0,01320	1	2	3	0	0,02919	2	2	1	1	0,01411	1	0	0	2
0,01323	3	3	2	2	0,02921	2	1	2	0	0,01412	1	0	1	1
0,01325	1	0	3	0	0,02923	2	0	0	2	0,01416	0	1	1	3
0,01328	1	1	3	1	0,02924	1	0	2	0	0,01416	3	3	1	3
0,01330	1	1	2	1	0,02924	2	0	2	2	0,01417	2	0	2	0
0,01332	3	0	2	2	0,02926	1	1	0	2	0,01425	0	2	1	0
0,01341	1	1	3	0	0,02926	1	3	0	2	0,01425	0	2	0	0
0,01348	3	0	2	0	0,02935	0	0	0	1	0,01429	0	1	2	0
0,01348	0	2	2	3	0,02935	2	3	2	0	0,01434	1	0	1	0
0,01356	2	2	2	2	0,02941	1	0	0	2	0,01435	1	0	0	3
0,01363	3	2	3	2	0,02946	1	3	2	0	0,01436	0	3	0	3
0,01366	2	2	2	1	0,02950	3	0	3	0	0,01437	0	3	1	1
0,01376	1	2	2	0	0,02950	1	2	3	0	0,01438	0	3	1	2
0,01379	1	0	2	0	0,02951	0	2	0	1	0,01440	0	3	0	2
0,01384	3	2	2	2	0,02953	3	0	0	2	0,01440	0	2	2	0
0,01394	1	1	2	0	0,02956	3	1	0	2	0,01446	3	2	0	0

0,01394	3	1	2	1	0,02961	0	3	2	0	0,01447	1	0	2	0
0,01395	2	3	2	2	0,02963	0	0	1	1	0,01453	0	1	2	3
0,01396	2	1	2	1	0,02967	1	1	2	0	0,01453	2	3	0	0
0,01400	0	2	1	3	0,02967	2	2	0	2	0,01455	0	2	1	3
0,01415	1	3	2	0	0,02971	0	0	3	0	0,01455	0	1	3	3
0,01424	2	2	2	0	0,02972	1	2	0	2	0,01456	0	2	2	3
0,01425	2	0	2	2	0,02973	3	3	1	2	0,01459	2	2	0	0
0,01428	2	1	2	0	0,02977	2	0	2	0	0,01460	3	3	0	0
0,01437	0	2	3	1	0,02980	1	2	2	0	0,01465	0	3	1	3
0,01439	3	3	2	0	0,02981	3	3	2	3	0,01467	0	2	3	3
0,01442	2	3	2	0	0,02990	3	0	2	0	0,01467	0	3	2	1
0,01446	1	0	2	2	0,02992	0	2	1	1	0,01467	2	0	3	3
0,01448	0	3	2	2	0,02993	3	3	2	0	0,01467	0	2	2	2
0,01498	0	1	2	2	0,02998	3	3	1	3	0,01470	0	1	2	2
0,01502	3	1	2	0	0,03013	0	2	0	3	0,01471	0	3	3	1
0,01514	3	3	0	0	0,03013	3	3	2	1	0,01473	0	0	2	0
0,01517	2	1	2	2	0,03014	0	2	0	2	0,01476	0	3	3	0
0,01520	0	3	2	0	0,03022	0	3	2	1	0,01484	2	3	3	3
0,01521	0	3	3	1	0,03031	3	3	2	2	0,01486	0	2	3	1
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0,01526	0	3	3	0	0,03040	3	2	2	3	0,01488	0	3	1	0
0,01527	1	1	2	2	0,03045	2	2	3	0	0,01489	0	3	2	0
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0,01537	0	1	3	0	0,03046	0	2	3	1	0,01491	1	2	3	3
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0,01538	0	1	3	1	0,03061	2	0	0	0	0,01493	0	3	0	0
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0,01542	0	0	0	0	0,03068	3	2	1	1	0,01497	1	1	3	3
0,01552	1	3	0	0	0,03074	1	0	0	0	0,01499	0	2	3	0
0,01557	0	2	2	0	0,03074	2	1	0	0	0,01509	0	1	3	0
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0,01557	0	2	2	1	0,03092	3	1	2	3	0,01517	2	2	3	3
0,01566	1	2	0	0	0,03096	3	2	2	2	0,01522	0	3	2	2
0,01576	0	3	0	0	0,03105	3	2	1	3	0,01528	0	1	2	1
0,01584	0	2	0	0	0,03124	0	1	1	0	0,01534	3	2	1	1
0,01584	1	1	0	0	0,03126	3	2	2	1	0,01536	3	3	3	3
0,01605	3	0	0	0	0,03131	0	2	3	0	0,01550	0	0	1	3
0,01608	1	0	0	0	0,03160	2	2	2	3	0,01557	1	2	0	0

0,01612	2	0	0	0	0,03172	3	2	3	1	0,01562	3	2	1	3
0,01615	2	1	0	0	0,03176	0	2	1	0	0,01564	3	0	0	0
0,01617	2	2	0	0	0,03179	0	3	0	0	0,01564	3	1	0	0
0,01621	3	1	0	0	0,03183	0	1	3	2	0,01565	2	1	0	0
0,01629	3	2	0	0	0,03192	1	3	0	0	0,01584	0	3	2	3
0,01706	0	0	3	1	0,03214	3	2	3	0	0,01586	0	3	3	2
0,01714	2	3	0	0	0,03224	3	0	0	0	0,01595	2	0	0	0
0,01799	0	2	2	2	0,03236	0	0	3	2	0,01606	1	1	0	0
0,01827	0	0	2	0	0,03237	0	1	0	0	0,01658	1	3	0	0
0,01846	0	0	2	1	0,03241	0	2	2	0	0,01683	0	0	2	3
0,01860	0	0	3	0	0,03244	1	2	0	0	0,01695	0	0	3	1
0,02071	2	1	3	2	0,03247	2	2	0	0	0,01698	0	0	3	0
0,02185	0	0	3	3	0,03249	2	3	0	0	0,01699	0	0	3	2
0,02221	0	0	2	2	0,03274	0	2	2	1	0,01701	0	0	3	3
0,02221	0	0	3	2	0,03283	0	1	2	0	0,01709	0	0	2	2
0,02239	0	0	2	3	0,03295	3	2	0	0	0,01716	0	3	3	3
					0,03301	3	2	0	2	0,01759	0	0	2	1
					0,03314	3	1	0	0	0,01783	2	0	3	1
					0,03340	0	0	2	0					
					0,03373	3	3	0	0					
					0,03394	0	0	1	0					
					0,03408	0	0	0	0					
					0,03419	0	2	0	0					
					0,04062	3	2	2	0					
WIND					**COAL**					**NGCC**				
RMSE	**tAR**	**tMA**	**sAR**	**sMA**	**RMSE**	**tAR**	**tMA**	**sAR**	**sMA**	**RMSE**	**tAR**	**tMA**	**sAR**	**sMA**
0,02017	1	3	1	0	0,05560	3	3	3	0	0,02068	0	0	2	2
0,02030	0	3	1	0	0,05899	3	0	3	0	0,02267	1	3	0	0
0,02068	2	3	1	0	0,05914	1	2	3	0	0,02281	2	2	0	0
0,02099	0	2	1	0	0,06011	1	1	3	0	0,02284	1	0	0	0
0,02122	0	0	1	0	0,06033	2	2	3	0	0,02289	2	0	0	0
0,02146	3	1	1	0	0,06098	3	1	3	0	0,02289	3	1	0	0
0,02166	0	3	2	0	0,06525	2	3	3	0	0,02291	1	1	0	0
0,02173	3	2	1	0	0,06559	1	3	3	0	0,02297	1	2	0	0
0,02175	0	1	1	0	0,06705	2	0	3	0	0,02308	3	0	0	0
0,02185	1	0	1	0	0,07017	3	3	2	3	0,02343	0	0	3	1
0,02186	2	0	1	0	0,07271	1	2	2	3	0,02375	0	0	0	0
0,02187	3	0	1	0	0,07579	1	2	3	1	0,02378	2	1	0	0

0,02217	2	3	2	0	0,07595	3	0	1	3	0,02411	0	3	0	0
0,02255	3	0	2	0	0,07600	3	0	3	1	0,02428	0	1	0	0
0,02272	3	2	2	0	0,07629	3	0	0	0	0,02453	0	2	0	0
0,02282	3	1	2	0	0,07702	1	0	3	0	0,02538	0	0	1	0
0,02301	1	2	2	0	0,07778	1	2	1	3	0,02540	3	2	0	0
0,02304	0	3	3	0	0,07792	3	0	2	3	0,02543	3	3	0	0
0,02310	0	2	2	0	0,07811	3	1	1	3	0,02630	0	0	3	0
0,02327	2	2	2	0	0,07816	3	0	1	0	0,02686	0	1	1	0
0,02329	3	3	2	0	0,07826	2	1	1	3	0,02688	0	3	1	0
0,02336	0	0	0	1	0,07872	2	2	1	3	0,02689	0	2	3	0
0,02341	2	0	2	0	0,07878	1	1	1	3	0,02695	0	2	1	0
0,02355	2	3	3	0	0,07886	3	1	0	0	0,02743	0	2	3	2
0,02359	1	2	1	0	0,07911	1	2	0	0	0,02779	0	3	3	2
0,02360	2	1	2	0	0,07924	2	1	0	0	0,02784	2	1	1	0
0,02369	2	2	3	0	0,07940	1	1	0	0	0,02789	1	0	1	0
0,02374	1	3	3	0	0,07947	2	0	3	3	0,02797	0	3	3	0
0,02382	0	0	2	0	0,08013	3	1	3	1	0,02799	1	2	1	0
0,02396	2	2	1	0	0,08014	1	1	3	1	0,02800	2	0	1	0
0,02397	2	1	1	0	0,08070	3	3	0	0	0,02803	2	2	1	0
0,02402	1	1	3	0	0,08086	2	2	0	0	0,02808	1	1	1	0
0,02406	1	0	3	0	0,08087	3	1	1	0	0,02818	1	3	1	0
0,02408	0	1	2	0	0,08163	1	2	1	0	0,02823	0	1	3	0
0,02410	0	0	3	0	0,08169	3	0	2	0	0,02826	2	3	0	0
0,02413	0	2	3	0	0,08193	1	3	0	0	0,02854	3	0	1	0
0,02414	1	0	2	0	0,08211	2	2	1	0	0,02888	0	0	0	1
0,02430	3	3	3	0	0,08231	3	0	0	3	0,02973	2	0	3	0
0,02437	0	1	2	2	0,08243	2	1	1	0	0,02975	0	0	2	0
0,02437	0	1	0	1	0,08247	2	0	0	0	0,03001	3	2	1	0
0,02455	0	1	3	0	0,08304	1	1	1	0	0,03017	0	0	2	3
0,02474	1	1	2	0	0,08305	3	0	3	2	0,03039	3	1	1	0
0,02505	0	0	2	2	0,08313	2	1	0	1	0,03080	0	1	2	0
0,02509	0	0	1	1	0,08425	2	2	2	3	0,03099	0	0	2	1
0,02510	0	3	0	1	0,08429	3	0	3	3	0,03114	0	3	2	0
0,02520	0	3	1	1	0,08431	3	1	2	0	0,03132	0	2	2	0
0,02528	0	1	1	1	0,08438	1	2	2	0	0,03138	2	3	1	0
0,02529	3	1	0	1	0,08451	1	3	1	3	0,03167	1	3	3	0
0,02534	3	0	0	1	0,08469	1	2	0	3	0,03193	0	0	3	2
0,02538	3	1	1	1	0,08479	3	0	0	1	0,03194	0	0	1	3

0,02539	3	0	2	3	0,08494	1	2	0	1	0,03201	1	0	3	0
0,02547	1	0	0	1	0,08504	3	0	1	1	0,03243	1	1	3	0
0,02547	3	0	1	1	0,08507	3	1	0	3	0,03255	0	1	2	3
0,02548	1	0	1	1	0,08508	2	2	2	0	0,03271	0	1	0	1
0,02554	0	3	0	2	0,08526	3	0	1	2	0,03272	1	2	3	0
0,02557	3	2	2	3	0,08540	1	3	1	0	0,03273	2	3	3	0
0,02558	3	1	0	2	0,08547	3	0	2	1	0,03307	0	0	3	3
0,02561	1	3	2	3	0,08551	2	2	0	3	0,03310	3	0	3	0
0,02562	1	2	2	3	0,08572	2	1	0	3	0,03380	0	0	0	2
0,02563	3	0	0	2	0,08579	1	1	2	0	0,03401	3	3	1	0
0,02564	0	1	1	3	0,08588	2	0	1	0	0,03414	3	3	3	0
0,02566	2	1	2	3	0,08603	2	0	1	3	0,03436	0	2	0	1
0,02571	2	2	2	3	0,08606	2	3	3	2	0,03457	0	1	2	1
0,02579	1	0	1	3	0,08621	2	3	3	3	0,03462	1	3	1	3
0,02581	1	1	1	0	0,08624	3	0	0	2	0,03466	0	1	0	2
0,02582	3	2	0	1	0,08651	3	2	0	3	0,03468	0	1	1	2
0,02585	0	3	1	2	0,08651	1	2	2	1	0,03477	0	1	1	3
0,02587	0	2	1	1	0,08659	1	2	1	1	0,03480	0	1	2	2
0,02588	0	0	3	1	0,08664	1	2	1	2	0,03487	0	0	1	2
0,02588	3	2	1	1	0,08665	2	2	0	1	0,03489	0	1	0	3
0,02589	2	3	2	3	0,08672	1	2	0	2	0,03500	1	3	2	3
0,02590	0	0	0	2	0,08685	1	1	0	3	0,03500	0	3	1	2
0,02591	1	1	1	3	0,08689	3	1	0	1	0,03503	3	2	3	1
0,02592	3	0	1	2	0,08703	1	3	2	0	0,03516	1	0	2	0
0,02598	3	2	0	2	0,08731	3	2	0	1	0,03520	1	3	2	2
0,02599	2	3	0	1	0,08808	2	2	1	1	0,03529	0	1	1	1
0,02603	0	1	0	2	0,08813	1	0	0	0	0,03537	1	3	3	1
0,02604	0	2	0	1	0,08815	3	3	1	3	0,03543	1	1	2	0
0,02610	2	0	0	1	0,08818	2	1	1	2	0,03571	1	3	2	0
0,02610	0	0	1	2	0,08826	2	2	1	2	0,03583	1	2	1	3
0,02615	2	0	1	1	0,08841	2	1	0	2	0,03588	0	0	0	3
0,02617	1	0	0	2	0,08842	2	2	2	1	0,03595	1	1	1	3
0,02619	1	2	0	1	0,08843	3	2	0	0	0,03599	0	3	2	3
0,02619	2	3	1	1	0,08852	3	1	1	1	0,03604	3	1	2	0
0,02621	2	1	0	1	0,08863	3	2	1	0	0,03606	1	2	2	0
0,02621	1	1	0	1	0,08865	3	1	1	2	0,03636	3	0	2	0
0,02621	0	1	1	2	0,08878	3	1	2	1	0,03639	1	2	2	2
0,02622	1	3	0	1	0,08885	2	2	0	2	0,03643	0	2	2	3

0,02622	3	2	1	2	0,08886	3	2	1	3	0,03644	1	2	2	3
0,02626	0	0	0	3	0,08893	3	2	2	0	0,03649	1	1	2	2
0,02628	1	2	1	1	0,08899	0	3	3	0	0,03651	0	1	3	3
0,02629	2	2	0	1	0,08912	2	0	2	0	0,03661	2	1	2	0
0,02630	2	1	1	1	0,08919	3	2	2	1	0,03664	0	3	0	2
0,02631	0	3	2	3	0,08950	1	1	0	1	0,03673	0	2	1	3
0,02633	2	3	0	2	0,08959	3	1	0	2	0,03683	2	0	2	2
0,02636	1	0	1	2	0,08971	3	2	0	2	0,03686	1	1	2	3
0,02637	1	3	1	1	0,08981	1	0	1	0	0,03689	2	3	3	2
0,02638	1	2	0	2	0,09020	1	1	2	1	0,03694	3	1	3	1
0,02639	2	2	1	1	0,09029	1	1	1	2	0,03698	1	1	3	3
0,02639	2	1	0	2	0,09029	1	1	1	1	0,03703	0	0	1	1
0,02640	0	2	0	2	0,09046	3	0	2	2	0,03720	0	3	1	1
0,02646	1	1	1	1	0,09048	1	2	2	2	0,03732	2	0	2	3
0,02646	0	1	0	3	0,09082	3	3	3	3	0,03733	3	0	2	2
0,02647	2	0	0	2	0,09098	1	3	0	1	0,03740	2	3	3	1
0,02649	1	3	0	2	0,09105	1	3	0	3	0,03743	1	2	3	1
0,02649	2	2	0	2	0,09110	2	3	3	1	0,03744	0	1	3	2
0,02657	2	3	3	2	0,09127	2	3	0	0	0,03756	3	0	2	3
0,02657	0	3	0	3	0,09144	1	1	0	2	0,03759	0	2	2	2
0,02659	2	3	1	2	0,09153	1	0	2	3	0,03771	2	1	1	2
0,02660	1	2	1	2	0,09176	3	1	3	2	0,03782	1	0	1	3
0,02661	1	1	2	3	0,09181	1	1	3	2	0,03782	1	0	2	2
0,02661	2	1	1	2	0,09197	3	3	1	0	0,03798	0	2	0	2
0,02664	1	1	0	2	0,09269	3	1	3	3	0,03809	1	3	1	2
0,02664	1	1	3	2	0,09295	3	1	2	3	0,03821	0	3	1	3
0,02665	2	2	3	2	0,09300	2	0	3	2	0,03828	2	3	2	0
0,02670	1	0	0	3	0,09312	2	0	3	1	0,03844	2	2	2	0
0,02672	2	2	1	2	0,09318	1	3	3	1	0,03847	0	3	2	2
0,02674	1	3	1	2	0,09327	2	2	2	2	0,03854	1	0	3	2
0,02676	0	2	1	2	0,09328	2	0	0	3	0,03858	0	1	3	1
0,02682	0	0	3	2	0,09331	0	0	3	2	0,03869	2	0	1	2
0,02682	2	0	1	2	0,09355	3	2	1	1	0,03876	1	1	1	2
0,02682	1	1	1	2	0,09358	1	1	3	3	0,03907	1	0	2	3
0,02684	0	3	3	2	0,09358	1	0	2	0	0,03912	2	3	2	2
0,02684	3	1	1	2	0,09369	0	3	0	0	0,03914	1	0	1	2
0,02686	2	1	3	2	0,09372	3	2	1	2	0,03916	1	3	0	1
0,02690	2	0	2	3	0,09387	1	3	1	1	0,03918	0	3	0	3

0,02698	1	3	2	1	0,09398	3	1	2	2	0,03919	0	3	0	1
0,02703	3	1	0	3	0,09398	1	3	1	2	0,03925	0	3	3	3
0,02713	0	3	2	1	0,09413	1	3	2	1	0,03928	1	1	3	1
0,02714	3	0	2	1	0,09413	3	2	2	2	0,03930	1	2	1	2
0,02720	0	0	2	1	0,09432	0	2	3	1	0,03934	2	2	2	2
0,02722	3	0	0	3	0,09444	2	0	0	1	0,03941	2	3	2	3
0,02727	0	1	3	2	0,09481	0	2	3	0	0,03945	3	2	1	3
0,02729	0	1	2	3	0,09508	1	1	2	2	0,03948	3	1	1	3
0,02732	0	0	2	3	0,09512	1	3	0	2	0,03959	2	2	3	2
0,02732	1	0	2	3	0,09544	3	2	3	3	0,03965	1	3	2	1
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0,02735	3	2	2	1	0,09589	0	2	0	0	0,03976	3	2	3	3
0,02735	0	2	2	3	0,09636	3	3	0	3	0,03976	3	3	3	1
0,02746	0	2	0	3	0,09657	1	0	1	3	0,03982	3	0	3	1
0,02757	0	0	3	3	0,09662	0	1	3	1	0,03985	3	2	2	2
0,02757	1	2	2	1	0,09708	2	0	1	1	0,03989	1	3	0	3
0,02759	2	1	2	1	0,09711	3	2	2	3	0,03991	3	0	1	2
0,02761	3	1	2	1	0,09728	0	1	0	0	0,03998	3	3	2	0
0,02763	0	1	2	1	0,09729	2	0	1	2	0,04002	3	3	2	3
0,02768	3	2	3	2	0,09730	0	0	3	3	0,04007	2	2	2	3
0,02772	2	2	2	1	0,09735	2	2	3	3	0,04010	3	2	2	3
0,02775	1	1	2	1	0,09742	1	1	2	3	0,04011	3	1	2	3
0,02776	1	0	3	2	0,09756	2	0	2	1	0,04016	3	1	0	1
0,02779	3	2	0	3	0,09777	2	3	1	0	0,04023	1	0	3	3
0,02794	0	0	1	3	0,09791	0	3	1	0	0,04023	2	1	3	1
0,02795	1	0	2	1	0,09821	3	3	2	1	0,04043	0	3	3	1
0,02795	3	2	3	3	0,09828	3	3	1	2	0,04044	2	1	2	2
0,02795	2	0	3	2	0,09839	3	3	1	1	0,04047	1	3	0	2
0,02796	3	3	1	0	0,09848	0	1	3	0	0,04048	2	1	3	2
0,02796	0	2	3	2	0,09873	3	3	0	1	0,04048	3	2	3	2
0,02798	1	1	0	3	0,09900	1	0	2	2	0,04056	3	3	1	2
0,02806	2	0	0	3	0,09907	3	3	0	2	0,04058	1	3	1	1
0,02809	1	2	0	3	0,09918	1	0	0	1	0,04069	0	2	2	1
0,02815	2	3	0	3	0,09950	2	0	0	2	0,04069	1	0	3	1
0,02819	2	1	0	3	0,10033	0	2	1	0	0,04072	0	2	1	2
0,02821	0	2	2	1	0,10115	1	0	0	3	0,04073	0	2	0	3
0,02831	1	3	0	3	0,10150	0	3	2	0	0,04087	3	2	1	2
0,02835	2	0	2	1	0,10166	0	1	1	0	0,04096	3	1	0	3

0,02836	3	3	2	1	0,10175	0	0	0	0	0,04098	3	1	1	2
0,02836	2	2	0	3	0,10207	1	3	2	2	0,04103	2	1	1	1
0,02900	0	3	1	3	0,10250	0	2	2	3	0,04122	1	2	2	1
0,02910	3	3	3	2	0,10285	0	1	2	3	0,04124	2	2	1	1
0,02945	3	0	3	1	0,10383	0	0	1	0	0,04142	1	2	0	1
0,02954	0	3	3	1	0,10467	1	0	1	1	0,04142	3	1	0	2
0,02960	3	0	1	3	0,10469	2	0	2	2	0,04144	2	1	2	3
0,02962	2	3	1	3	0,10484	0	0	3	0	0,04146	3	3	2	2
0,02964	3	2	1	3	0,10490	1	0	1	2	0,04149	0	2	3	1
0,02974	1	3	1	3	0,10515	1	0	2	1	0,04159	0	2	1	1
0,02977	1	2	1	3	0,10519	2	3	1	3	0,04177	1	2	0	3
0,02984	2	1	1	3	0,10555	2	1	1	1	0,04184	0	2	3	3
0,02991	3	1	1	3	0,10588	1	0	3	1	0,04190	3	3	3	2
0,02997	2	2	1	3	0,10599	0	0	2	3	0,04203	3	3	1	3
0,03000	0	1	3	1	0,10614	0	2	2	0	0,04213	1	0	2	1
0,03005	0	2	1	3	0,10623	0	3	3	3	0,04228	1	1	2	1
0,03005	3	3	0	3	0,10641	0	3	0	1	0,04246	0	3	2	1
0,03014	3	2	3	1	0,10686	0	3	1	3	0,04252	3	0	2	1
0,03017	3	3	0	2	0,10714	0	3	2	3	0,04255	1	0	1	1
0,03035	2	3	3	3	0,10769	1	0	0	2	0,04286	2	0	1	1
0,03037	3	3	1	1	0,10771	0	1	2	0	0,04290	1	2	0	2
0,03040	1	1	3	3	0,10811	0	0	2	2	0,04302	1	2	1	1
0,03042	3	3	1	2	0,10844	2	3	0	1	0,04310	2	1	0	2
0,03047	2	1	3	1	0,10928	0	3	3	2	0,04310	1	1	1	1
0,03056	3	3	0	1	0,10936	2	3	0	3	0,04311	1	0	0	2
0,03065	2	2	3	1	0,10997	0	2	3	3	0,04314	2	1	0	3
0,03066	2	3	3	1	0,11042	0	1	3	3	0,04314	1	0	0	3
0,03069	2	2	3	3	0,11099	0	1	0	1	0,04320	3	3	3	3
0,03076	2	0	1	3	0,11122	0	0	0	1	0,04322	2	0	0	3
0,03079	0	2	3	1	0,11132	0	3	0	3	0,04327	1	1	0	3
0,03082	1	3	0	0	0,11172	0	2	0	1	0,04333	3	0	0	3
0,03109	1	1	3	1	0,11233	0	0	2	0	0,04336	2	0	0	2
0,03120	3	3	3	1	0,11263	2	3	1	2	0,04351	2	1	2	1
0,03135	0	1	3	3	0,11274	2	3	1	1	0,04358	2	3	2	1
0,03145	0	3	3	3	0,11304	0	0	1	3	0,04361	1	1	0	2
0,03146	2	3	0	0	0,11315	0	0	2	1	0,04370	3	3	2	1
0,03160	0	3	2	2	0,11429	0	3	1	1	0,04372	3	2	1	1
0,03189	1	0	3	1	0,11434	0	3	2	2	0,04393	3	0	0	1

0,03190	1	1	2	2	0,11451	0	3	1	2	0,04400	1	1	0	1
0,03192	3	2	2	2	0,11464	0	3	2	1	0,04401	2	3	0	1
0,03202	3	3	1	3	0,11585	0	3	0	2	0,04411	2	0	0	1
0,03206	2	1	2	2	0,11586	0	2	1	3	0,04427	1	0	0	1
0,03206	3	2	0	0	0,11621	2	3	0	2	0,04428	2	2	2	1
0,03207	1	2	2	2	0,11678	0	1	1	3	0,04446	2	3	0	3
0,03209	3	0	2	2	0,11742	2	0	2	3	0,04447	3	0	1	1
0,03209	3	0	3	3	0,11756	0	3	3	1	0,04461	3	1	2	1
0,03219	3	1	2	2	0,11762	1	3	2	3	0,04471	3	2	2	1
0,03220	2	2	2	2	0,11775	1	0	3	3	0,04507	3	0	0	2
0,03227	2	3	2	2	0,11821	0	2	3	2	0,04522	3	1	1	1
0,03231	3	1	0	0	0,11899	0	2	0	3	0,04550	2	2	0	3
0,03283	1	0	2	2	0,11915	0	1	0	2	0,04569	2	2	0	1
0,03286	0	2	0	0	0,11966	0	2	1	1	0,04580	2	3	0	2
0,03301	1	0	3	3	0,11985	2	3	2	2	0,04600	2	3	1	1
0,03301	0	2	3	3	0,11993	0	1	1	1	0,04629	2	1	0	1
0,03312	3	3	3	3	0,12002	0	2	0	2	0,04629	3	2	0	3
0,03317	0	2	2	2	0,12012	0	1	3	2	0,04648	3	3	0	3
0,03325	3	3	2	2	0,12013	0	0	1	1	0,04685	3	3	0	2
0,03342	0	0	0	0	0,12031	0	2	1	2	0,04689	2	2	0	2
0,03362	0	3	0	0	0,12036	0	1	0	3	0,04740	2	0	3	1
0,03375	2	0	0	0	0,12056	0	2	2	1	0,04765	3	3	0	1
0,03399	2	0	3	3	0,12090	0	1	1	2	0,04872	3	2	0	2
0,03403	0	1	0	0	0,12101	0	1	2	1	0,04922	3	2	0	1
0,03414	1	0	0	0	0,12119	0	1	2	2	0,05725	1	3	3	3
0,03415	2	0	2	2	0,12160	1	0	3	2					
0,03446	3	3	0	0	0,12336	0	0	0	3					
0,03455	3	0	0	0	0,12344	0	0	0	2					
0,03477	3	0	3	2	0,12446	0	0	1	2					
0,03533	2	1	0	0	0,12518	0	2	2	2					
0,03541	2	2	0	0	0,13077	2	1	2	3					
0,03546	1	2	0	0										
0,03570	3	3	2	3										
0,03645	1	1	0	0										
NGCT...					**...NGCT**									
RMSE	**tAR**	**tMA**	**sAR**	**sMA**	**RMSE**	**tAR**	**tMA**	**sAR**	**sMA**					
0,01263	0	0	3	3	0,02163	2	0	2	0					
0,01266	0	0	2	3	0,02168	1	1	3	1					

0,01363	0	0	2	2	0,02179	2	1	2	0					
0,01384	0	0	3	0	0,02185	1	3	3	0					
0,01402	0	1	2	2	0,02185	1	0	2	0					
0,01419	0	2	2	2	0,02195	3	1	3	0					
0,01443	0	0	1	3	0,02195	3	2	1	3					
0,01443	0	1	3	3	0,02195	1	3	0	2					
0,01465	0	0	0	3	0,02200	2	3	0	1					
0,01475	0	1	2	3	0,02204	2	2	1	3					
0,01500	0	0	1	1	0,02206	3	0	3	0					
0,01505	0	0	0	1	0,02206	2	2	0	3					
0,01510	0	0	1	0	0,02207	3	1	0	3					
0,01517	0	0	2	1	0,02208	2	1	1	3					
0,01518	0	0	1	2	0,02212	2	1	0	3					
0,01525	0	0	0	2	0,02218	3	3	1	3					
0,01527	0	3	2	2	0,02221	1	3	1	2					
0,01536	0	0	2	0	0,02238	2	3	3	2					
0,01550	0	0	0	0	0,02242	2	1	2	3					
0,01554	0	3	3	3	0,02247	2	3	1	1					
0,01562	0	1	0	0	0,02256	2	3	0	2					
0,01571	0	2	3	3	0,02260	2	3	3	0					
0,01580	0	1	3	1	0,02262	3	3	2	0					
0,01598	0	0	3	2	0,02269	2	1	3	2					
0,01599	0	1	1	3	0,02277	1	3	2	1					
0,01602	0	1	1	0	0,02278	1	3	2	2					
0,01613	0	1	3	0	0,02278	1	3	3	1					
0,01613	0	1	0	3	0,02287	1	3	1	3					
0,01615	0	1	0	1	0,02294	1	3	0	3					
0,01616	0	3	0	0	0,02295	2	2	3	2					
0,01626	0	2	0	0	0,02299	2	3	1	2					
0,01642	0	0	3	1	0,02300	1	1	3	2					
0,01648	2	1	0	0	0,02305	3	3	3	2					
0,01650	3	1	0	0	0,02316	1	2	3	0					
0,01652	3	2	0	0	0,02330	2	3	0	3					
0,01656	0	1	2	1	0,02333	2	3	1	3					
0,01665	0	1	1	2	0,02340	1	1	3	0					
0,01666	0	1	2	0	0,02347	2	2	3	0					
0,01676	0	1	0	2	0,02347	2	3	3	1					
0,01700	1	0	0	0	0,02351	2	3	2	2					

84

0,01707	2	1	1	0	0,02353	3	3	3	0				
0,01710	3	1	1	0	0,02358	2	3	2	1				
0,01711	2	2	1	0	0,02369	2	0	3	0				
0,01717	0	3	1	0	0,02373	2	0	3	1				
0,01721	3	2	1	0	0,02391	3	0	1	3				
0,01723	3	3	1	0	0,02404	1	1	1	3				
0,01730	0	2	1	0	0,02407	1	2	0	1				
0,01731	2	0	0	0	0,02410	2	0	1	3				
0,01734	1	3	0	0	0,02425	2	1	3	0				
0,01737	0	3	3	2	0,02433	1	2	1	1				
0,01742	0	1	3	2	0,02450	1	2	0	3				
0,01744	1	1	0	0	0,02463	1	2	1	3				
0,01752	3	0	0	0	0,02470	3	0	3	1				
0,01759	2	2	0	0	0,02473	1	2	3	1				
0,01759	1	2	0	0	0,02473	3	2	3	1				
0,01795	0	3	2	3	0,02475	1	2	2	2				
0,01804	0	1	1	1	0,02475	3	0	3	2				
0,01805	1	0	1	0	0,02475	3	2	3	3				
0,01815	3	2	2	0	0,02478	1	2	2	1				
0,01818	2	3	0	0	0,02479	1	2	0	2				
0,01821	2	0	1	0	0,02500	1	2	1	2				
0,01823	3	0	1	0	0,02505	1	1	0	3				
0,01826	1	1	1	0	0,02505	1	1	2	2				
0,01836	1	2	1	0	0,02518	3	0	2	2				
0,01840	1	3	1	0	0,02519	3	0	0	3				
0,01869	0	2	0	1	0,02521	1	0	3	0				
0,01871	0	2	2	3	0,02522	2	0	0	3				
0,01898	0	2	2	0	0,02533	3	3	3	1				
0,01911	2	3	1	0	0,02535	3	2	2	2				
0,01928	0	3	2	0	0,02545	1	1	0	1				
0,01929	3	3	3	3	0,02548	1	1	2	1				
0,01930	0	3	0	1	0,02553	3	1	2	2				
0,01953	0	3	1	3	0,02554	3	3	2	2				
0,01955	0	2	2	1	0,02557	2	0	2	2				
0,01967	0	2	1	3	0,02559	3	0	0	1				
0,01983	3	2	1	2	0,02559	3	3	2	1				
0,01988	0	3	0	3	0,02563	2	3	2	3				
0,01990	3	1	0	2	0,02564	3	0	2	1				

0,01991	0	2	0	3	0,02578	1	1	1	1					
0,01993	2	2	0	2	0,02594	1	0	1	3					
0,01994	0	3	2	1	0,02602	3	0	1	1					
0,01994	2	1	1	2	0,02637	3	1	2	1					
0,01994	0	3	3	1	0,02638	1	1	0	2					
0,01995	3	3	0	0	0,02642	3	1	3	3					
0,01995	2	1	0	2	0,02644	2	0	2	1					
0,02003	0	2	1	2	0,02657	3	0	0	2					
0,02007	0	2	3	0	0,02661	2	3	3	3					
0,02007	0	2	0	2	0,02670	1	1	1	2					
0,02012	3	3	1	2	0,02673	2	0	0	1					
0,02016	2	2	1	2	0,02686	1	2	3	3					
0,02023	1	3	2	0	0,02693	2	0	3	3					
0,02029	0	2	1	1	0,02696	3	0	1	2					
0,02039	2	2	1	1	0,02704	1	0	3	2					
0,02043	2	1	1	1	0,02710	2	0	1	1					
0,02048	0	2	3	2	0,02739	2	1	3	3					
0,02057	0	3	3	0	0,02742	3	1	3	1					
0,02057	0	3	1	2	0,02753	2	0	0	2					
0,02061	0	2	3	1	0,02770	1	2	2	3					
0,02061	3	3	1	1	0,02785	1	0	0	3					
0,02070	0	3	1	1	0,02796	3	0	2	3					
0,02073	0	3	0	2	0,02796	2	0	1	2					
0,02075	2	2	0	1	0,02810	3	2	2	3					
0,02078	3	1	0	1	0,02817	1	1	3	3					
0,02080	2	1	0	1	0,02829	2	2	3	3					
0,02119	2	2	2	0	0,02833	1	0	3	1					
0,02127	2	3	2	0	0,02854	3	3	2	3					
0,02138	2	2	2	1	0,02894	1	1	2	3					
0,02142	2	2	2	2	0,02906	2	2	2	3					
0,02148	1	3	1	1	0,02925	1	0	2	2					
0,02149	1	3	3	3	0,02954	1	0	0	1					
0,02151	1	2	2	0	0,02960	1	0	1	1					
0,02152	1	3	0	1	0,02980	1	0	0	2					
0,02156	3	2	2	1	0,03002	2	0	2	3					
0,02157	2	1	2	1	0,03004	3	1	2	3					
0,02159	3	0	2	0	0,03033	1	0	2	1					
0,02159	1	1	2	0	0,03055	1	0	1	2					

| 0,02160 | 2 | 2 | 3 | 1 | 0,03239 | 1 | 0 | 3 | 3 | | | | | |
| 0,02162 | 2 | 1 | 2 | 2 | 0,03260 | 1 | 0 | 2 | 3 | | | | | |

Table B.2: Root-mean-square error of tested exponential smoothing models.

M: multiplicative, A: additive, N: none

| Nuclear				Hydro				Solar				Wind			
RMSE	Error	Trend	Seas.	RMSE	Error	Trend	Seas.	RMSE	Error	Trend	Seas.	RMSE	Error	Trend	Seas.
0,00672	M	N	M	0,03141	A	A	A	0,01255	A	N	A	0,02359	M	N	A
0,00697	A	N	A	0,03245	M	M	M	0,01263	M	N	A	0,02409	A	N	A
0,00767	M	A	A	0,03375	M	A	M	0,01358	A	A	A	0,02424	M	A	A
0,00827	M	N	A	0,03459	M	A	A	0,01398	M	N	M	0,02486	M	M	M
0,00877	A	A	A	0,03550	M	N	M	0,01419	M	A	A	0,02513	M	A	M
0,01092	M	M	M	0,03562	A	N	A	0,01799	M	A	M	0,02517	M	N	M
0,01210	M	A	M	0,03831	M	N	A	0,01946	M	M	M	0,02615	A	A	A
Coal				NGCC				NGCT							
RMSE	Error	Trend	Seas.	RMSE	Error	Trend	Seas.	RMSE	Error	Trend	Seas.				
0,05811	M	A	A	0,03457	M	A	M	0,01837	A	A	A				
0,06230	M	M	M	0,03680	M	M	M	0,02118	M	A	A				
0,06399	M	N	M	0,03968	M	N	M	0,02212	M	N	A				
0,06431	M	A	M	0,04364	M	N	A	0,02336	A	N	A				
0,06518	A	N	A	0,04376	A	N	A	0,02350	M	M	M				
0,07128	M	N	A	0,05031	A	A	A	0,02479	M	N	M				
0,07797	A	A	A	0,05056	M	A	A	0,02572	M	A	M				

APPENDIX C

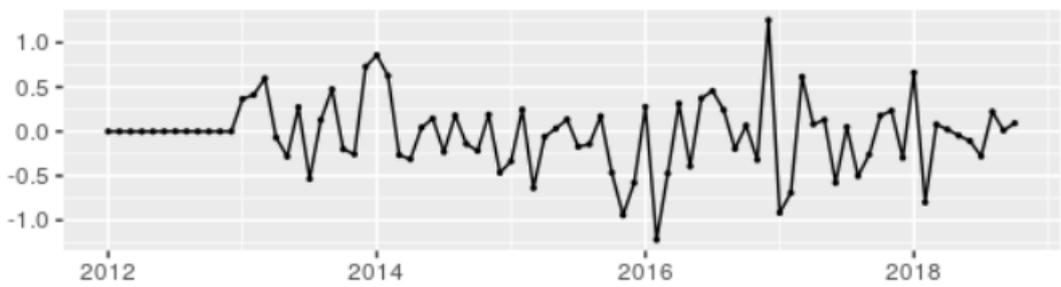# RESIDUAL DIAGNOSTICS
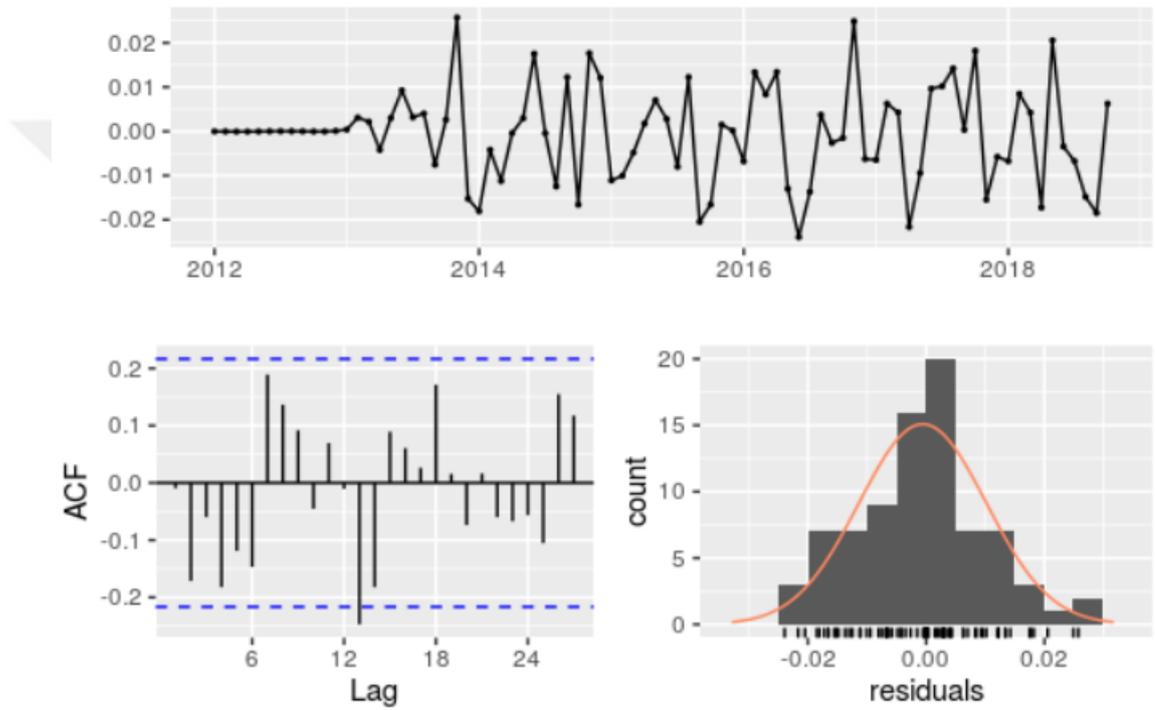
(a) Nuclear Power
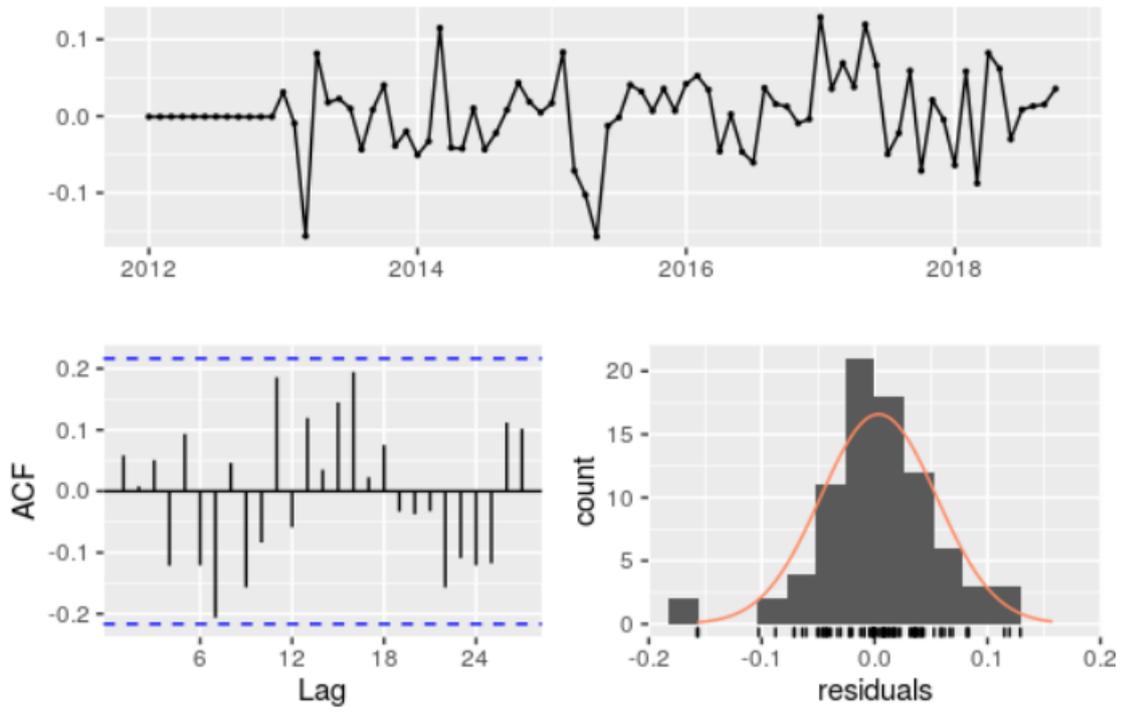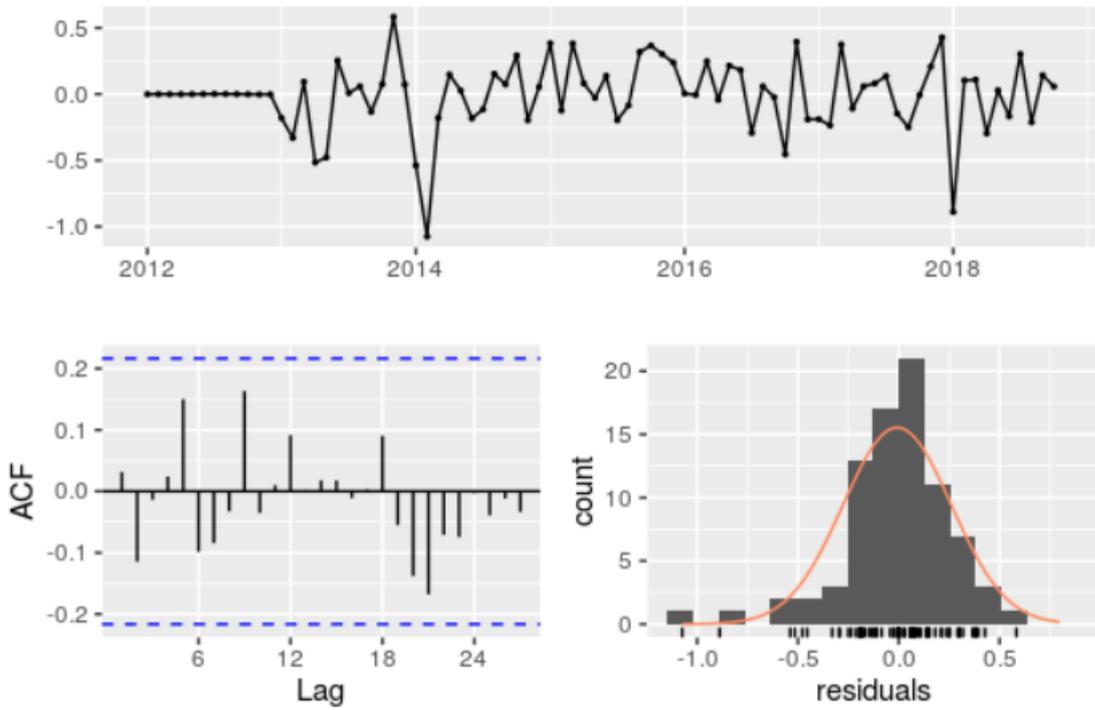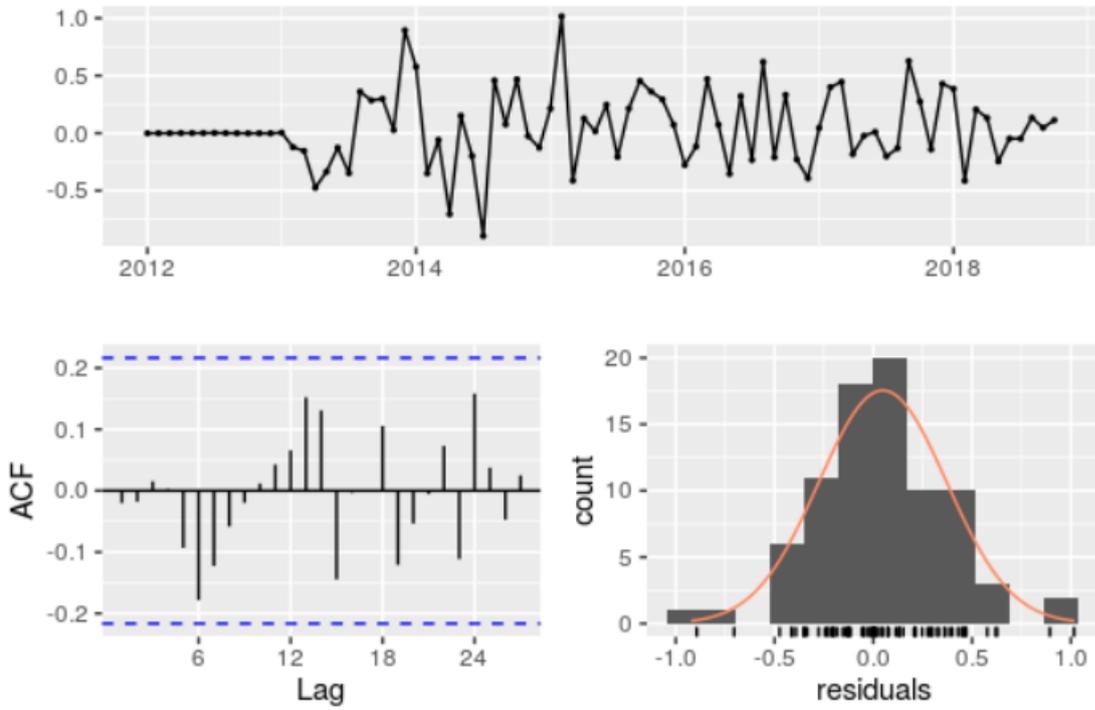
(b) Hydro Power
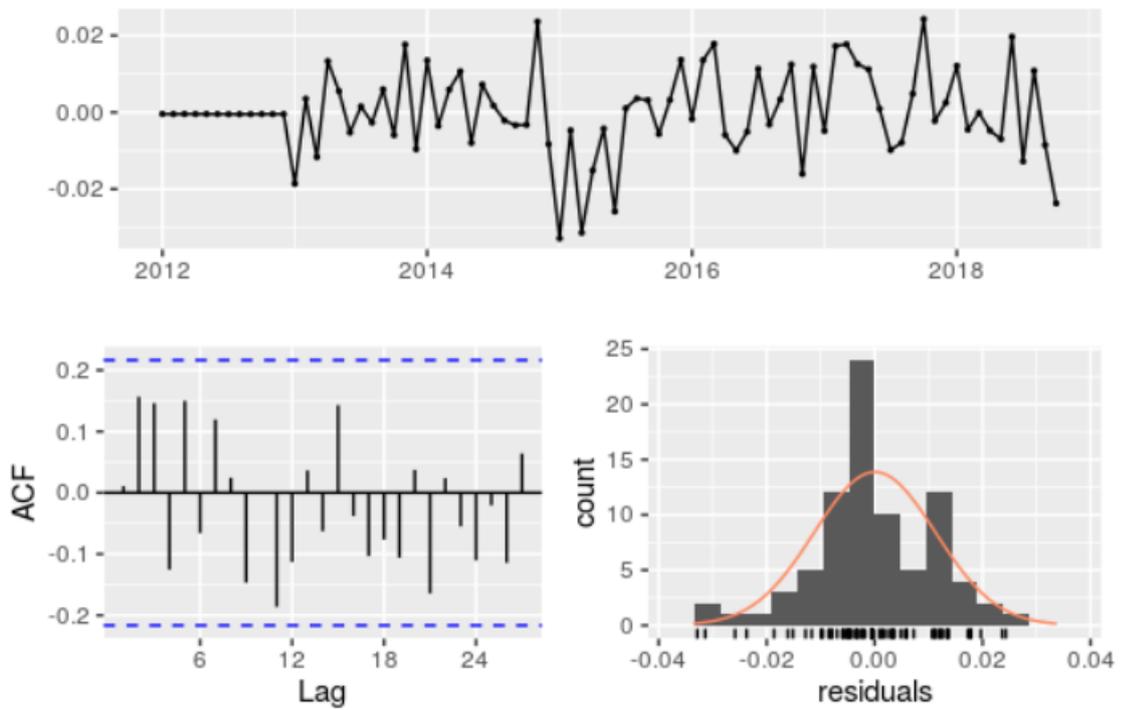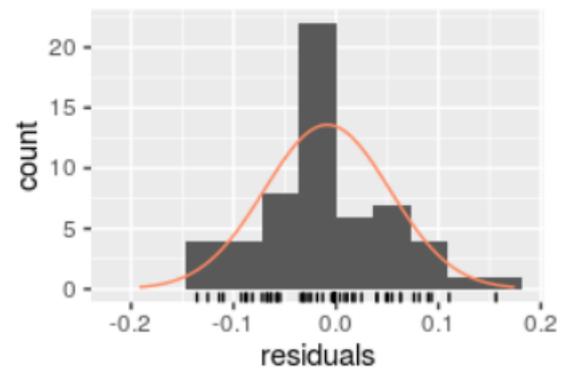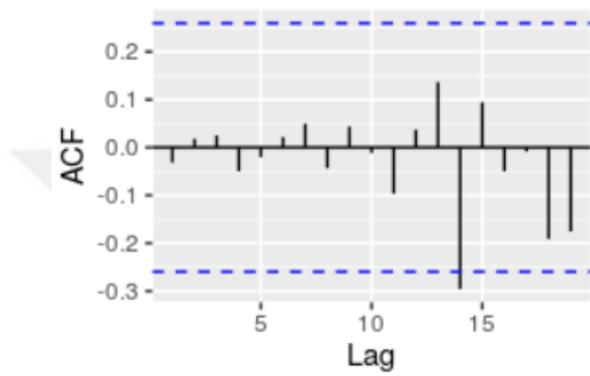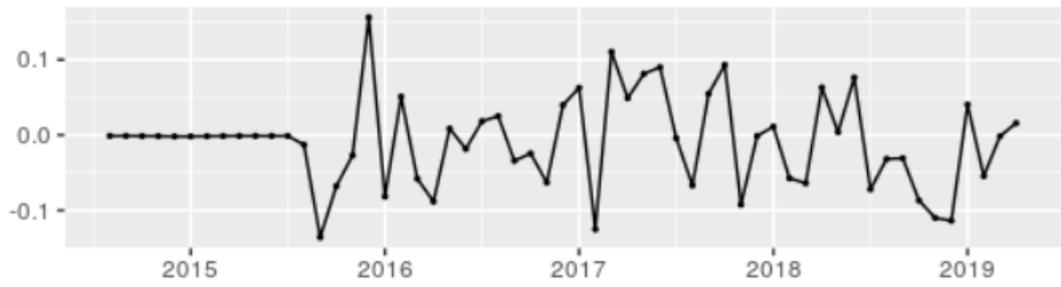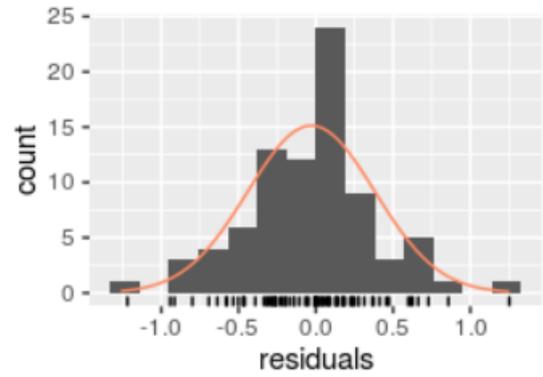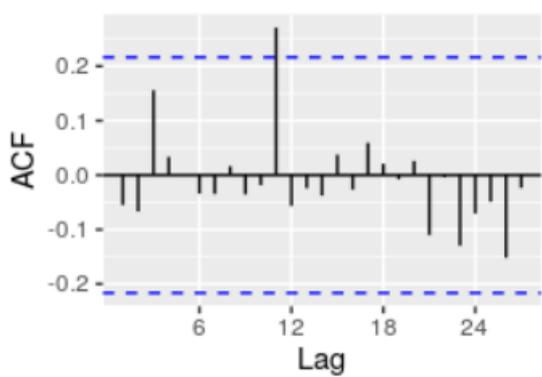
(c) Wind Power

(d) Solar Power

(e) Coal-fired

(f) Natural Gas-fired Combined Cycle

(g) Natural Gas-fired Combustion Turbine

Figure C.1: Residuals