DTU Wind

Resilience of weather dependent energy systems under extreme generation and demand scenarios

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Approval

This thesis has been prepared in the period from August 2022 to January 2023 at the department of Wind and Energy Systems at the Technical University of Denmark, DTU, in partial fulfillment for the degree Master of Science in Sustainable Energy.

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or processional qualification except as specified.

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Signature

29-01-2023

Date

Abstract

Energy systems with a high penetration of variable renewable energy (VRE) may be particularly vulnerable to imbalances between production and demand. In this study, I investigate the inter-annual weather variability in such an energy system. The weather variability impacts the generation of energy from wind, solar and hydro power as well as the demand for energy. I develop an energy demand model to identify the dependency on weather variables, while I rely on existing weather dependent generation data. I use the energy planning tool Balmorel to optimize a European energy system in 2050 based on an average weather year. The system is afterwards exposed to a range of 35 historical weather years (1982-2016) to assess the dispatch of energy.

A key parameter for evaluating the system is the use of dispatchable fuels to supplement the production from VRE. Natural gas provides the most flexibility to ensure balance across weather years, and the consumption more than doubles from the lowest consuming year to the highest consuming year. This has consequences for the electricity price and carbon emissions that show similar volatility. However, the electricity mix was consistently above 80% VRE in all the tested weather years. A key challenge is also to ensure that the installed capacity is adequate in all weather conditions. However, the result of this investigation is not clear.

There are several historical weather years where low production from VRE conicide with high demand due to cold weather. It is therefore an important finding in this study that the joint probability of multiple undesirable weather conditions must be considered when planning energy systems.

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Contents

1 Introduction

Renewable energy is predicted to play a core role in order the meet the European Union's goal of becoming climate neutral by 2050 [1]. However, the nature of wind, solar and hydro power is variable, and the variability exists on multiple time scales. The variations seen within a given weather year has been the subject of many studies, while the variability between different weather years is a newer field attracting attention. Demand for energy is associated with variability as well, and it leaves a joint probability of high demand and low generation happening simultaneously. Consequently, one may question the long-term robustness of an energy system based on a high share of renewables.

I therefore seek to answer to the following problem statement:

How will a weather dependent energy system optimized for an average weather year behave when exposed to the inter-annual variability of other weather years?

To answer this question, I investigate the behaviour of a future European energy system subjected to 35 historical weather years. I develop new demand models based on weather hindcasting. Similar hindcasts of weather driven generation from wind, solar and hydro power already exist, and I will use those data sets in this study. For the simulation of the energy system, I have collaborated with Ea Energy Analyses and use their model and existing data set.

Simulating an energy system for several decades across a whole continent results in multi-dimensional data sets. I will therefore consider the results from an geographically aggregate system perspective. A key result is the use of dispatchable generation since this will reveal how dependent the energy system is on supporting fuels. Other metrics include electricity price and carbon emissions. Finally, I investigate if the invested capacity is adequate under all weather conditions.

I present some of the existing literature on the topic in chapter 2 and explain the motivation for this particular study. In chapter 3, I outline the scope of the project in terms of geography, temporal and climatic extent. In chapter 4, I describe the methodology for modelling electricity and heat demands. In chapter 5, I present the energy system model, its data sources and assumptions along with the procedure for simulating different weather years. In chapter 6, I validate the demand model and energy system model to ensure they resemble reality adequately. I present the results of the optimized energy system in chapter 7, and analyse its dynamics in different weather years. I discuss the strengths and weaknesses of using multiple weather years in section 8 as well as the methodological limitations.

2 Literature review

In order to meet climate targets in forthcoming years, energy systems based on a high share of variable renewable energy (VRE) have been investigated as a solution. In an energy system where supply and demand have to be in balance at all times, the intermittency of VRE has been a focal point of criticism [2]. The german term *dunkelflaute* (dark doldrum) captures those concerns, as it describes a weather phenomenon characterised by calm winds and overcast skies [3]. It can have various degrees of severity depending on the temporal and spatial extent. Studies have therefore focused on simulating VRE variability in high time resolution, and multiple measures have been proposed to alleviate the consequences. Single locations can experience more pronounced variability in wind, but the severity decreases when the geographical scope is extended. Transmission lines can provide such geographical smoothing [4]. Studies also find that sector coupling is a key enabler for high penetration of VRE [5]. This means a tighter connection between sectors to utilize synergies. This can be electrification of transport, where charging can offer temporal flexibility. Other examples of flexibility include green hydrogen production and electrification of heating. Along with storage and flexible power plants, models have shown that these measures can enable high penetration of VRE. This is famously promoted by the 100% Renewable Energy Strategy Group [6].

Studies of energy systems are often based on models that simulate a single weather year [7]. Energy systems will therefore be optimised to handle *intra-annual* variations, i.e. the variability seen within that single year. However, those intra-annual variations will be different depending on which year is chosen. When seen on a larger time scale, these differences add up to *inter-annual* variability. Thus, the system may still fail to handle lower-frequency events taking place less than once per year.

Price and Zeyringer (2022) demonstrate with highRES-Europe a model of the European energy system in high spatial and temporal resolution [8]. They use several decades of weather data to model the inter-annual variability of VRE generation. They find that investments in flexible generation are particularly sensitive to weather year, while transmission grid expansions are less sensitive.

While dunkelflaute entails generation side issues, weather induced imbalances in energy systems can occur as a consequence of variability in both generation and demand. For instance, one can imagine that a particularly cold pan-European winter could lead to higher demands and exacerbate the consequences of dunkelflaute.

Raynaud et al. (2018) define the term *energy droughts* considering balances between weather dependent demand and supply [9]. Such a drought is defined as a period where less than 20% of demand is supplied by VRE. They find that a diversification of the energy mix can decrease both the duration and frequency of energy droughts. The focus of that study is on quantifying the probability of such energy droughts from a statistical stand point. The energy system model is simplified and does for instance not include interconnection between regions.

Ruhnau and Qvist (2022) studied storage requirements for a 100% renewable energy system in Germany including both demand and generation side inter-annual variability [4]. They find that different weather years can lead to substantial differences in investments in energy storage. They emphasise the importance of considering multiple weather years to avoid underestimating storage needs.

The contribution to literature I provide in this study is a pan-European simulation of 35 weather years in a highly integrated energy system. A comprehensive scope such as this should shine light on low-frequency weather events but also allow the benefits of interconnections, sector coupling and other sources of flexibility. It is based on a time coherent data set of weather dependent supply and demand. I optimize the energy system using an average weather year and test the operational robustness in multiple weather years. The study can therefore be seen as a sensitivity analysis to studies of energy systems that use single weather years.

To study the weather dependency of demand, I will also introduce new models. Weather dependent demand models exist (see e.g. [10] and [11]), but are often based on the aggregate electricity demand. I will introduce a demand model with a focus on end-use separating demand into different categories with different weather dependency.

3 Scope

In the following, I establish the scope of the study in line with the problem statement.

3.1 Spatial scope

I include the following countries in this study: Austria, Belgium, Switzerland, Czech Republic, Germany, Denmark, Estonia, Finland, France, Great Britain, Italy, Lithuania, Luxembourg, Latvia, Netherlands, Norway, Poland and Sweden.

The spatial scope is seen in fig. 3.1. Most countries have a single region, but Denmark, Norway, Sweden and Germany are divided into multiple regions.

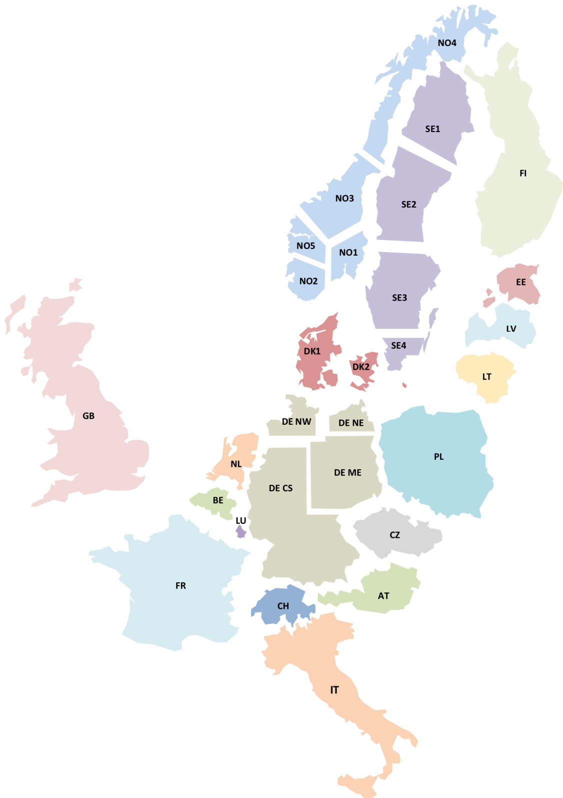


Figure 3.1: Countries and regions included in the study.

3.2 Temporal scope

I distinguish between two temporal scopes, which should be considered strightly independent of each other.

Weather years refer to historical years in which the weather behaved in a certain way. I will consider 35 different weather years from 1982-2016. The wind resource is for instance defined with hourly generation profiles and annual full load hours for different weather years, but without any assumptions about the installed capacity.

Scenario years refer to years with particular realizations of the energy system. That system has a certain composition of technologies and demand requirements. For instance, the system in scenario year 2020 may be based primarily on fossil fuels and with limited demand from electric vehicles, whereas scenario year 2050 may be primarily based on VRE and with high demand from electric vehicles. I limit the scenario years to 2030, 2040 and 2050 without considering years in between.

When simulating the energy system, I will for instance expose the optimized energy system in scenario year 2050 to the weather year 1996. The system will thus behave differently than it actually did in 1996, because the capacities and demand requirements originate from a particular expectation of how 2050 will unfold.

3.3 Climatic scope

Weather systems are complex and may interact with society in many different ways. I consider the weather as either resources to the energy generation or drivers of energy demand. I will therefore not study the impacts of rare, highly stochastic events on security of supply. These could be damage on transmission lines from storms or lack of cooling water for thermal power plants as a result of high temperatures.

I have selected the following weather variables: Wind speed as an input to wind turbines, solar irradiance as input to solar photovoltaics (PV), water inflow to hydro power plants and amount of daylight as well as ambient temperature as inputs to energy demand.

The weather variables are in all cases based on reanalysis data of the past weather. It should be noted that such data is not an exact reproduction of the past weather, be rather computed approximations utilizing both ground measurements, satellite observations and climate models [12]. I consider only weather variations as seen in the historical weather years. While the weather is unlikely to repeat itself in the future, I exclude future climate variability from the analysis, as it requires a comprehensive approach outside the scope of this study.

4 Energy demand modelling

The aim of the energy demand modelling is to simulate demand profiles for classic electricity and low temperature heat in all weather years. I will assume that all other demand types (electricity for electric vehicles, power-to-X and high temperature industrial heat) are weather independent. Furthermore, I generate an annual demand correction factor to adjust the demand level according to the weather year. I model the demands on a regional basis, which means individual demand models are fitted for each region. All demands are modelled having UTC time stamps as index. I used python for modelling, and the code is available on Github [13].

4.1 Demand categories

I define the two outputs of demand model in the following way:

Classic electricity: Electricity demand in households, the commercial sector and industries excluding consumption related to electric vehicles, low temperature heating, power-to-X and high temperature industrial usage.

Heat demand: Demand for low temperature heat (space heating and hot water) in households, the commercial sector and industries

It is important to clearly distinguish between these two end uses. The classic electricity profile should for instance not reflect the consumption pattern from electrical heating, but only contain the end use demand for classic electricity. Likewise, the heat demand profile should reflect the end demand for heat and not the particular load pattern of an electric boiler. There are multiple reasons why demands are best defined in terms of end use. First of all, the load pattern from electric heating will depend on the amount of electrification of heating in a given system and a given scenario year. The energy system model may eventually choose to provide heat based on electricity, but this is an endogenous decision that should not be presupposed in the input electricity profile. Second, the energy system model assumes that classic electricity is relatively inflexible in time, whereas heating is more flexible. That is the justification for having two separate models for simulating electricity demand and heat demand respectively.

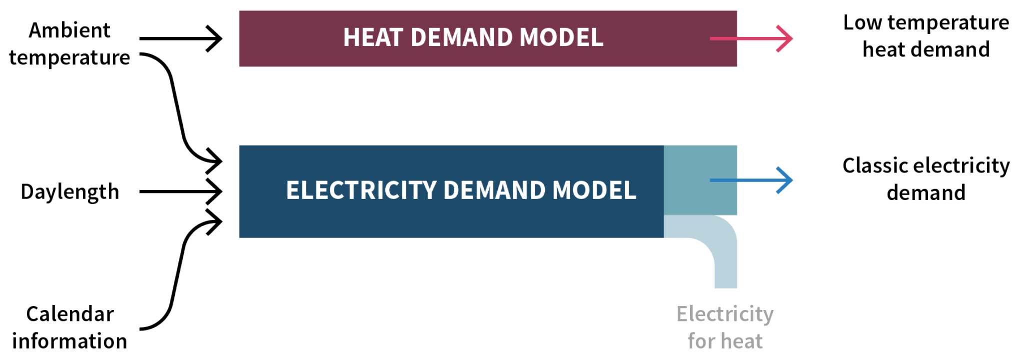


Figure 4.1: Conceptual illustration of the demand modelling.

4.2 Electricity demand model

Electricity consumption for different European bidding zones is collected in the ENTSOE Transparency platform. I use the time series *Actual Total Load* (regulated by article [6.1.A]) [14] which is defined as net generation minus net export minus stored electricity. For convenience, I retrieve the data set from Open Power System Data [15]. I divide the data into a set used for model training (years 2015-2018) and model testing (year 2019) used for an out-of-sample test of model accuracy. This requires the assumption that the demand pattern stays the same throughout the period used for modelling.

The method I use is known as load hindcasting. It is a process of synthesizing historical loads with a consistent load profile [16]. In other words, the simulated demand profile will reflect the dynamics of electrical devices used in the training period, but under the influence of historical weather. I use a linear least squares regression model with both static and dynamic regressors. The modelling approach is inspired by [16] and [17].

The aim of the model training is to fit a model that resembles the measured electricity consumption y_t in the training data. The subscript t denotes time and the resolution is hourly. The model forms a linear combination of exogenous regressors $\mathbf{X}_t$, autoregressive regressors y_{t-i}, a constant offset c and outputs a response variable $\hat{y}_t$.

$$\hat{y}_t = \mathbf{a}\mathbf{X}_t + \sum_{i=1}^{I}(b_i y_{t-i}) + c \tag{4.1}$$

The residual term ϵ_t is a measure of the deviation between the model response $\hat{y}_t$ and the measured data y_t.

$$\epsilon_t = y_t - \hat{y}_t \tag{4.2}$$

The model fitting constitutes an optimization problem with the aim of minimizing the sum of squared residuals. This is done by finding appropriate values for $\mathbf{a}$ and $\mathbf{b}$.

$$\min_{\mathbf{a},\mathbf{b}} \sum_{t=1}^{T} \epsilon_t^2 \tag{4.3}$$

An ordinary least square problem can be solved to guaranteed optimality. However, since I impose certain constraints on the model, I solve the optimization problem numerically using *lsq_linear* from the python package *SciPy* with solver *lsmr* [18]. I define an adequate fit by the tolerance 10^{-10} or a maximum number of iterations of 10^4.

I investigate the validity and accuracy of the fitted model in section 6.1.1. With a well-behaving model and optimized coefficients $\mathbf{a}^*$ and $\mathbf{b}^*$, it is possible to simulate the demand for any historical time period given the corresponding input regressors. Note, I use the measured y_{t-i} for the model fitting. For the hindcast simulation, I use $\hat{y}_{t-i}$ since the measured demand is unknown. Furthermore, I assume $\epsilon_t = 0$ in the simulation which will give a central estimate of the demand. The simulation is initialized 48 hours before the start of the simulation period to stabilize the autoregressive effects.

4.2.1 Selection of regressors

Electricity demand can be driven by many different variables, but I will generally distinguish between weather related regressors and non-weather related regressors.

I use *day of the week*, *holidays* and *hour of the day* as regressors to explain non-weather related patterns in the power demand. All are discrete variables with certain levels. They are modelled as dummy variables, thus each level is given its own binary variable (e.g. 24 variables for ”hour of the day”).

To capture the weather related behaviour in the demand, I use *daylength* and *ambient temperature*.

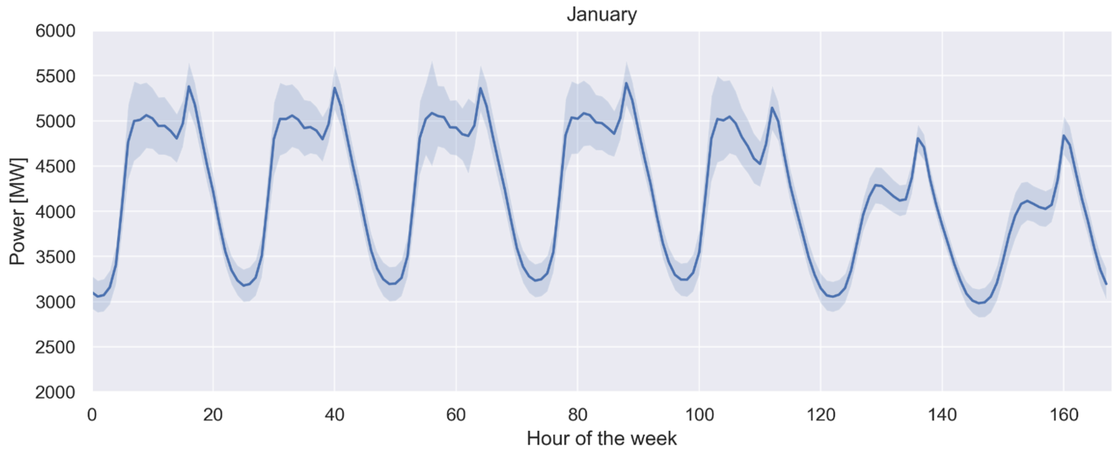


Figure 4.2: Example of weekly demand structure in Denmark in January in the training period. Standard deviation is marked in light blue.

Day of the week: The average daily demand changes over the week as seen in fig. 4.2. Industry activity is likely the reason for higher demand in weekdays and lower demand in weekends. I model this behaviour using three dummy variables for weekdays, saturdays and sundays.

Hour of the day: There is a diurnal cycle visible in fig. 4.2, which is because of the daily patterns of people, including sleep during the night, work during the day and cooking in the evening. I use 24 different dummy variables to capture the hourly behaviour.

Holidays: National holidays are clearly visible in the demand data, as they tend to make people deviate from the normal consumption patterns. I retrieve holidays from the python library *holidays* [19]. I add certain additional holidays where I find it necessary (most importantly around Christmas and New Year) to achieve a better fit (see appendix A). Each holiday is given its own dummy variable, thus the model can only fit the coefficient relating to a specific holiday based on instances of that same holiday. Holidays can be seen as another day type (similar to to the variable denoting day of the week). Thus, when a holiday variable is active, I set the dummy variable denoting the day of the week to 0. This ensures a consistent day type dummy system, where only one day type can be active at a time.

Daylength: I use the daylength to capture the seasonal patterns in demand. I model it as the average amount of time with daylight per day in a given region. A more accurate representation of daylight on a given day would be irradiance, but it is a more volatile variable, and I find that it has a lower explanatory power in terms of electricity demand. Daylength is therefore not strictly related to weather, but based on a mathematical model of Earth's tilt angle relative to the sun. The specific model is available from the the python package *SunTimes* [20]. I constrain the regression model to enforce a negative a coefficient for this regressor based on the assumption that people consume less electricity in the summer than in the winter.

Temperature: I include the ambient temperature to explain the demand due to electrical heating and to some degree seasonal behaviour. Temperature is location specific, and to cover all regions consistently, I introduce a grid with a distance between points of 100 km (see fig. 4.3). I request temperature measurements at these locations from interpolated ERA5 reanalysis data [12]. The relationship between electricity demand and temperature is non-linear as heating is typically switched off above a certain temperature. To account for this in a linear model, I model temperature as a piece-wise function. I use 15 °C as break point based on [21]. The temperature regressor T is split in two and the term in eq. (4.1) related to temperature has the following structure above and below the temperature threshold:

$$\left\{ \begin{array}{ll} \sum_k a_{k,1} T_{k,t} & T_{k,t} \leq 15\,^{\circ}\mathrm{C} \\ \sum_k a_{k,1} T_{k,t} + a_{k,2}(T_{k,t} - 15) & T_{k,t} > 15\,^{\circ}\mathrm{C} \end{array} \right\} \tag{4.4}$$

where $a_{k,1}$ and $a_{k,2}$ are the two fitting coefficients at each temperature location k. The model is constrained to enforce $a_{k,1} \leq 0 \; \forall k$. This is based on the assumption that a lower temperature below the threshold leads to higher demand. Since the temperature profiles are likely to be similar, this constraint will also minimize the risk of multicollinearity. I make no assumptions about the demand trends above the threshold.

Lagged demands: I include autoregressive regressors to capture the inertia in the change of demand. This is mainly to dampen the effect of fluctuating temperatures, as the thermal mass of the building will smoothen the heat demand. I include lagged time steps $t-1$ and $t-2$, as the measured data showed two significant lags in a plot of the partial autocorrelation function.

Interactions: Some regressors may also have a combined impact that is different from the simple sum of the individual impacts. E.g. the demand has a different hourly distribution depending on the day of the week. I model such interactions by creating new regressors containing the product of the following interacting regressors:

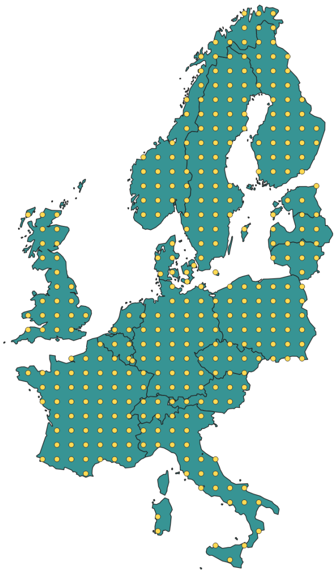
- Day of the week $\times$ Hour of the day
- Holiday $\times$ Hour of the day
- Daylength $\times$ Hour of the day

4.2.2 Clustering of temperature profiles

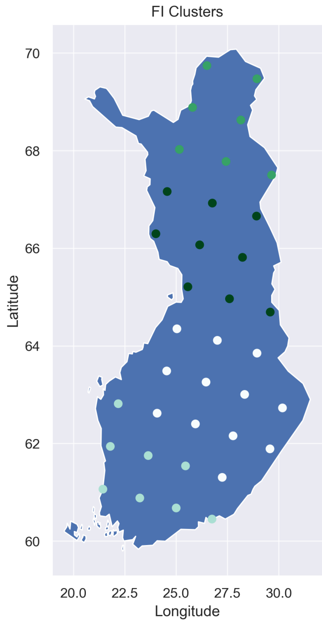
Demand in a particular location responds to the local ambient temperature. As a counter example, the demand in southern Finland would probably not correlate well with the temperature measured in northern Finland. This speaks in favour of including several of the gridded temperature profiles, as it allows the regression model to assign weights based on the explanatory power of each profile. However, including too many similar profiles will also risk multicollinearity issues. In other words, the regression is unable to give weights to the temperature regressors, if the profiles are almost identical.

I reduce the number of profiles using K-means clustering from the python library *scikit-learn* [22]. This will reduce the number of similar temperature profiles, while preserving profiles that are distinctly different.

I adjust the number of clusters such that regions have 0.4 clusters per degree latitude they span. A minimum of at least 1 cluster per region is enforced. This results for instance in 4 clusters in Finland, 4 clusters in France, 3 clusters in Germany and 1 cluster in Denmark West. The temperature at each cluster is a population weighted average of all temperature profiles belonging to that cluster. I obtain the JRC 2018 1 km population grid from Eurostat [23] and resample to 25 km resolution.



(a) Temperature sample locations with 100 km spacing



(b) Example of clusters in Finland

Figure 4.3: Model geography

4.2.3 Temperature dependency of different types of electricity demand

Since the power demand model is fitted on aggregate meter readings, it is not possible to know which parts of the electricity consumption is related to which end use. Especially electric heating will have a characteristic impact on the modelled profile. As explained in section 4.1, I aim at modelling a clean classic electricity profile.

With the fitted model, it is possible to simulate a weather year given the temperature of the historical year. But it is also possible to input a synthetic temperature profile where a temperature threshold is imposed. I therefore simulate all weather years where input temperatures are clamped to 15 °C whenever they go below this threshold. I choose 15 °C as it is consistent with the break point of the piece-wise temperature regressors. The two profiles, the actual and the synthetic, are illustrated in fig. 4.4. They represent two extremes; one profile that contains all the low temperature effects on electricity consumption and one that contains none of the effects.

I assume that most of additional demand below the threshold can be attributed to electric heating. But the ambient temperature may also influence other behavioural patterns than heat consumption. It could be the case that people tend to stay more inside, watch more television, use the kitchen more etc. in cold weather. Thus, classic electricity may still have some amount of temperature dependency, but it is not trivial to determine how much.

However, annual statistics [24] exist that estimate the demand for classic electricity and electricity used for heating. For instance, a hypothetical region may use 95% of electricity to serve classic demands and 5% for heating according to the reference. The synthetic simulation mentioned above might instead suggest a 90%/10%-split. The final classic electricity profiles are obtained as a mix of the two profiles in fig. 4.4 to approximate the split reference.

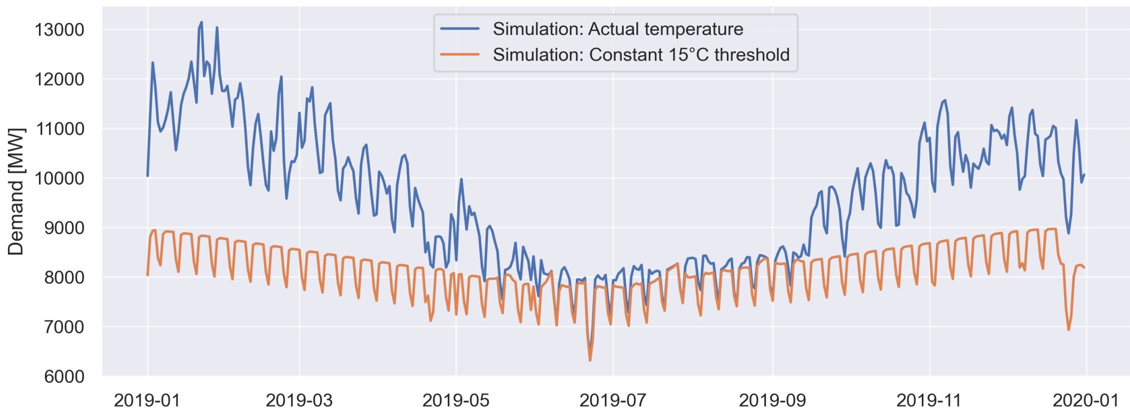


Figure 4.4: Example of temperature dependency in demand in Finland in 2019. Resampled to daily mean for illustration.

4.3 Heat demand model

Heat can be delivered by a multitude of different sources, not just electricity. The heat demand profile should therefore reflect the end use as objectively as possible without assuming specific dynamics of the technology providing it. An often used metric for heat demand in energy modelling is heating degree days (see e.g. [25]). I model the number of heating degree days (HDD) at each cluster location k in a region based on the Eurostat definition [21]:

$$\mathrm{HDD}_{k,t} = \left\{ \begin{array}{ll} 18 - T_{k,t} & T_{k,t} \leq 15\,°\mathrm{C} \\ 0 & T_{k,t} > 15\,°\mathrm{C} \end{array} \right\} \quad \forall k \tag{4.5}$$

where $T_{k,t}$ is the daily mean ambient temperature and t represents daily time steps. The time series is later upsampled to hourly resolution.

I model the heat demand profile $\mathrm{HD}_{k,t}$ assuming that 75 % of heating is temperature dependent (space heating) and 25 % is temperature independent (hot water). This is based roughly on [26], although different splitting factors exist.

$$\mathrm{HD}_{k,t} = 0.75 \frac{\mathrm{HDD}_{k,t}}{\sum_t \mathrm{HDD}_{k,t}} + 0.25 \frac{1}{\sum_t t} \quad \forall k \tag{4.6}$$

The sum of $\mathrm{HD}_{k,t}$ over a year is 1. An example of is seen in fig. 4.5. The final heat demand in a region is a population weighted average of heat demands across all clusters.

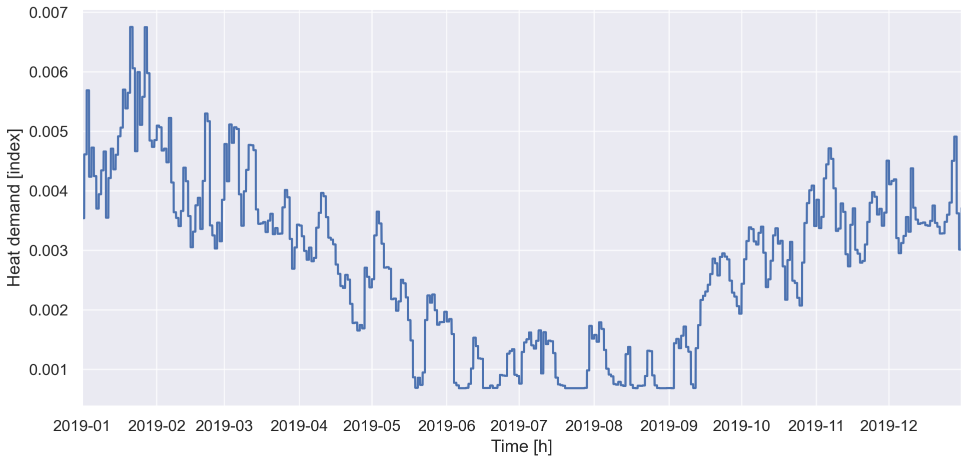


Figure 4.5: Example of heat demand profile for Finland in 2019.

4.4 Demand correction factors

Apart from the electricity and heat profiles, I generate a correction factor that explains how the annual demand in a given weather year deviates from an average year. This enables an simple calculation of demands in a given scenario year as the product of the scenario demand and the weather dependent correction factor. The demand correction factors are given in appendix J.

In the case of district and individual heating, I scale 75 % of the heat demand by a factor. I define this as the deviation of the annual number of heating degree days from the long term mean of all weather years. I assume the remaining 25 % of heat demand is temperature independent and is therefore not scaled by any factor.

For classic electricity, I define the correction factor as the deviation of the annual consumption from the long term mean.

Figure 4.6: Example of demand correction factors in South West Norway.

5 Energy system modelling

In this chapter, I introduce the energy system model along with the main assumptions and data inputs. Furthermore, I describe the procedure used for investments and simulating different weather years.

5.1 Balmorel model

Balmorel is an optimization model for energy planning based on an open source code modelled in GAMS [27]. The specific version I describe below and apply has been further developed by Ea Energy Analyses [28]. The input data set for Balmorel (unless otherwise stated) is the December 2022 version of the in-house data set used by Ea Energy Analyses. I denote this data set *existing Balmorel data*.

Balmorel solves an optimization problem to find the least-cost energy system under a given set of constraints. The objective is to minimize the total cost of the system: generation costs of electricity and heat, fuel and externality costs, generation and transmission investment costs and unit commitment costs.

It is subject to various constraints that limit the solution space; electricity and heat demands, transmission line capacity, storage constraints, unit commitment constraints and policy constraints.

Balmorel is modelled as a perfect, liberalised market with an hourly time resolution resembling the European day-ahead market. Similar to this market, Balmorel does not guarantee that the exact energy dispatch is feasible in the physical grid.

Balmorel operates with three levels of geography; (1) *countries*, (2) *regions* within countries where the electricity demands are defined and (3) *areas* within regions where heat demands and energy generation are defined. Electricity can flow unconstrained within a region. Exchange of electricity between regions is constrained by the net transfer capacity of the transmission lines. District heating is modelled for Scandinavia, the Baltic and Germany. Individual heating is modelled for all countries.

A Balmorel year consists of 52 weeks and 168 hours per week. The year has to start on a Monday with time step 00:00-01:00. Thus, the input demand and generation profiles must be sliced to fit this format. The start and end UTC time stamps for each weather year is given in appendix B.

For energy production and demand, Balmorel distinguishes between annual levels (annual energy demand and full load hours) and higher resolution profiles (normalized hourly or weekly profiles). These two parameters can be defined independently, but linear scaling of the profile takes place to align it to the annual metric.

While Balmorel has full foresight within a year, it is not able to anticipate future years. Consequently, I will not study the compounded effect of successive weather years.

Existing capacity is included until end of lifetime (exogenous decommissioning) or until it is economically optimal to shut it down (endogenous decommissioning).

Policy restrictions constrain the solution space in addition to the physical constraints. For instance, there are limitations to investments in certain technologies. These constraints represent in many cases political or assumed limitations, but can also indicate physical limitations (e.g. maximum resource potential for offshore wind in a given area). Similarly, there are limits on the expansion rate of transmission lines. There are also policies for penalising negative externalities. This includes most notably an emission cost of 128 EUR20/tCO_2eq. in 2030 increasing to 190 EUR20/tCO_2eq. in 2050. The weighted average cost of capital (WACC) for investments is 5%.

Additional inputs for the energy system model are given in appendix F.

5.2 Energy demand

Balmorel distinguishes between two overall types of demand: heat and electricity. They can further be divided into the categories shown in table 5.3. The optimization process can find synergies between sectors (e.g. electrification of heating and storage of heat) to satisfy demands in a least-cost manner.

I assume that only classic electricity and low temperature heat are weather dependent. Consequently, I assume the remaining demands are weather independent and are as given in the existing Balmorel data set.

5.2.1 Annual demand levels

Annual electricity demand projections are part of the existing Balmorel data set. It is primarily based on a combination of the European Commission's MIX scenario from the European Green Deal, ENTSOE TYNDP 2022 Global Ambition scenario and REPowerEU [29]. Likewise, district heating demands are part of the existing data set. These existing annual levels are given in table 5.1 and table 5.2, and I will assume they represent an average weather year. Thus, to represent the levels in a given scenario and weather year, I scale the relevant levels by the correction factors explained in section 4.4.

The overarching political ambition to reduce greenhouse gas emissions fosters an electrification of transport, heating and industry towards 2050. Whereas the classic electricity demand stays almost constant, new demands are introduced as a replacement for fossil fuels in the mentioned sectors. Most notable is power-to-X which constitutes almost 1/3 of the total electricity demand in 2050.

	2030	**2040**	**2050**
Classic electricity	2680	2681	2685
Electric vehicles	158	298	432
Industry heat	64	222	386
Power-to-X	388	998	1914
Other	26	55	74
Total	3316	4255	5491

Table 5.1: Electricity demand [TWh] in the average weather year [24].

	2030	**2040**	**2050**
Individual heating	1277	1291	1302
District heating	348	345	343
Total	1625	1636	1645

Table 5.2: Heat demand [TWh] in the average weather year [24]. Note that it represents end use demand and electricity can be used to supply this.

5.2.2 Profiles

The time varying profiles of classic electricity and low temperature heat are modelled as outlined in chapter 4. The same profiles and correction factors are given to all relevant areas within a region.

5.2.3 Flexibility

Balmorel allows flexibility in meeting energy demands (demand response) at certain costs as outlined in table 5.3.

Demand type	**Flexibility**	**Flexibility cost**
Classic electricity	10% of average demand can be moved up to 2 hours in time.	15-30 EUR/MWh
Electric vehicles	65 % of demand can be moved up to 4 hours while obeying driving constraints.	15 EUR/MWh
Individual heating	Average demand can be moved up to 2 hours	10 EUR/MWh
District heating	Demand can be fulfilled both using electricity and conventional fuels.	Alternative fuel and emission costs
Industry heat	Alternative fuels can be used as a backup to electricity.	Alternative fuel and emission costs
Power-to-X	Demand is constant and storage can be added to allow flexible use of electrolyzers.	Cost of electrolyzers and storage.

Table 5.3: Flexibility assumptions for electricity demands in scenario year 2050 [30].

Note that individual heating has no fuel switching flexibility. Furthermore, it is an exogenous investment (sunk cost not subject to optimization) and a combination of heat pumps and electric boilers. I base the variation of the heat pump coefficient of performance on a reference year in the existing data set. The actual coefficient in a given weather year would be different.

5.3 Energy generation

Examples of wind, solar pv and hydro power profiles are given in appendix C. Full load hours for all weather years and areas are given in appendix K.

5.3.1 Wind and solar power

Solar PV and wind generation data is obtained from the DTU CorRES model [31]. The model is based on the ERA5 weather reanalysis data set [12]. For the wind data sets, the ERA5 wind speeds are further calibrated using the Global Wind Atlas for improved accuracy [32]. The data set is available as hourly normalised generation profiles and the generation assumes a specific deployment of plants in a given location.

The data is available aggregated to the geographical zones used in ENTSOE's Pan-European Climate Database (PECD). In general, I have mapped the national zones to the Balmorel areas. In cases where Balmorel has multiple generation areas per country, I have applied lower level PECD zones.

For wind power, different generation profiles are available using different turbine technologies and placement assumptions (known as resource grades). Wake losses are considered in the wind farm assumptions. I restrict the set of wind turbine technologies to the following:

1. Existing turbines: Generation is based on the 2019 mix of onshore and offshore turbine technologies respectively and corresponding power curves.
2. New investments:
   (a) Onshore: Specific power $277\,\mathrm{W/m^2}$, hub height $100\,\mathrm{m}$, resource grade B
   (b) Offshore: Specific power $370\,\mathrm{W/m^2}$, hub height $155\,\mathrm{m}$, standard resource grade

For solar PV, the CorRES model uses ERA5-Land meteorological reanalysis data and converts the irradiance to power using the python package *pvlib* [31]. Of all possible locations, solar units are assumed to be placed in the 50 % best locations with south-facing panels and tilt angles resembling existing installations. Thus, these represent ideal conditions that are more likely at utility scale solar farms rather than small-scale rooftop installations.

Cost assumptions of wind turbines and solar power are given in appendix F.

5.3.2 Hydro power

The amount of hydro power available for dispatch is determined by the hydrological conditions for a given location and weather year. The actual dispatch of hydro power is determined endogenously by the energy system model, but water inflow profiles must be given exogenously.

Hydro inflow profiles are available in the PECD and published by ENTSOE as part of the 2022 European Resource Adequacy Assessment (ERAA) [10]. They model a transfer function fitting weather reanalysis data to the natural water inflow in a training period (2010-2017). Based on this function and historical weather data, they hindcast the water inflow for the period 1982-2016. Different scenario years are available (2024-2030) where different capacities are assumed. I use 2024 as a conservative choice, since hydro power requires very specific conditions and may not be easily expandable. I calculate the full load hours based on the annual sum of water inflows and the capacity stated in the ERAA data set. And I use the same capacity to normalize the inflow profiles as input to Balmorel.

I consider the following grouped hydro resources:

1. Run of river and pondage are hydro plants with little to no storage capacity (max 24 hours) and have weekly inflows given.
2. Reservoir and open loop pump storage are hydro plants with natural water inflow, storage capacity and the possibility of pumping water from the lower reservoir to the upper one. I resample the given daily inflows to hourly resolution using linear interpolation.

Closed loop hydro plants are part of Balmorel and modelled as storage. They do not have natural water inflows, and I will therefore not consider the weather impact due to their weak link to weather variables.

In the ERAA data, all hydro power in Norway, Finland and Sweden is modelled as hydro reservoirs. Using the data as such will lead to an overestimation of flexibility by this energy source, since some capacity is run of river. Thus, for these countries, I use the inflow profiles from reservoir plants as an approximation of run-of-river. I upsample the weekly data to hourly resolution using linear interpolation. Reservoir plants allow a greater inflow per time than what can be produced by the installed capacity (because of the storage capacity). To use these profiles as run of river, I have therefore clipped the capacity factor to a maximum of 1. Finally, I have calibrated Norway and Sweden by scaling inflow and full load hours with a factor of 0.9 to better approximate historical production.

I assume no endogenous investments in hydro power are possible. Only already planned expansions in the existing data set are included.

5.4 Procedure for simulation

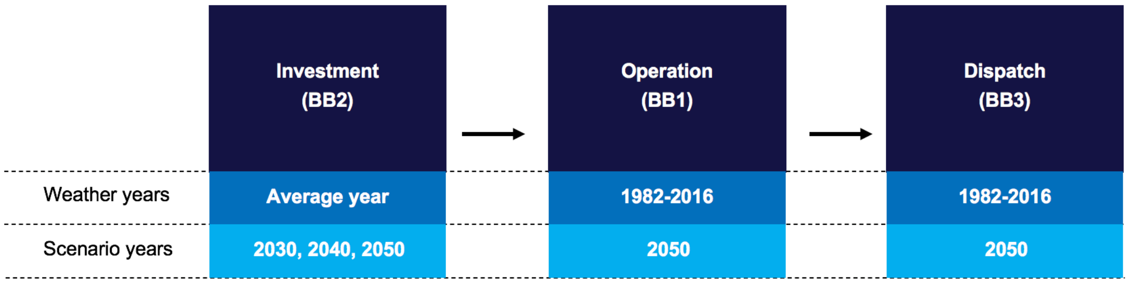


Figure 5.1: Overview of the simulation procedure for the energy system.

The procedure for simulating the energy system is outlined below and shown in fig. 5.1.

5.4.1 Investment model (BB2)

I construct an average year for making investment decisions (in Balmorel known as a BB2 run). Full load hours in each area are based on the long term average of weather years considered. The demand correction factor is similarly the long term mean and is by definition 1. I base demand and generation profiles on weather year 2012, as this year approximated the long term annual average of weather variables.

To make the optimization problem computationally tractable, I reduce the number of time steps to 26 weeks and 12 hours per week. Time aggregation is applied to group and average hours with similar characteristics. The resulting 312 time steps should ideally reflect the variation of the full year.

Investments are made for scenario years 2030, 2040 and 2050 consecutively. Thus, investments made in 2030 will be available as existing infrastructure in 2040 and 2050.

5.4.2 Operation model (BB1)

I only consider scenario year 2050 for operation and dispatch. All weather years are simulated individually as possible scenario variations of 2050. Investments and existing capacities from BB2 are available, but no additional investments are possible in BB1.

For each weather year, operations are planned for the whole year based on an annual foresight. I consider all 52, each with 12 representative hours, and time aggregation is therefore applied. This is done to plan the use of storage optimally over the year (including hydro, power-to-X and batteries). The result is an assignment of storage start and end level for each week that is passed on to the dispatch model.

5.4.3 Dispatch model (BB3)

For dispatching energy, I consider all 52 weeks and 168 hours per week with no time aggregation. Weeks are run sequentially, thus the foresight of the model is limited to one week. This model ensures that demand is satisfied within each hour while complying with all other constraints.

If the model is unable to meet the demand with the given capacities and constraints, it can utilise a backstop technology. It is a virtual technology that is modelled based on a gas turbine. It has no investment cost, but instead a variable O&M cost of 10.32 EUR20/MWh in addition to a fuel cost of 16.05 EUR20/GJ. The high cost ensures it is only dispatched as a last resort. Backstop generation serves as an evaluation measure of how much energy cannot be dispatch by the current system for a given weather year. Backstop capacity is similarly a measure of the additional needed capacity.

6 Model validation

In this chapter, I validate the electricity demand model and the energy system model to ensure they can deliver sufficiently accurate results.

6.1 Electricity demand model validation

Before applying the demand model, they should be validated and tested for accuracy. Note that a unique model for each region exists, which would be too comprehensive to show in this report. Examples are given in this section, and other variations are available in appendix D.

6.1.1 Regression model diagnostics

A well-behaving linear regression model should fulfill basic requirements to produce valid results as described in [33]. First of all, the input data should be accurately measured. Some outliers are present in the original demand data from ENTSOE. They appear as sharp spikes indicating excessive demand ramping. I will assume they are errors in the data that should be ignored or removed. This can both impact the accuracy of the model fitting and the result of the out-of-sample validation. The spikes are rare enough that they should have low impact on the fitting as it aims at minimizing the total sum of squared residuals. However, if they represent actual demand ramps, it should be noted that the model is not suited for reproducing such rare stochastic events. This would require a dedicated security of supply analysis.

Secondly, the model assumes a linear relationship between the response variable and the regressors. As seen in fig. 6.1, the effect of temperature on demand is non-linear, but it can be approximated relatively well with piece-wise temperature regressors and a break point at 15 °C. The model has some problems reproducing demands seen at high ambient temperatures, as seen in the figure above 25 °C. This is especially visible in France and Italy. This is because of the autoregressive part of the model which gives inertia in the response to changes in the regressors. Hours with very high temperatures do not last long enough to yield a strong response from the model. This is a consequence of the model being optimized for low temperatures. Disabling the autoregressive part of the model would negatively impact the precision in the colder months.

As an alternative to the regression model, I performed some tests with a simple machine-learning tool, Random Forest, in the initial stages of the modelling process. The strength of such a model is that it is not bounded by the linearity assumption. However, the results were similar to the regression model. Eventually, I chose not to proceed with the Random Forest model, as the functioning of such a model is not as easily explainable as a standard regression model.

The third assumption is that the regressors are independent. If a regressor can be formed as a linear combination of one or more of the other regressors, the model will be unable to assign accurate coefficients. If for example two temperature profiles are very similar, the model is unable to tell if the demand changes because of one or the other temperature profile. Initial model runs included temperature profiles from all gridded sample points with no restrictions on model coefficients. It resulted in temperature coefficients with very high positive and and negative values. These values appeared arbitrary, likely as a result of the reasons mentioned above. To remedy this, I reduced the number of temperature regressors by clustering and I enforced constraints on the temperature and daylength coefficients, as previously explained. This has reduced multicollinearity issues to a minimum.

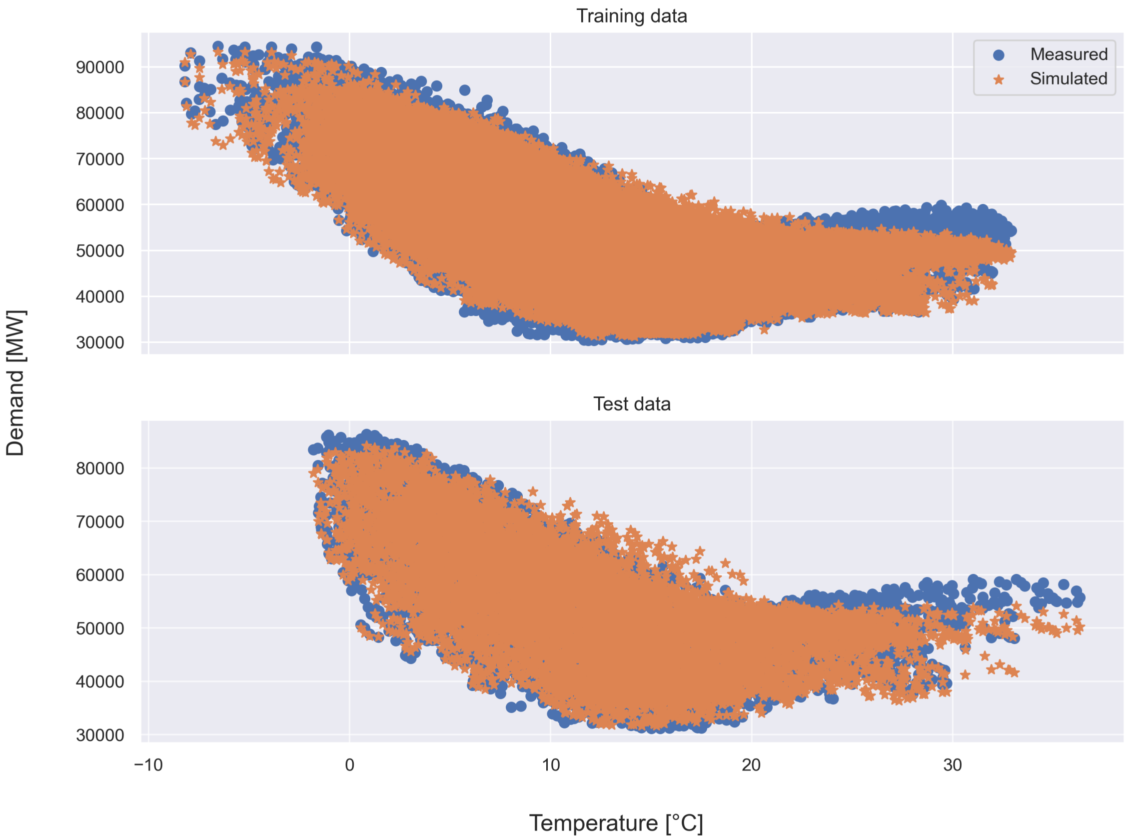


Figure 6.1: Example of scatterplot of electricity demand and temperature for France.

The fourth basic requirement of a linear model is that the residuals are independent and identically distributed (i.i.d). If the residuals are not independent of each other, they may show some pattern, which means that there are still trends left in the reference y_t not accounted for in the fitted response $\hat{y}_t$. It can be a result of one or more missing regressors. The residuals in fig. 6.2 show some amount of autocorrelation in lag 24 which implies there is still some diurnal structure not accounted for by the regressors. However, the dummy system representing the hour of the day should be sufficient to capture this structure and the autocorrelation at this lag is not easily redeemable. Apart from this, no significant autocorrelation is visible.

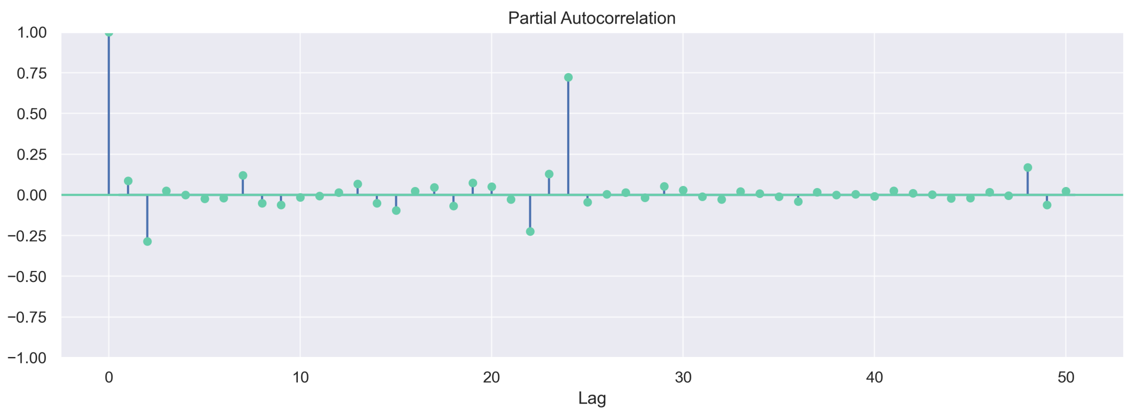


Figure 6.2: Example of partial autocorrelation in residuals for the model fitted to France.

I have calculated the Pearson correlation coefficient between training residuals in different regions (see appendix E for a full overview). While it is not always the case, the residuals in some neighbouring regions appear to correlate. For instance, Poland and Czech Republic have a coefficient of 0.66, NO1 and NO2 have a coefficient of 0.65 and France and Belgium have a coefficient of 0.61. This suggests that there could be some trends left in the residuals that affect locations in close proximity simultaneously. It is likely that it could be improved further by including more relevant regressors. They could be weather related (e.g. precipitation), but they could also be related to specific cultural behaviour (e.g. time pattern of using the kitchen). However, in order to avoid overfitting the model, I have followed the approach of including only regressors that have a clear, explainable effect on the demand.

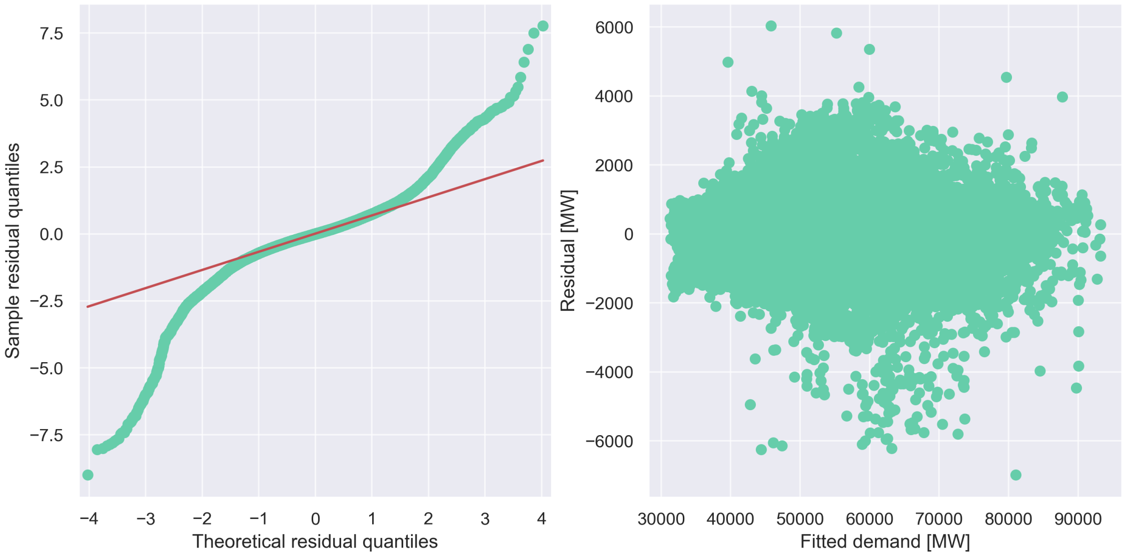


Figure 6.3: Example of QQ-plot assuming Gaussian residuals (left) and fitted-vs-residual plot (right). Based on training residuals for the model fitted to France.

The requirement of an identical residual distribution implies that all residuals are samples from the same probability distribution. It is often assumed that it is a normal distribution with mean 0 and constant variance, i.e. $\epsilon \sim N(0, \sigma^2)$, although the type of distribution is not essential. The constant variance implies that the residuals are homoscedastic, i.e. the variance is independent of the response and thus the regressors. The QQ-plot in fig. 6.3 shows that the distribution of the residuals deviate from a theoretical normal distribution. However, the histogram in fig. 6.4 shows that a t-distribution can give a better fit. The mean approximates zero and the same distribution appears to fit both the residuals of the training period and the test period. Having an accurate model of the residual distribution is mainly important if one wishes to determine uncertainty intervals. The homoscedasticity assumption is not severely violated, although the residuals tend to be a little higher for medium size loads.

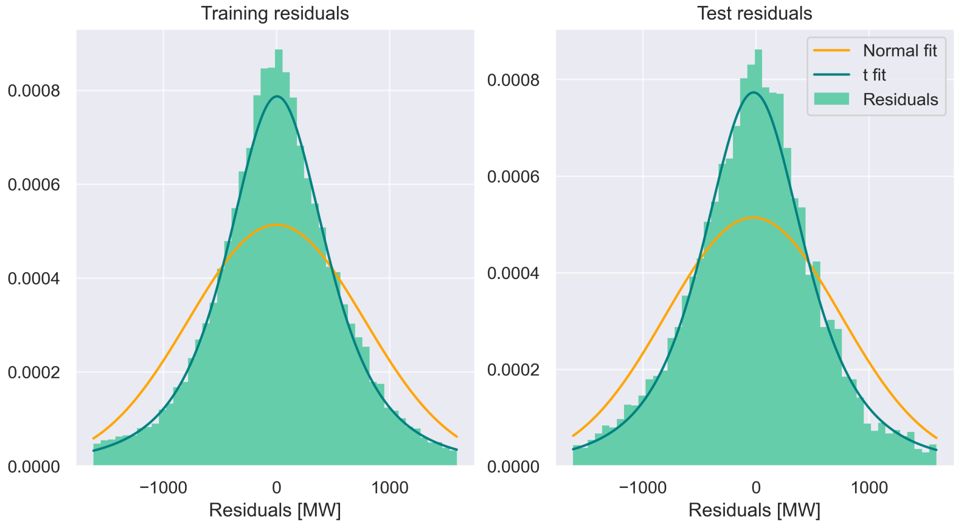


Figure 6.4: Example of training- and test residual distribution for the model fitted to France. Training residuals are from the model fitting (2015-2018). Test residuals refer to the residuals of the test period (2019) using 1-step ahead prediction.

6.1.2 Demand model accuracy

To validate the model accuracy, I use mean absolute percentage error (MAPE) as an overall measure inspired by [16]:

$$\text{MAPE} = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{\hat{y}_t - y_t}{y_t}\right| \times 100\% \tag{6.1}$$

where $\hat{y}_t$ is the model response and y_t is a reference response.

I calculate MAPE to perform (1) an out-of-sample validation using measured demand in 2019 as the reference response and (2) a hindcast validation using electricity demands modelled by ECMWF [11] as the reference response. Note that I perform MAPE validation using the simulated electricity profile with the full temperature dependency.

An example of the out-of-sample performance of the model is given in fig. 6.5. The prediction intervals are based on 1000 Monte Carlo simulations of the test year, where each time step is given an error term sampled from the t-distribution of the residuals of the fitted model. From this range of simulations, I use the 2.5 and 97.5 percentile for each time step to form the interval visible in the figure. Note that the intervals are for validation and illustration purposes only. The actual demand profile used for the energy system modelling in chapter 5 uses a central demand estimate and is therefore treated as deterministic.

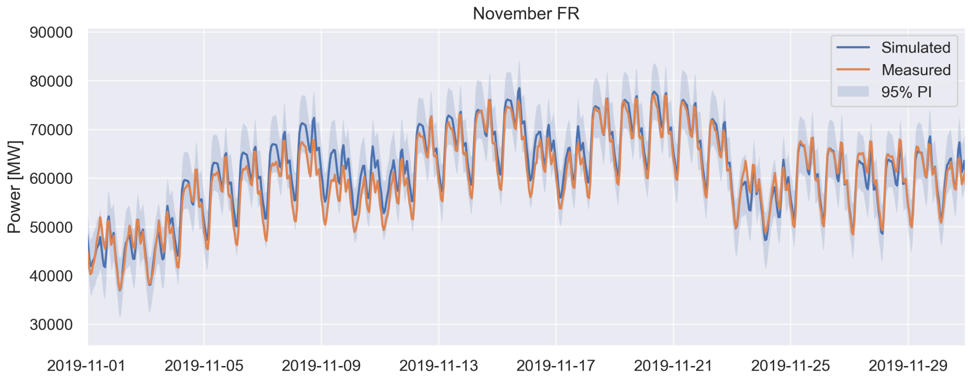


Figure 6.5: Example of out-of-sample validation for France

A table of MAPE for all regions is available in appendix D.

The out-of-sample MAPE is between 3-6% for most regions, but with some notable outliers. Luxembourg (MAPE: 15%) is a much smaller region than some of the others and individual stochastic behaviour will dominate more than in larger regions. In Great Britain (MAPE: 12%), the measured data showed many of the aforementioned spikes in demand. In south-mid Norway, NO5 (MAPE: 7.91%), there is an offsets between the training and test data. This can be a violation of the assumption that the demand pattern stays the same between 2015-2019 (e.g. because of electric vehicle adoption). It could also be because of region boundaries being redefined. Switzerland (MAPE: 6.21 %) shows a lot of volatility that the model cannot fully capture. Weekly and diurnal patterns are not as regular as in other regions.

The MAPE of the hindcast is also between 3-6% for most regions, with some notable outliers in Luxembourg (MAPE: 32.5%), Poland (MAPE: 11.4%) and Austria (MAPE: 10.5%). The issues in the regions are generally related to the demand level being offset, while the trends over time are similar.

6.1.3 Validation of temperature dependency of classic electricity

I remove parts of the temperature dependency in the electricity demand to synthesise a classic profile as described in section 4.2.3. The initial simulation dictates that all temperature dependency in demand below 15 °C is due to electric heating. On an annual basis, it amounts to the electricity shares seen in fig. 6.6 used for classic consumption and electrical heating. For comparison, a reference split based on [24] is also given. The initial model split captures accurately that e.g. France and Finland have more electric heating than e.g. Denmark. There is some deviation in Norway, parts of Sweden and Switzerland. They tend to have more temperature dependent behaviour in their classic electricity than assumed by the model, which is the reason for the deviation. The model attempts to correct for this in the final classic electricity profiles as described in section 4.2.3. Note that the reference is most likely also based on an estimate of the split, since accurate measurements would require separate meters within each building.

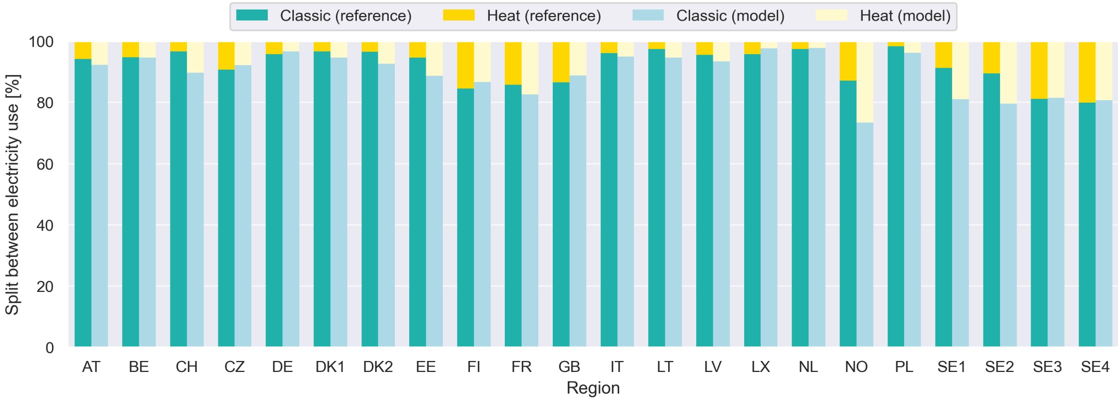


Figure 6.6: Initial model split between classic electricity and electricity used for heating. Reference based on [24].

6.2 Energy system model validation

Before obtaining results from a future energy system, it is important to first assure that the current energy system can be reproduced with reasonable accuracy. I therefore simulate the dispatch from the existing capacities in scenario year 2016 and using weather year 2016. This should be comparable to the operation of the actual energy system in 2016 (available from the ENTSOE Transparency Platform [14]). I make the comparison based on annual average electricity prices and annual dispatch of electricity from wind, solar PV and hydro generation.

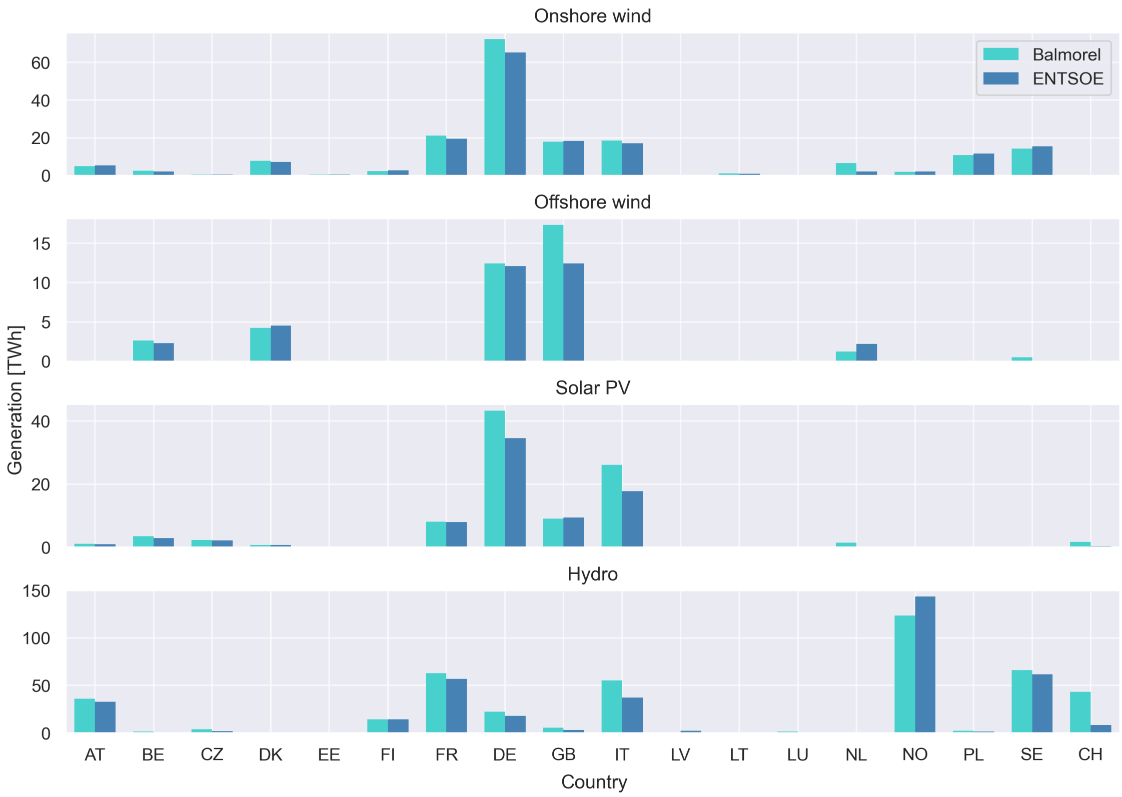
An initial test showed that some existing generation capacities were missing in the existing data set. I have updated the most important wind, solar and hydro capacities based on data available in the ENTSOE Transparency platform.

The result of the validation is shown in fig. 6.7. There is some noticeable discrepancy. The onshore wind generation in Germany deviates from the measured, which could be result of congestion issues. Germany only has one bidding zone but is modelled with 4 regions in Balmorel. It could also be an inaccuracy in mapping PECD areas to Balmorel areas. Regarding offshore wind in Great Britain, the ENTSOE data might be inaccurate. The UK Department for Business, Energy Industrial Strategy reports a production of 16.4 TWh in 2016 [34], which is closer to the Balmorel generation.

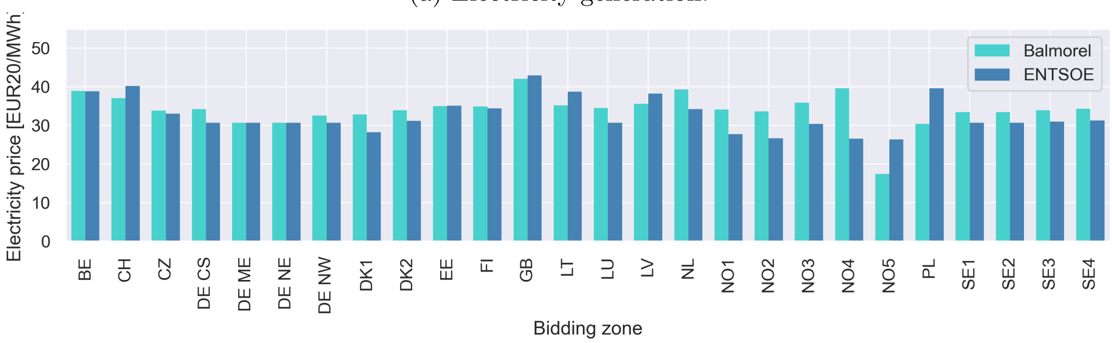
The solar generation in Germany and Italy is overestimated in Balmorel. The CorRES data is based on south facing panels, which is mostly true for industrial scale plants, rather than households. It is furthermore possible that some generation from household panels is measured below meter.

Countries with large hydro reservoirs (e.g. Norway) are challenging to validate, as the production in one year may be the result of inflow from previous years. In the case of Switzerland, the International Energy Agency reports a production of 36.7 TWh in 2016 [35], indicating a possible inaccuracy in the ENTSOE data.

Electricity prices seem to be within the expected range and follow the right trends across bidding zones. However, an annual average can be the result of many different distributions of hourly prices, which are not visible in the plot. The electricity price in parts of Norway is overestimated, while in other parts underestimated. This could be a sign that the transmission line capacities in Balmorel are not entirely correct or the distribution of hydro capacities is not correct.



(a) Electricity generation.



(b) Electricity prices. France, Italy and Austria are not available.

Figure 6.7: Comparison of Balmorel results in scenario year 2016 and ENTSOE statistics from the same year.

7 Results

In this chapter, I first present the optimized future energy system. This is followed by the dispatch results of the 2050 system for the average weather year and weather years 1982-2016. As the focus is on the robustness of the aggregate system, the results are given as a total for all countries (unless otherwise stated).

7.1 Optimized system capacities

This exogenous growth in demand and political ambition to reduce greenhouse gas emissions drives the model to make new power capacity investments as seen in table 7.1.

	2030	**2040**	**2050**
Bio and waste	18	26	27
Electric storage	35	73	174
Natural gas plants	127	127	127
Offshore wind	124	280	433
Onshore wind	266	385	496
Solar PV	571	784	1195
Total	1140	1675	2452

Table 7.1: New power capacity investments [GW] accummulated over scenario years.

Investments in solar PV and wind turbines make up 86% of the new power capacity investments in 2050. The installed capacities in individual countries relative to the assumed capacity potential can be seen in appendix G. Onshore wind and solar PV capacities are particularly limited. The installed amounts of onshore wind is equal to the maximum in almost all countries indicating that the model sees further benefits in expanding these capacities, if the constraint could be relaxed. The same is seen for offshore wind in France and Italy as well as solar PV in several central-southern European countries.

To integrate the large share of VRE, the model has invested in 174 GW/1.04 TWh of electric grid storage by 2050. Furthermore, it proves optimal to invest in 127 GW natural gas capacity in addition to the existing 140 GW.

Heating is increasingly electrified towards 2050. District heating areas invest in 29 GW large scale heat pumps and 1.7 TWh heat storage. Individual heating areas have 321 GW heat pumps and 141 GW electric boilers installed in 2050 along with 424 GWh heat storage. The large district heating storage indicates that there is flexibility potential which could bring benefits to the whole system.

The invested electrolyzer capacity is 582 GW along with 148 TWh hydrogen storage in 2050. The transmission grid all over Europe is expanded to allow more exchange of electricity between regions. It appears that there is further expansion potential, as the model reached a limit of 3 GW expansion by 2050 between most regions.

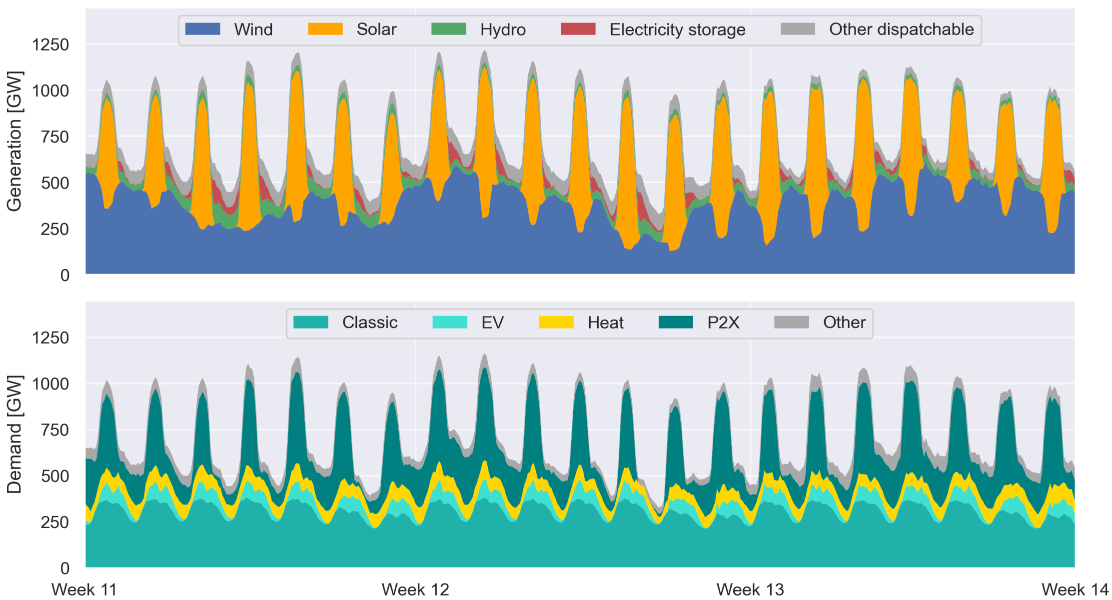
Additional capacity results are given in appendix G.

7.2 Dispatch 2050: average weather year

The energy model is able to serve the demand in the average weather year with an aggregate electricity generation mix of 7% hydro, 26% solar PV and 55% wind. Due to the intermittent nature of VRE, this naturally requires flexibility in the system to remain in balance. An example case of this is seen in fig. 7.1 considering generation and consumption in a single country (Denmark) as well as the aggregate group of countries.

A major source of flexibility is provided by the electrolyzer capacity along with the hydrogen storage. The electrolyzer capacity has 3292 full load hours in the average year, meaning there is a considerable overcapacity to provide flexibility.

(a) Denmark



(b) Aggregation of all countries

Figure 7.1: Hourly generation and consumption of electricity. Example for the average weather year in scenario year 2050.

In fig. 7.1a, the production of power-to-X is seen to be especially active during the high wind periods in Denmark. Solar gives spikes each day, and to integrate this, the model curtails wind. Offshore wind has the highest variable O&M cost, so it is most cost efficient to curtail this. Denmark is interlinked with neighboring countries, and there is a strong import and export at the same time, suggesting that Denmark acts as a bridge connecting demand and production in neighbouring countries. In this time frame, Denmark can balance the demand side flexibility, VRE production and import/export such that the use of dispatchable generation is almost none.

When considering the aggregate system for the same time period in fig. 7.1b, the variations are smoother. Wind generation follows similar trends, but with smoother variations. There is still curtailment of wind in the middle of the day to integrate solar. Interestingly, dispatchable plants are operating at the same time as wind is curtailed. This indicates congestion in the system. However, the gas plants are operating quite flexibly (820 full load hours) along with hydro power and electricity storage. Instead of dispatching constantly as a baseload capacity, they mostly fill the gaps left by the VRE as seen in the figure. Batteries and hydro power tend to operate in the hours between sun set and sun rise. It is worth noting that the hourly structure of the consumption profile no longer resembles today's profile with a peak in the evening. The classic demand is rather small compared to the additional, flexible demands. In the aggregate system in this time window, electrolyzers tend to follow the diurnal cycle of the sun.

In summary, the energy system is able to utilize a multitude of flexibility options ranging from electricity exchange, storage, dispatchable generation and demand response. When dispatching energy with hourly resolution, there is a need for 8 GW/520 GWh of backstop generation. This is a result of slightly suboptimal planning in the operation model. This amount should be seen in relation to the need for backstop generation in other weather years.

7.3 Dispatch 2050: weather years 1982-2016

The following results are from the dispatch of the energy system in scenario year 2050 described in section 7.1 but with variations from weather years 1982-2016.

7.3.1 Aggregate overview

The use of dispatchable generation is an overall indicator of which weather years the VRE resources are least adequate. A detailed composition is seen in fig. 7.2, which reveals that the inter-annual flexibility of these fuels is primarily provided by natural gas.

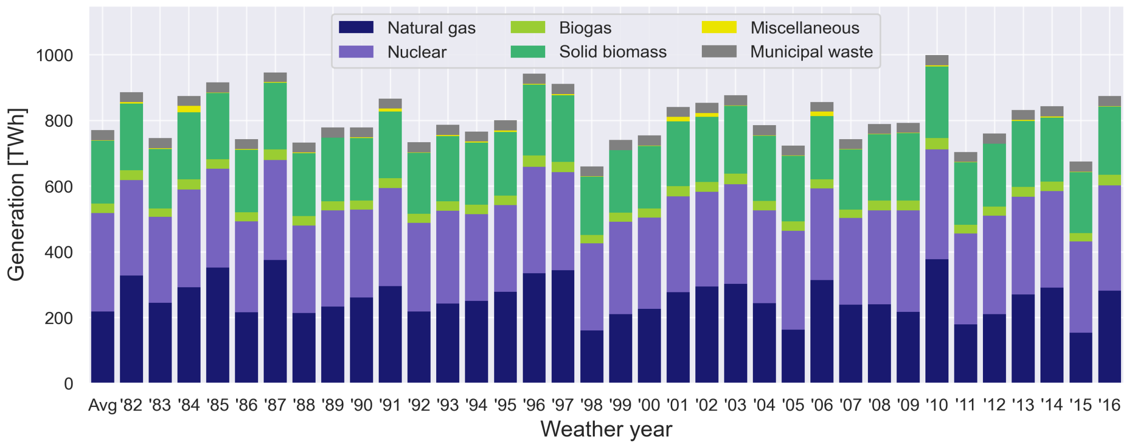


Figure 7.2: Composition of dispatchable generation in different weather years

Gas consumption ranges from 154 TWh in weather year 2005 to 378 TWh in weather year 2010. Nuclear also provides some flexibility ranging from 261 TWh in weather year 1983 to 334 TWh in 2010. A full overview is seen in appendix H.

The need for dispatchable generation seems to be particularly driven by a combination of heat demand, wind and hydro generation.

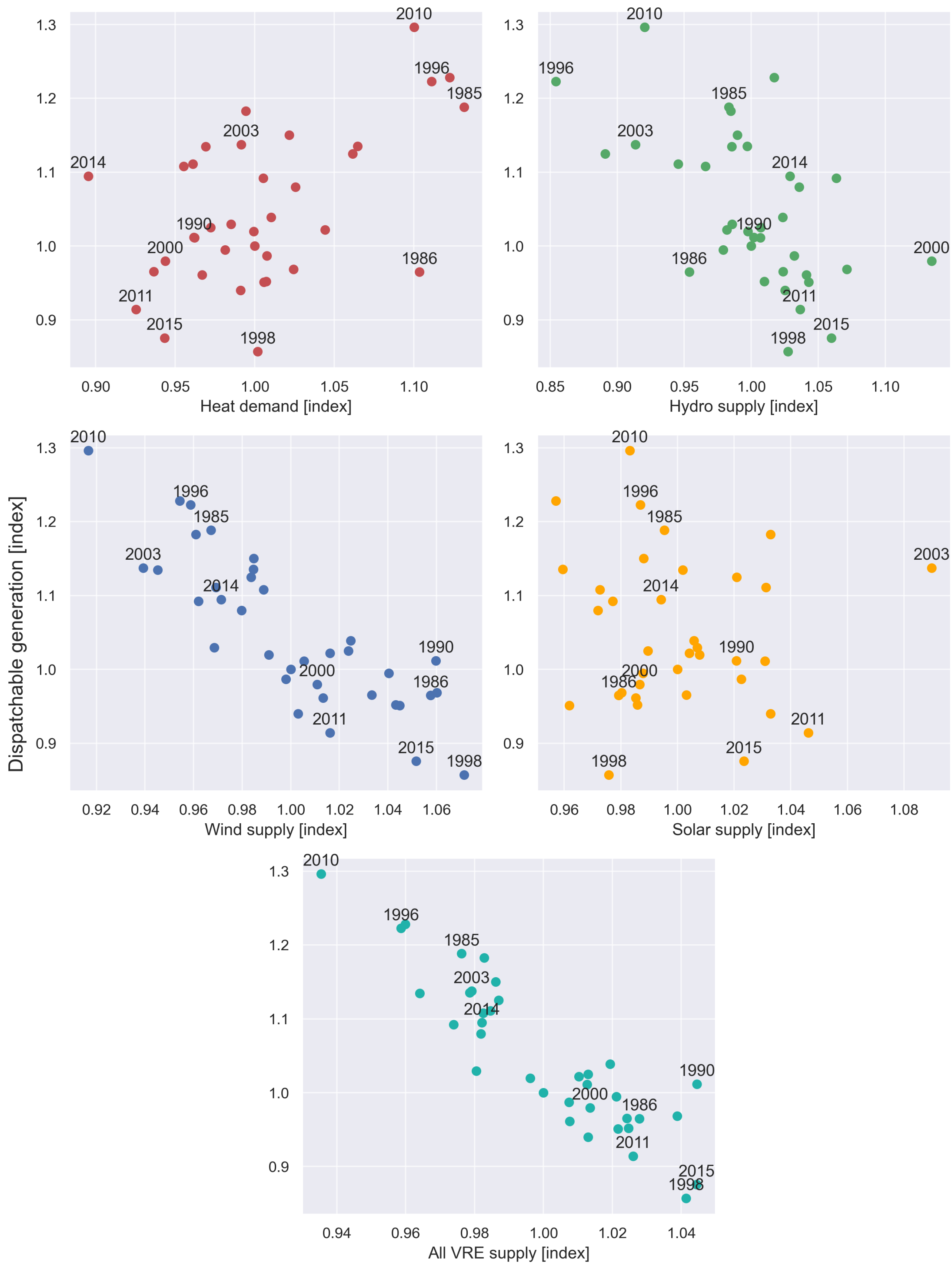


Figure 7.3: Scatter plots showing dependency between weather related inputs and dispatchable generation. Indices use the average weather year as basis. Supply is defined as generation without curtailment.

Scatter plots are given in fig. 7.3 relating the weather induced supply and demand of energy to the consumption of dispatchable fuels. The values are indexed using the average weather year as basis. The cold weather years of 1996 and 2010 are some of the most demanding in terms of dispatchable generation. In those years, the cold weather is combined with below average hydro and wind production, which exacerbates the challenge and leads to the highest needs for dispatchable generation. Weather year 2010 has the highest consumption (30% above the average), despite 1996 being both colder and dryer. This is because 2010 has the lowest wind production of all the weather years considered. Wind is the single largest source of electricity in the system and provides more than 50% in all weather years. The system is therefore particularly sensitive to inter-annual variations in wind. Contrary to 2010, the most favourable wind year (1998) reduces the use of dispatchable fuels by almost 15 % compared to the average year. The inter-annual variation of solar has low impact on the need for dispatchable generation as seen in fig. 7.3. In contrast, hydro has a more clear correlation, despite hydro constituting a smaller share of the energy mix than solar. It could be due to the fact that hydro reservoir plants can be seen as semi-dispatchable, and therefore better able to replace the role of e.g. natural gas.

The generation in absolute terms across weather years is seen in fig. 7.4. Despite the challenges posed by different weather years, dispatchable generation remains less than 20% of the total electricity mix. The other >80% can be supplied by VRE.

An overview of multiple parameters in all weather years is given in fig. 7.5. There is a strong connection between the use of dispatchable generation, electricity prices and emissions. As mentioned, natural gas provides most of the inter-annual flexibility, and it is associated with fuel costs and carbon emissions. The boxplots in fig. 7.5 show the regional spread of the annual average price. The boxes denote the 25th, 50th and 75th percentiles, the whiskers show the minimum-maximum range without outliers and dots represent outliers. The 50th percentile (mean) ranges from 53 EUR20/MWh in weather year 1998 to 90 EUR20/MWh in weather year 2010. The same two weather years emit 99 $MtCO_2eq$. and 206 $MtCO_2eq$., respectively. Note that dispatchable generation is seen to have higher percentage deviations than solar, wind and hydro. This is a result of dispatchable generation constituting a smaller share of the total electricity mix.

The magnitude of the needed backstop capacity does not seem to have a trivial connection to the aggregate representations of the weather years. A more detailed analysis is available in section 7.3.4.

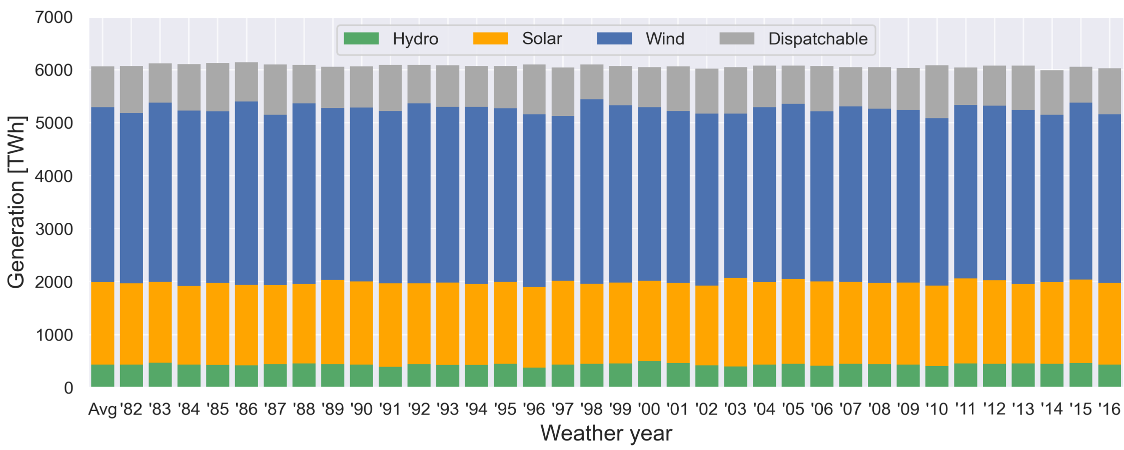


Figure 7.4: Electricity generation mix across all weather years. Curtailed VRE energy is deducted.

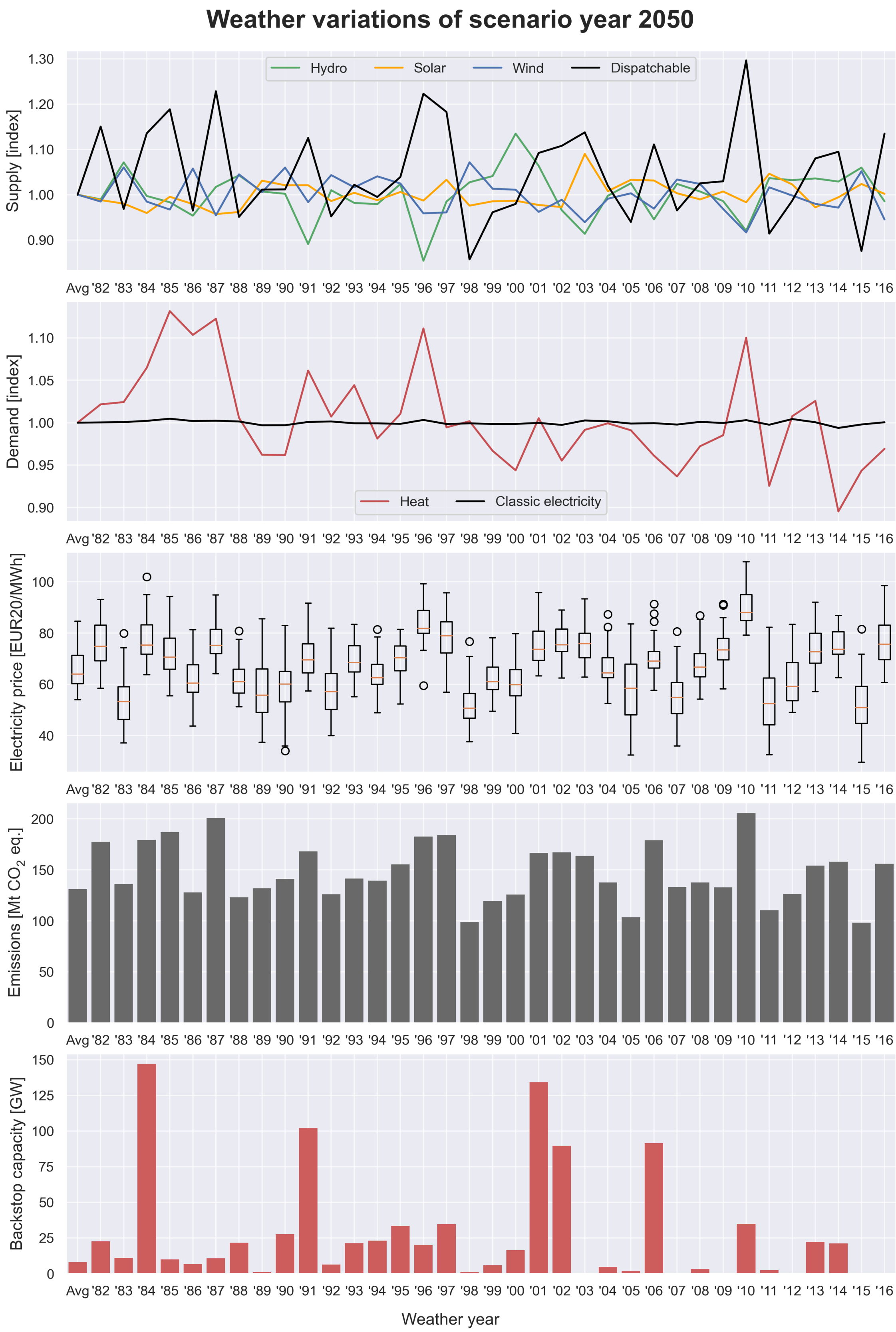


Figure 7.5: Overview of weather year variations of scenario year 2050. Supply is defined as generation without curtailment to show the available VRE resource. Indices use the average weather year as basis. The box plot of electricity prices shows the regional spread of annual average prices.

The dynamics of electric heating is shown in fig. 7.6. Individual heating is electrified entirely (as an exogenous decision), while district heating generates 34% of its heat from electricity in the average year. In the coldest years, the use of electricity in district heating decreases. The reason for this is that district heating has fuel switching flexibility. It increases the use of thermal plants primarily based on biomass and fossil fuels to supply the heat in very cold years where electricity is expensive and scarce. Individual heating has only the option to store a limited amount of heat and can only switch between heat pumps and electric boilers. Therefore, individual heating has quite limited inter-annual flexibility, whereas district heating has more.

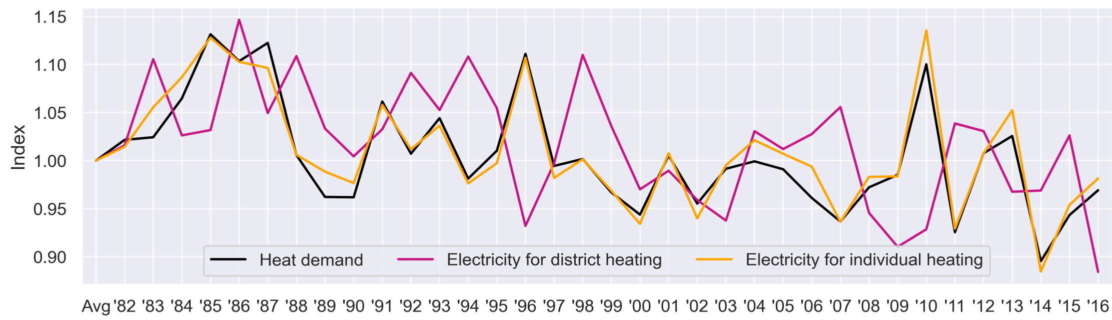


Figure 7.6: Inter-annual dynamics of electrification of heating.

7.3.2 Geographical overview

In fig. 7.7 and fig. 7.8, the geographical spread of electricity prices is shown as boxplots per region and price maps for certain years. There is a pronounced north-south division noticeable. Similar to the behaviour of the 2016 system in section 6.2, the lowest electricity prices are found in northern Europe. However, it is also here the most volatility is seen. The cold weather and low wind/hydro of 2010 leads to average prices of 80-90 EUR20/MWh, whereas the high wind and the medium hydro conditions in weather year 1998 yield average prices of 32-42 EUR20/MWh in the same regions.

Southern Europe (especially Italy) have high average electricity prices. They are exacerbated by unfavourable weather conditions, but they are consistently higher than or as high as in the north. Both solar and wind capacities in these countries are limited by the assumed potential constraints (see appendix G). If the model was allowed to expand VRE and/or transmission, the prices could be lower.

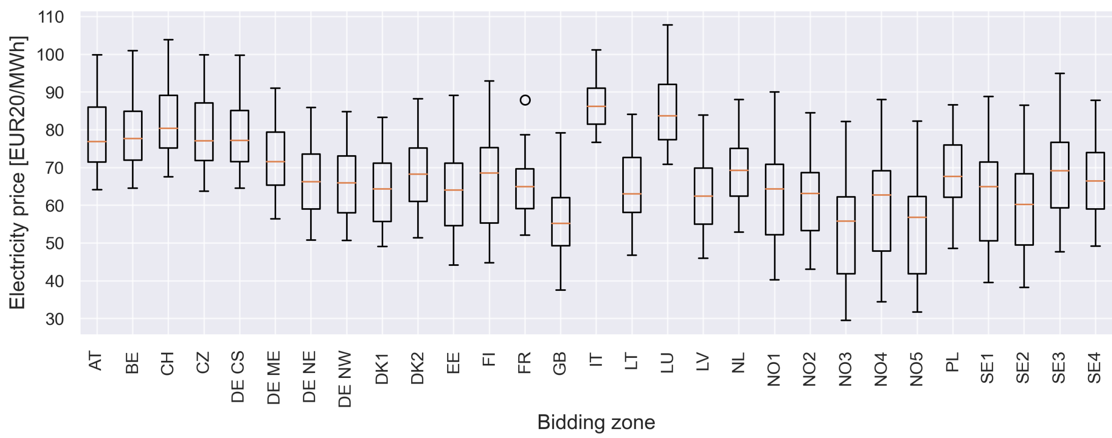
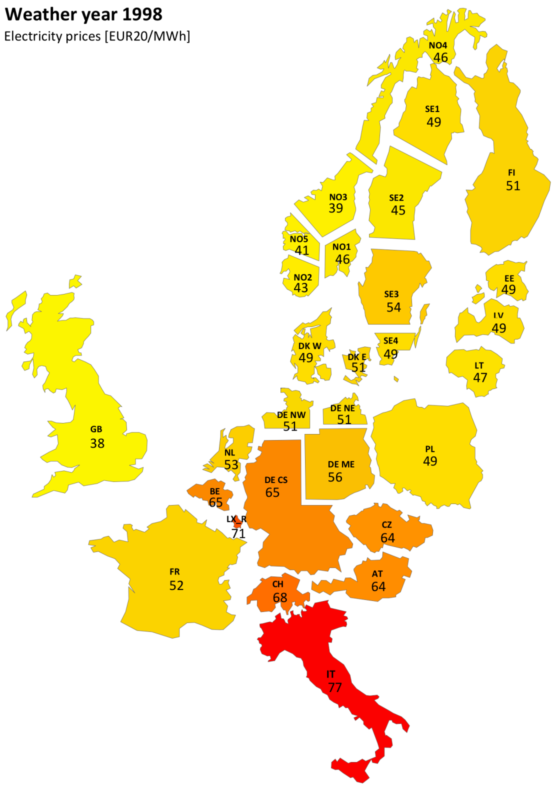
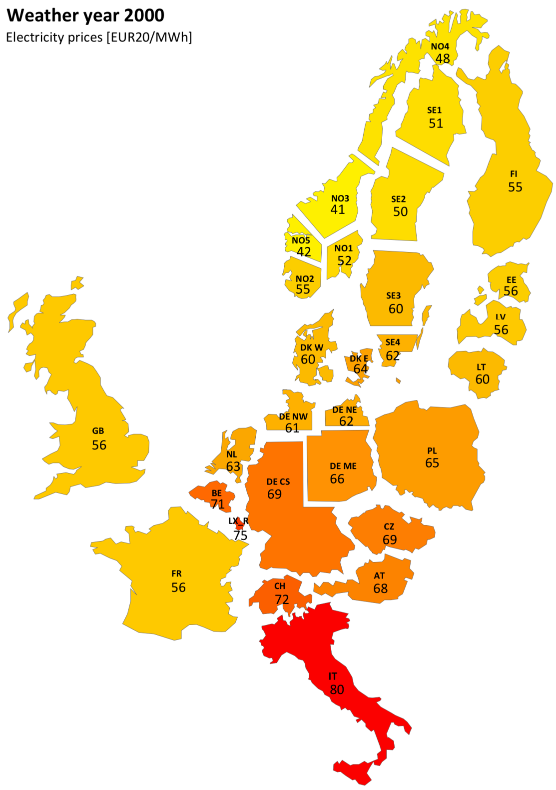


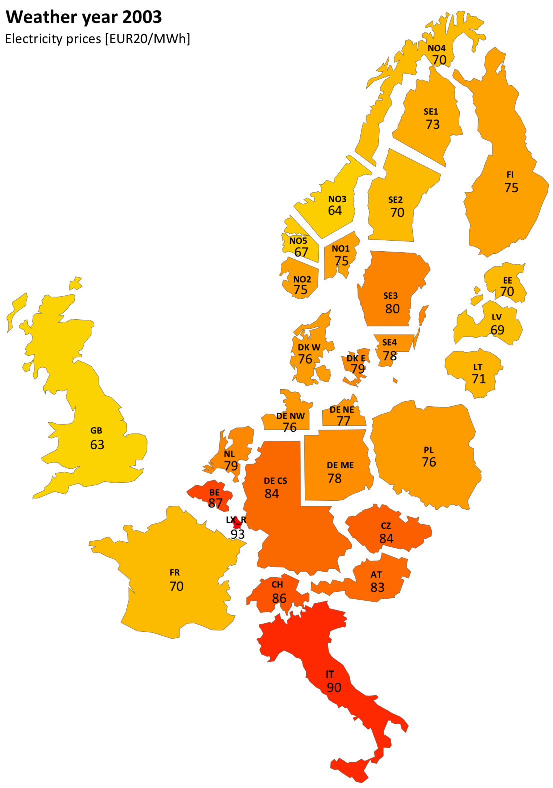
Figure 7.7: Inter-annual variability of annual average electricity prices per bidding zone.



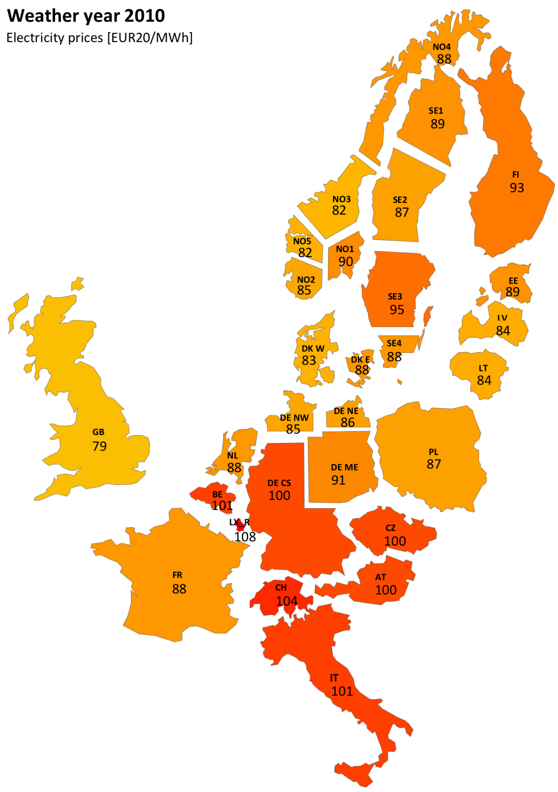
(a) 1998: High wind, mid-high hydro, mid-low solar, mid temperature



(b) 2000: Mid wind, high hydro, mid solar, high temperature



(c) 2003: Low wind, low hydro, high solar, mid-high temperature

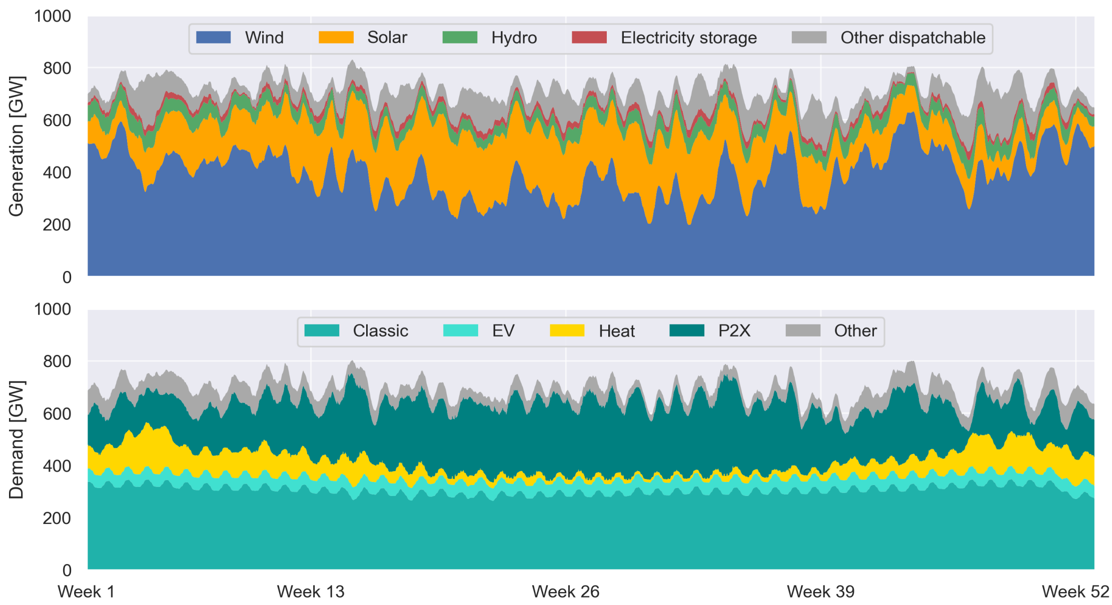


(d) 2010: Low wind, low hydro, mid solar, low temperature

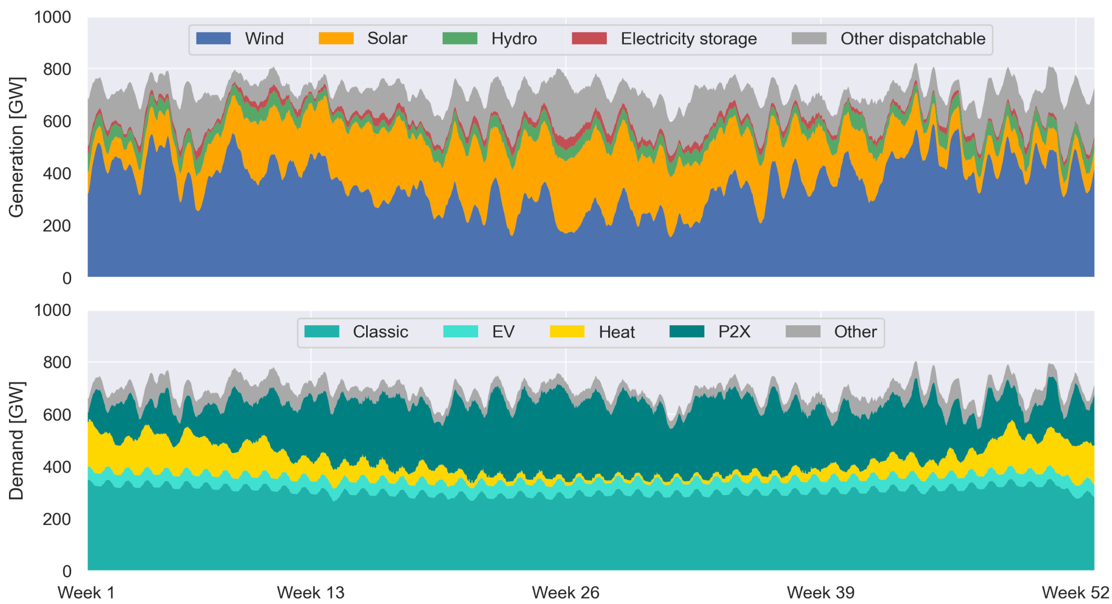
Figure 7.8: Geographical variations in annual average electricity prices.

7.3.3 Intra-annual variations of selected weather years

The variations within weather year 2010 and 1998 are shown in fig. 7.9 to exemplify two extremes in terms of need for dispatchable fuels. In weather year 2010, the heat demand is at an elevated level for several months, whereas the same level is only reached a few weeks in weather year 1998. In 2010, the cold weather coincides with volatile wind, and dispatchable fuels must backup the wind to deliver the energy needed for heating. The wind production in 2010 is low over the summer, and while solar power is complementary, it is not sufficient to satisfy the demand for power-to-X. Consequently, dispatchable fuels are used significantly more for two-three consecutive months over the summer compared to 1998.



(a) Variations within weather year 1998



(b) Variations within weather year 2010

Figure 7.9: Comparison of two weather years in scenario year 2050. Rolling 4-day average for illustration.

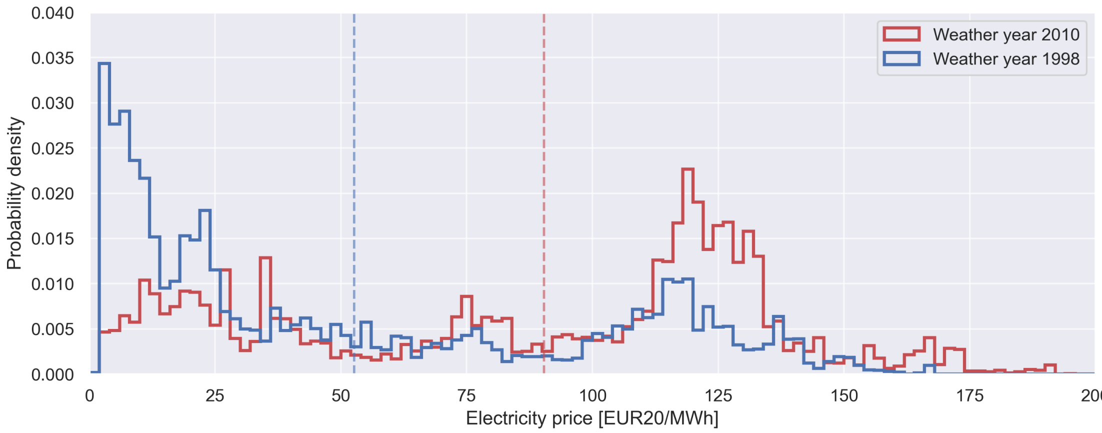


Figure 7.10: Distribution of electricity prices in 2050 for weather years 1998 and 2010. Observations represent hourly averages across bidding zones. Dashed lines indicates annual averages. A few outliers around 340 EUR20/MWh for 2010 are not visible in this figure.

The annual average prices considered in fig. 7.5 and fig. 7.8 do not show the hourly distribution that can have more volatility. Histograms based on hourly prices for the two example weather years are seen in fig. 7.10. Both example weather years have two peaks; one close to 0 EUR20/MWh and one around 120 EUR20/MWh. The first peak represents presumable hours where VRE sets the price and the second one where dispatchable fuels set the price. It is therefore clear that significant volatility is seen within a year. Increasing the number of hours where VRE is a price setter can lower the prices significantly.

7.3.4 Capacity adequacy

The variation in demand for gas is one issue that electricity producers may need to handle. This requires the infrastructure and market incentives to provide highly variable amounts each year. What seems to be a more critical issue is to have the needed capacity installed for the most extreme weather years. In Balmorel, this is denoted as backstop capacity and is modelled as a virtual, limitless gas turbine. This is a potentially important measure, as it can reveal how the investments made in the average year may be insufficient in a particular weather year. The backstop capacity was illustrated in fig. 7.5 and is also given as a table along with the corresponding fuel usage in appendix I.

The backstop capacity indicates that up to approximately 147 GW of additional power capacity and 17 TWh of electricity is needed in the most extreme weather year. Compared to the installed 267 GW gas plants, this could indicate severe inadequacy. However, there seems to be no trivial connection between the backstop capacity and the annual weather variables in fig. 7.5.

I have investigated the most severe cases (weather years 1984, 1991 and 2001) in greater time resolution. Some similarities appear which are exemplified with a high time resolution example of 2001 seen in fig. 7.11. A low wind period appears for several consecutive days in week 34. Meanwhile, the demand for power-to-X follows the diurnal pattern of solar PV production, but the flexibility is insufficient to respond to the low wind situation. Other power plants must therefore dispatch instead of wind. Thermal power plants are modelled with a certain downtime for maintenance, and in many cases, the availability is lowest in the same summer weeks as discussed here. In summary, these conditions necessitate backstop generation.

The hourly power-to-X demand is modelled as constant, but in each week, the operation of the electrolyzer production is planned such that it reaches certain storage levels. This is done in the operation model based a time aggregate overview of the year. If the time aggregated week for instance indicates high wind, the electrolyzer will indirectly be scheduled to run at high load in this week to reach the target storage levels. This limits the electrolyzer flexibility to respond to a low wind situation if that should appear instead.

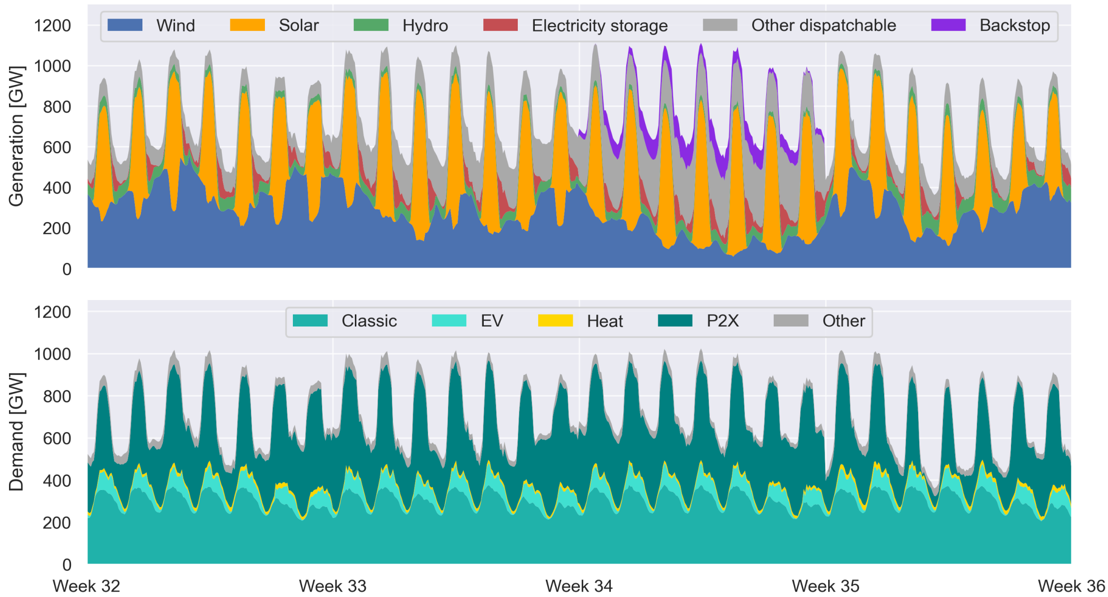


Figure 7.11: Example of backstop usage in weather year 2001.

Interestingly, the operation model actually plans to use backstop when planning the full year. This indicates that there is no way to restructure the operation schedule to avoid insufficient generation. However, whereas the operation model expects a need for additional 6 GW capacity in 1984, the dispatch model actually finds a need for 147 GW. This indicates instead that the operation model has inaccurate information when planning the year.

On the one hand, it is unlikely that the real operators of electrolyzers have perfect foresight to plan production of power-to-X over a whole year to reach annual targets. Thus, there could be situations where demand for power-to-X dictates that it has to be produced despite unfavourable weather conditions. On the other hand, the demand may be price elastic enough to react to the market signals. If the system is unable to provide enough electricity, the price will rise considerably, which in turn may lower the demand for power-to-X.

In summary, I cannot conclude how severe the capacity inadequacy is. It can be a result of model limitations as described above, it can be a result of intricate local weather conditions or it can be a combination of both.

8 Discussion

In this chapter, I put the main results into a wider perspective and discuss the applicability of using different weather years in studies of energy systems. I will also relate the limitations of the methods to suggestions for further studies.

8.1 Main findings

Natural gas is suggested by the model as a key driver to mitigate inter-annual variability in weather dependent energy systems. It is seen that the use of natural gas is two and a half times higher in the lowest weather year compared to the highest. The European countries have committed themselves to reaching carbon neutrality in 2050 [1], so it is debateable whether natural gas is a feasible fuel. The model dispatches this fuel for purely economical reasons, but in principle biogas could offer the same flexibility (given that this resource is plentiful). This would decrease the emissions seen in fig. 7.5, but likely increase the cost and exacerbate the cost difference between years. While the increase of natural gas is significant by itself, it stays below 7% in the electricity mix. The generation of power is consistently above 80% VRE across all weather years.

Weather years 1996 and 2010 are two of the years that required the most dispatchable generation. This is due to a combination of cold weather and low production from wind and hydro. This stresses the importance of using time coherent data sets to shine light on the joint probability of weather events.

While extreme weather years can lead to emissions as high as 206 $MtCO_2$eq., it is still lower than in the 2016 system which was 970 $MtCO_2$eq. (and did not include transport, industry heat and expansion of individual heating).

8.2 Inter-annual variability in studies of energy systems

As I have investigated inter-annual weather variations in this study, it naturally raises the question: In which cases can multiple weather years give additional insights compared to using a single year? I see at least three use cases.

The first way to use the data set is to assess the stability and operation of an already planned energy system. This is what I have focused on in this study. Even if the system is not optimized to handle extreme weather years, society will still expect a fully functional energy system to be operating during those time periods. A study such as this can therefore reveal which measures the system utilizes to remain in balance and what the economic and environmental consequences are. Is the amount of gas usage feasible? Is the cost difference between weather years tolerable? It can also reveal if the planned system has enough capacity or flexibility. This is a question I have not been able to give a clear answer to, but still one that is highly relevant and should be investigated further.

The second use case for multiple weather years is for particular planning problems related to security of supply. Examples of this could be investments in gas plants, storage facilities or biomass value chains. Such a study can for instance help in the design of capacity mechanisms [36] in the energy markets, such that the right incentives exist to invest in infrastructure that ensures a certain standard of security of supply.

The third way of using different weather years is as a sensitivity study to general investment planning. Should investments be planned based on relatively rare weather conditions? This is probably an unlikely case, as it is expensive to invest in large capacities that sit idle most of the time. However, it is also unlikely that society will implement the exact capacities recommended by an energy planning tool. Having multiple weather years can help in quantifying the uncertainty range of those investments. It can for instance be used to explore the trade-off between building more VRE generation and building backup capacity. This data set could therefore be an extra tool to guide decision makers when planning the energy system. I used 35 weather years in this study, but it may be enough to only use some of the most extreme for future studies.

A simplified example of such a sensitivity study is seen in table 8.1. Using weather year 2010, the model invests in higher VRE capacities overall since the VRE capacity factor is lower and because more energy is needed for heating.

	Average year	**Weather year 2010**
Bio and waste	27	30
Electric storage	174	166
Natural gas plants	127	125
Offshore wind	433	493
Onshore wind	496	497
Solar PV	1195	1309
Total	2452	2619

Table 8.1: Comparison of new power capacity investments [GW] in scenario year 2050. Investments are made based on the average year and weather year 2010 (low wind, low hydro, mid solar, low temp).

8.3 Limitations of methods used

The methodology I suggest in this study is limited to historical weather years. This is not to postulate that the weather in 2050 will be exactly like what was seen historically. But simulating a multitude of weather years can suggest variations of what 2050 could look like. However, this approach neglects the fact that the climate is changing. There is consistent agreement in literature that ambient temperature increases, which in turn reduces heat demand and increases the demand for cooling. But there is much more disagreement about the impacts of climate change on wind speed and solar irradiance [37]. While it is outside the scope of this study, it is still highly relevant to improve energy models that can simulate the future weather more accurately.

Another potential expansion to the model is related to security of supply such that infrastructure failures are part of the simulation. It could be weather-induced breakdowns of transmission lines or power plants. It could also be accidents more stochastic in nature that just happen to coincide with unfavourable weather conditions.

Each weather year in this study is simulated independently of the others. It means that I cannot conclude how consecutive extreme weather years may affect the energy system. Furthermore, it is also a simplification that entails some limitations for the long-term storage. They are characterized by charge cycles that can span multiple seasons and therefore overlap years. It will impact both heat storage, hydrogen storage and more, but I will illustrate the potential issues by considering two different ways of modelling hydro reservoirs.

One method (which is what I use for the results) is based on allocating *water volumes*. In the operation (BB1) model, the time aggregated full year is considered and start/end storage levels are decided for all weeks. The dispatch (BB3) model is later free to dispatch optimally within the weeks, as long as it starts and ends at the correct levels. Consequently, the allocated hydro power is forced to be dispatched within each week, even if some less valueable resource (e.g. wind) turns out to be available in greater amounts than first assumed in the operation planning.

The other method (which I initially used) estimates the *water value* for each week of a given year in the operation (BB1) model. Thus, when the water is later dispatched (BB3 model), it bids into the market with that value. The advantage is that the dispatch model is not forced to dispatch the water. Consequently, it may not use a full years inflow of water and will leave the reservoir levels at another level in the end of the year than it was in the beginning of the year. This is a more realistic representation of how hydro systems actually work, since an entire years inflow is not necessarily supposed to be used within that year. However, as I run the model with each weather year independently, the storage levels are not connected across weather years. Leaving some water in one year will therefore not benefit the energy system in the next year, and for that reason, I find that the method based on allocating water volumes gives the most consistent representation of weather years. However, forcing hydro power to be used may also lead to curtailment of more VRE at times where it would be most efficient to save the hydro resource for later use.

In fig. 8.1, it is visible how the water volume model tends to make a sharper divide between high and low electricity prices. Inexpensive hydro power is allocated and results in a number of hours with low electricity prices. In turn, this leads to a need for more expensive fuels in hours where the hydro power would be better used. The difference between the water value and water volume model depends on how well the time aggregated operation model represents the full year.

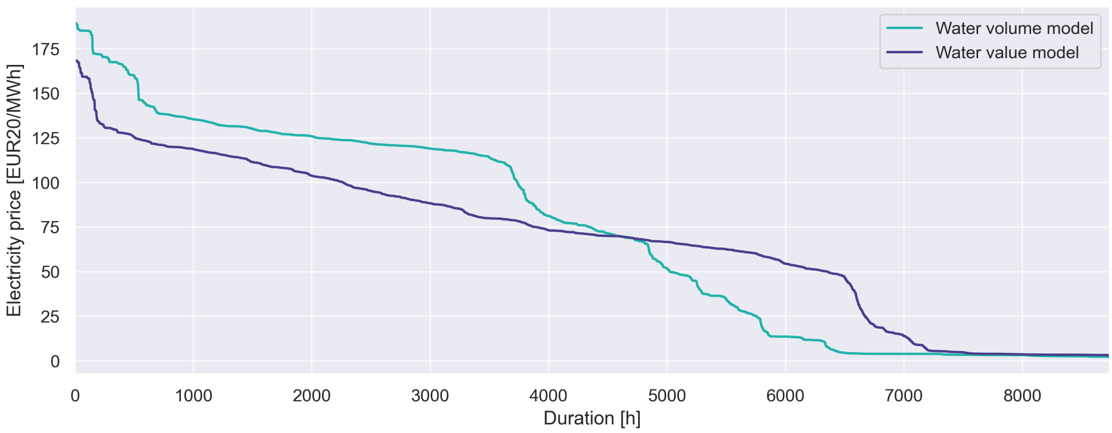


Figure 8.1: Example of how the choice of hydro power model impacts price duration curves. Average electricity prices in Norway in scenario year 2050 and weather year 2003.

9 Conclusion

In this study, I have investigated the impacts of inter-annual variability on a weather dependent energy system optimized for an average weather year. This includes long-term effects and more rare events than what can be seen within a typical weather year. I used a comprehensive set of 35 weather years (1982-2016) to simulate both demand and generation side weather variability.

Demand response of power-to-X, interconnections and storage provided flexibility within a given year, but the flexibility across multiple years was provided primarily by gas plants. This resulted in variations in natural gas consumption ranging from 154 TWh to 378 TWh in different weather years. Similarly, the average electricity price and CO2 emissions varied from 53 EUR20/MWh and 99 MtCO_2eq. to 90 EUR20/MWh and 206 MtCO_2eq. The most price volatility was seen in northern Europe, while prices in southern Europe were consistently in the higher end of the range.

While these variations can pose significant challenges by themselves, a key challenge for the energy system operators is to have sufficient capacity for the most extreme periods. I investigated this as well, but the results were less clear. In some weather years, the energy system needed up to 147 GW of additional capacity, but it did not show a clear connection to the weather of that year. It is likely a result of suboptimal dispatch planning in the model, but it requires further investigation to conclude with certainty.

Some of the most challenging weather years were 1996 and 2010 due to the combined effects of low wind and hydro production and high heat demands. The inter-annual variability of solar power was more moderate and did not have a significant impact on the energy system.

Despite the challenges posed by different weather years, the energy system managed to maintain an electricity mix based on more than 80% wind, solar and hydro power in all weather years. The critical task is therefore to be prepared for the remaining gaps left by VRE and ensure sufficient dispatchable capacity and fuel supply chains.

Even though rare weather events may not be the basis for investments, studies such as this can prove helpful as a sensitivity analysis to investment problems based on a single weather year. It can also reveal challenges in meeting long term decarbonisation targets. Several of the years that required the most dispatchable generation had a combination of low VRE generation and high demand. This stresses the importance of using long-term time coherent data sets to shine light on the joint probability of multiple undesirable weather events.

Bibliography

[1] European Commission. *Delivering the European Green Deal.* n.d. URL: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal/delivering-european-green-deal%5C_en.

[2] Breyer C et al. *On the history and future of 100% renewable energy systems research.* 2022. URL: https://doi.org/10.1109/ACCESS.2022.3193402.

[3] Li B et al. *Quantifying the Predictability of a Dunkelflaute Event by Utilizing a Mesoscale Model.* 2020. URL: https://doi.org/10.1088/1742-6596/1618/6/062042.

[4] Ruhnau O and Qvist S. *Storage requirements in a 100% renewable electricity system: extreme events and inter-annual variability.* 2022. URL: https://https://doi.org/10.1088/1748-9326/ac4dc8.

[5] Gea-Bermúdeza J et al. *The role of sector coupling in the green transition: A least-cost energy system development in Northern-central Europe towards 2050.* 2021. URL: https://doi.org/10.1016/j.apenergy.2021.116685.

[6] Global100REStrategyGroup. *Joint declaration of the global 100% renewable energy strategy group.* 2022. URL: https://global100restrategygroup.org/.

[7] Coker PJ et al. *Interannual weather variability and the challenges for Great Britain's electricity market design.* 2020. URL: https://doi.org/10.1016/j.renene.2019.12.082.

[8] Price J and Zeyringer M. *highRES-Europe: The high spatial and temporal Resolution Electricity System model for Europe.* 2022. URL: https://doi.org/10.1016/j.softx.2022.101003.

[9] Raynaud D et al. *Energy droughts from variable renewable energy sources in European climates.* 2017. URL: https://doi.org/10.1016/j.renene.2018.02.130.

[10] ENTSOE. *European Resource Adequacy Assessment 2022 edition.* 2022. URL: https://www.entsoe.eu/outlooks/eraa/2022/.

[11] ECMWF. *Climate and energy indicators for Europe from 1979 to present derived from reanalysis.* 2022. URL: https://doi.org/10.24381/cds.4bd77450.

[12] Hersbach H et al. *The ERA5 global reanalysis.* 2020. URL: http://dx.doi.org/10.1002/qj.3803.

[13] Kruse JCR. *Energy demand model.* 2023. URL: https://github.com/JensChrKruse/JC-Energy-demand-model.git.

[14] ENTSO-E Transparency Platform. *Total load per bidding zone per market time unit.* n.d. URL: https://transparency.entsoe.eu/.

[15] Wiese F et al. *Open Power System Data – Frictionless data for electricity system modelling.* 2020. URL: https://doi.org/10.1016/j.apenergy.2018.11.097.

[16] Black JC and Henson WLW. *Hierarchical Load Hindcasting Using Reanalysis Weather.* 2014. URL: https://doi.org/10.1109/TSG.2013.2278475.

[17] Koivisto MJ et al. *Statistical modeling of aggregated electricity consumption and-distributed wind generation in distribution systems using AMR data.* 2015. URL: https://doi.org/10.1016/j.epsr.2015.08.008.

[18] SciPy Steering Council. *SciPy.* 2022. URL: https://scipy.org/.

[19] Maurizio Montel et al. *python-holidays.* 2022. URL: https://python-holidays.readthedocs.io/.

[20] Mathis P. *suntimes 1.1.2.* 2022. URL: https://pypi.org/project/suntimes/.

[21] Eurostat. *Heating and cooling degree days - statistics.* 2020. URL: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Heating_and_cooling_degree_days_-_statistics.

[22] Pedregosa F et al. *scikit-learn*. 2022. URL: https://scikit-learn.org/.
[23] Eurostat. *GEOSTAT*. 2021. URL: https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution-demography/geostat.
[24] Ea Energy Analyses. *Existing Balmorel data set*. 2022.
[25] Brown T et al. *PyPSA-Eur-Sec: A Sector-Coupled Open Optimisation Model of the European Energy System*. 2021. URL: https://pypsa-eur-sec.readthedocs.io/.
[26] Eurostat. *Energy consumption in households*. n.d. URL: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy%5C_consumption%5C_in%5C_households#Energy%5C_consumption%5C_in%5C_households%5C_by%5C_type%5C_of%5C_end-use.
[27] Wiese F et al. *Balmorel open source energy system model*. 2018. URL: https://doi.org/10.1016/j.esr.2018.01.003.
[28] Ea Energy Analyses. *Balmorel User Guide*. n.d. URL: https://www.ea-energianalyse.dk/en/publications/3063/.
[29] Ea Energy Analyses. *Electricity price projections*. 2022.
[30] Ea Energy Analyses. *Demand buckets and related flexibility*. 2022.
[31] Koivisto MJ and Leon JPM. *Pan-European wind and solar generation time series (PECD 2021 update)*. 2022. URL: https://doi.org/10.11583/DTU.c.5939581.v3.
[32] Murcia JP et al. *Validation of European-scale simulated wind speed and wind generation time series*. 2022. URL: https://doi.org/10.1016/j.apenergy.2021.117794.
[33] Poole MA and O'Farrell PN. *The assumptions of the linear regression model*. 1970.
[34] Energy Industrial Strategy UK Gov. Department for Business. *Wind powered electricity in the UK*. 2020. URL: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment%5C_data/file/875384/Wind%5C_powered%5C_electricity%5C_in%5C_the%5C_UK.pdf.
[35] IEA. *Countries and regions*. 2023. URL: https://www.iea.org/countries.
[36] European Commission. *Capacity mechanisms*. n.d. URL: https://energy.ec.europa.eu/topics/markets-and-consumers/capacity-mechanisms_en.
[37] Bloomfield HC et al. *Quantifying the sensitivity of european power systems to energy scenarios and climate change projections*. 2021. URL: https://doi.org/10.1016/j.renene.2020.09.125.
[38] Swisher P et al. *Competitiveness of a low specific power, low cut-out wind speed wind turbine in North and Central Europe towards 2050*. 2022. URL: https://doi.org/10.1016/j.apenergy.2021.118043.
[39] Energistyrelsen. *Technology Data*. 2022. URL: https://ens.dk/en/our-services/projections-and-models/technology-data.

A Custom holidays for the energy demand model

As part of the energy demand modelling, custom holidays in addition to those provided by the *holiday* library [19] are added to improve the fit. In the few cases where individual country holidays are added, they are mainly included to fix consistency issues.

Month	**Day**	**Country**	**Holiday**
1	1	All	New Years Day
5	1	All	Int Workers day
6	5	DK	Grundlovsdag
10	31	DE	Reformationstag
12	21	All	Christmas Vacation
12	22	All	Christmas Vacation
12	23	All	Christmas Vacation
12	24	All	Christmas Eve
12	25	All	First Christmas Day
12	26	All	Second Christmas Day
12	27	All	Christmas Vacation
12	28	All	Christmas Vacation
12	29	All	Christmas Vacation
12	30	All	Christmas Vacation
12	31	All	New Years Eve
5	5	NL	Liberation Day
1	6	SE	Three Kings' Day

Table A.1: Custom holidays used for the energy demand model.

B Balmorel years

Time series data used in Balmorel has to follow a certain pattern. Thus, a *calendar year* has to be sliced to fit a *Balmorel year* consisting of 8736 hours and starting on a Monday. Due to these constraints, some Balmorel years are seen to overlap multiple calendar years.

	Start time	**End time**
1982	1982-01-04 00:00:00	1983-01-02 23:00:00
1983	1983-01-03 00:00:00	1984-01-01 23:00:00
1984	1984-01-02 00:00:00	1984-12-30 23:00:00
1985	1985-01-07 00:00:00	1986-01-05 23:00:00
1986	1986-01-06 00:00:00	1987-01-04 23:00:00
1987	1987-01-05 00:00:00	1988-01-03 23:00:00
1988	1988-01-04 00:00:00	1989-01-01 23:00:00
1989	1989-01-02 00:00:00	1989-12-31 23:00:00
1990	1990-01-01 00:00:00	1990-12-30 23:00:00
1991	1991-01-07 00:00:00	1992-01-05 23:00:00
1992	1992-01-06 00:00:00	1993-01-03 23:00:00
1993	1993-01-04 00:00:00	1994-01-02 23:00:00
1994	1994-01-03 00:00:00	1995-01-01 23:00:00
1995	1995-01-02 00:00:00	1995-12-31 23:00:00
1996	1996-01-01 00:00:00	1996-12-29 23:00:00
1997	1997-01-06 00:00:00	1998-01-04 23:00:00
1998	1998-01-05 00:00:00	1999-01-03 23:00:00
1999	1999-01-04 00:00:00	2000-01-02 23:00:00
2000	2000-01-03 00:00:00	2000-12-31 23:00:00
2001	2001-01-01 00:00:00	2001-12-30 23:00:00
2002	2002-01-07 00:00:00	2003-01-05 23:00:00
2003	2003-01-06 00:00:00	2004-01-04 23:00:00
2004	2004-01-05 00:00:00	2005-01-02 23:00:00
2005	2005-01-03 00:00:00	2006-01-01 23:00:00
2006	2006-01-02 00:00:00	2006-12-31 23:00:00
2007	2007-01-01 00:00:00	2007-12-30 23:00:00
2008	2008-01-07 00:00:00	2009-01-04 23:00:00
2009	2009-01-05 00:00:00	2010-01-03 23:00:00
2010	2010-01-04 00:00:00	2011-01-02 23:00:00
2011	2011-01-03 00:00:00	2012-01-01 23:00:00
2012	2012-01-02 00:00:00	2012-12-30 23:00:00
2013	2013-01-07 00:00:00	2014-01-05 23:00:00
2014	2014-01-06 00:00:00	2015-01-04 23:00:00
2015	2015-01-05 00:00:00	2016-01-03 23:00:00
2016	2015-12-28 00:00:00	2016-12-25 23:00:00

Table B.1: Start and end UTC time stamps of each Balmorel year

C Examples of generation profiles

In the examples in this section, variations of intra-annual variability is seen from different weather years.

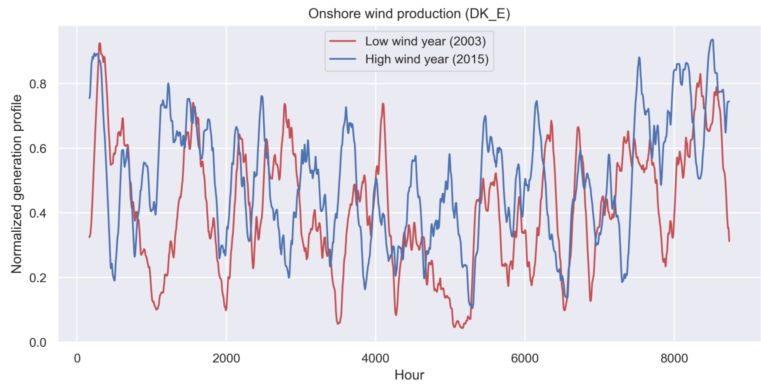


Figure C.1: Example of future onshore wind generation profiles in DK2. Year 2003: 3879 full load hours. Year 2015: 4448 full load hours. Weekly rolling mean for illustration.

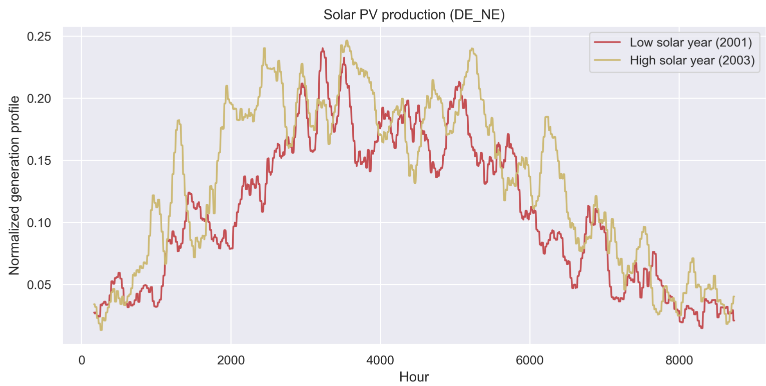


Figure C.2: Example of solar PV generation profiles in DE NE. Year 2001: 939 full load hours. Year 2003: 1146 full load hours. Weekly rolling mean for illustration.

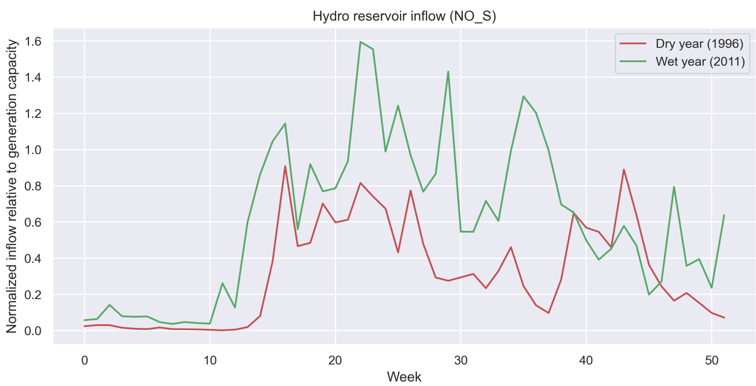


Figure C.3: Example of hydro reservoir profiles in NO2. Year 1996: 2487 full load hours. Year 2011: 4887 full load hours.

D Electricity demand model MAPE

	Out-of-sample	Hindcast
AT	3.79	10.53
BE	3.89	3.38
CH	6.21	4.21
CZ	3.64	4.98
DE NE	3.72	6.93
DE NW	3.72	
DE ME	3.72	
DE CS	3.72	
DK1	5.54	3.71
DK2	3.70	
EE	3.53	3.50
FI	3.61	2.47
FR	4.11	3.38
GB	12.59	6.36
IT	5.18	8.24
LT	7.20	4.97
LU	15.00	32.51
LV	3.23	2.33
NL	6.32	2.82
NO1	5.00	3.90
NO2	3.68	
NO3	6.11	
NO4	3.28	
NO5	7.91	
PL	3.16	11.37
SE1	7.57	3.52
SE2	6.75	
SE3	4.11	
SE4	5.34	

Table D.1: Mean absolute percentage error (MAPE) of electricity demand models [%].

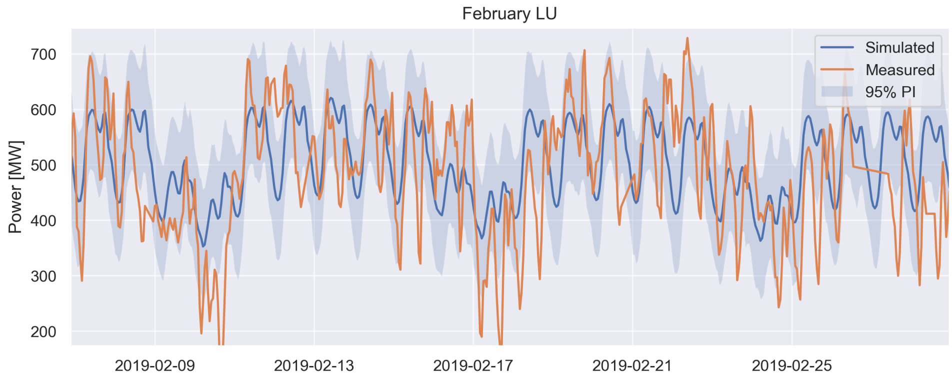


Figure D.1: Example of out-of-sample validation for Luxembourg model.

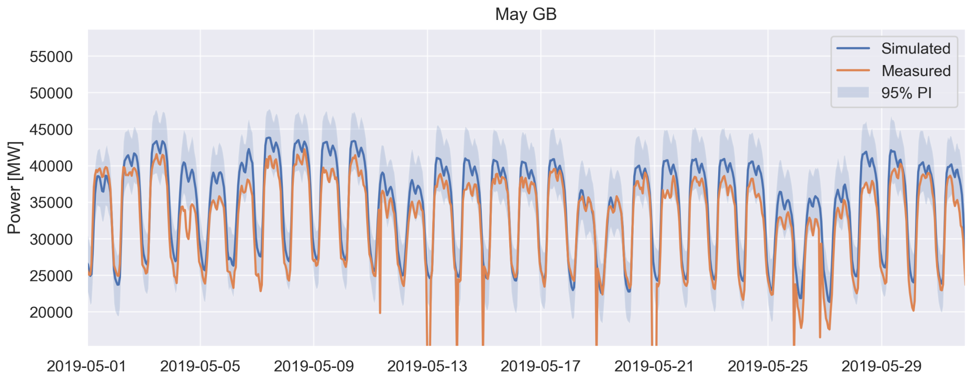


Figure D.2: Example of out-of-sample validation for Great Britain model.

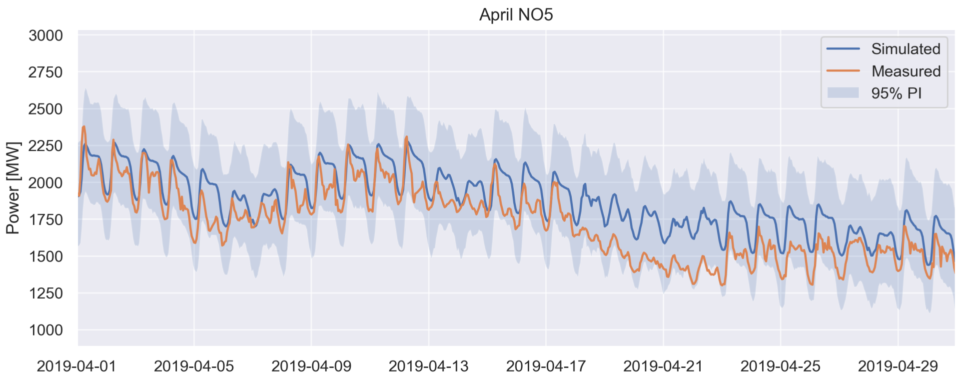


Figure D.3: Example of out-of-sample validation for NO5 model.

E Correlation in electricity demand model residuals

	AT	BE	CH	CZ	DE	DK1	DK2	EE	FI	FR	GB	IT	LT	LU	LV	NL	NO1	NO2	NO3	NO4	NO5	PL	SE1	SE2	SE3	SE4
AT		0.28	-0.04	0.38	0.41	0.21	0.26	0.22	0.13	0.2	0	0.35	0.24	0.07	0.22	0.26	0.22	0.13	0.12	0.09	0.07	0.39	0.04	0.08	0.28	0.24
BE	0.28		-0.01	0.29	0.52	0.31	0.34	0.06	0.04	0.61	0.14	0.37	0	0.16	0.01	0.54	0.26	0.16	0.12	0.11	0.12	0.21	0.07	0.1	0.28	0.26
CH	-0.04	-0.01		-0.01	-0.05	0.01	0	-0.03	-0.06	0.06	0.12	-0.04	-0.06	0.01	-0.03	0.02	0	0.01	0.02	0.01	0.01	-0.05	0	-0.02	-0.04	-0.04
CZ	0.38	0.29	-0.01		0.52	0.21	0.32	0.37	0.13	0.25	-0.05	0.41	0.39	0.02	0.42	0.31	0.27	0.14	0.11	0.08	0.08	0.67	0.06	0.1	0.42	0.34
DE	0.41	0.52	-0.05	0.52		0.33	0.41	0.24	0.18	0.38	0.03	0.48	0.2	0.1	0.23	0.51	0.31	0.19	0.16	0.11	0.12	0.46	0.06	0.11	0.41	0.37
DK1	0.21	0.31	0.01	0.21	0.33		0.4	0.12	0.05	0.21	0.1	0.23	0.07	0.06	0.1	0.37	0.25	0.16	0.13	0.1	0.11	0.19	0.06	0.07	0.28	0.26
DK2	0.26	0.34	0	0.32	0.41	0.4		0.21	0.13	0.22	0.07	0.26	0.15	0.05	0.21	0.41	0.32	0.17	0.16	0.1	0.12	0.31	0.05	0.09	0.39	0.35
EE	0.22	0.06	-0.03	0.37	0.24	0.12	0.21		0.45	0.08	-0.05	0.17	0.56	-0.01	0.67	0.14	0.22	0.1	0.09	0.08	0.05	0.45	0.05	0.08	0.37	0.26
FI	0.13	0.04	-0.06	0.13	0.18	0.05	0.13	0.45		0.03	-0.07	0.04	0.35	0.01	0.39	0.03	0.11	0.05	0.04	0.05	0.02	0.19	0.04	0.05	0.24	0.17
FR	0.2	0.61	0.06	0.25	0.38	0.21	0.22	0.08	0.03		0.13	0.35	0.04	0.15	0.03	0.44	0.24	0.14	0.13	0.09	0.09	0.12	0.06	0.07	0.21	0.18
GB	0	0.14	0.12	-0.05	0.03	0.1	0.07	-0.05	-0.07	0.13		0.05	-0.1	0.05	-0.04	0.15	0.05	0.06	0.06	0.06	0.06	-0.05	0.03	0.01	-0.02	0.01
IT	0.35	0.37	-0.04	0.41	0.48	0.23	0.26	0.17	0.04	0.35	0.05		0.2	0.06	0.17	0.47	0.24	0.15	0.13	0.11	0.11	0.49	0.05	0.08	0.28	0.28
LT	0.24	0	-0.06	0.39	0.2	0.07	0.15	0.56	0.35	0.04	-0.1	0.2		-0.01	0.63	0.08	0.15	0.07	0.07	0.06	0.03	0.51	0.03	0.05	0.3	0.23
LU	0.07	0.16	0.01	0.02	0.1	0.06	0.05	-0.01	0.01	0.15	0.05	0.06	-0.01		-0.02	0.1	0.06	0.04	0.04	0.04	0.04	0.01	0.02	0.02	0.03	0.05
LV	0.22	0.01	-0.03	0.42	0.23	0.1	0.21	0.67	0.39	0.03	-0.04	0.17	0.63	-0.02		0.1	0.19	0.09	0.09	0.08	0.05	0.53	0.04	0.07	0.37	0.26
NL	0.26	0.54	0.02	0.31	0.51	0.37	0.41	0.14	0.03	0.44	0.15	0.47	0.08	0.1	0.1		0.34	0.22	0.21	0.15	0.15	0.28	0.07	0.1	0.34	0.32
NO1	0.22	0.26	0	0.27	0.31	0.25	0.32	0.22	0.11	0.24	0.05	0.24	0.15	0.06	0.19	0.34		0.31	0.65	0.36	0.18	0.29	0.06	0.12	0.39	0.31
NO2	0.13	0.16	0.01	0.14	0.19	0.16	0.17	0.1	0.05	0.14	0.06	0.15	0.07	0.04	0.09	0.22	0.31		0.32	0.54	0.65	0.15	0.03	0.08	0.21	0.18
NO3	0.12	0.12	0.02	0.11	0.16	0.13	0.16	0.09	0.04	0.13	0.06	0.13	0.07	0.04	0.09	0.21	0.65	0.32		0.42	0.23	0.15	0.03	0.07	0.17	0.15
NO4	0.09	0.11	0.01	0.08	0.11	0.1	0.1	0.08	0.05	0.09	0.06	0.11	0.06	0.04	0.08	0.15	0.36	0.54	0.42		0.45	0.11	0.03	0.04	0.13	0.11
NO5	0.07	0.12	0.01	0.08	0.12	0.11	0.12	0.05	0.02	0.09	0.06	0.11	0.03	0.04	0.05	0.15	0.18	0.65	0.23	0.45		0.09	0.02	0.05	0.13	0.12
PL	0.39	0.21	-0.05	0.67	0.46	0.19	0.31	0.45	0.19	0.12	-0.05	0.49	0.51	0.01	0.53	0.28	0.29	0.15	0.15	0.11	0.09		0.05	0.11	0.44	0.37
SE1	0.04	0.07	0	0.06	0.06	0.06	0.05	0.05	0.04	0.06	0.03	0.05	0.03	0.02	0.04	0.07	0.06	0.03	0.03	0.03	0.02	0.05		0.11	0.02	0.02
SE2	0.08	0.1	-0.02	0.1	0.11	0.07	0.09	0.08	0.05	0.07	0.01	0.08	0.05	0.02	0.07	0.1	0.12	0.08	0.07	0.04	0.05	0.11	0.11		0.18	0.05
SE3	0.28	0.28	-0.04	0.42	0.41	0.28	0.39	0.37	0.24	0.21	-0.02	0.28	0.3	0.03	0.37	0.34	0.39	0.21	0.17	0.13	0.13	0.44	0.02	0.18		0.43
SE4	0.24	0.26	-0.04	0.34	0.37	0.26	0.35	0.26	0.17	0.18	0.01	0.28	0.23	0.05	0.26	0.32	0.31	0.18	0.15	0.11	0.12	0.37	0.02	0.05	0.43	

F Important energy system input

		2030	**2040**	**2050**
CAPEX	mEUR20/MW	1.374	1.232	1.133
Fixed O&M	tEUR20/MW	15.085	13.579	12.490
Variable O&M	EUR20/MWh	1.616	1.539	1.341

Table F.1: Onshore wind cost inputs [38].

		2030	**2040**	**2050**
CAPEX	mEUR20/MW	1.800	1.680	1.640
Fixed O&M	tEUR20/MW	39.000	34.000	33.000
Variable O&M	EUR20/MWh	3.890	3.420	3.250

Table F.2: Offshore wind cost inputs [39].

		2030	**2040**	**2050**
CAPEX	mEUR20/MW	0.397	0.348	0.321
Fixed O&M	tEUR20/MW	6.292	5.686	5.321
Variable O&M	EUR20/MWh	0	0	0

Table F.3: Solar PV cost input [24].

	2030	**2040**	**2050**
Biogas	7.44	7.44	7.44
Coal	2.42	2.25	2.08
Natural gas	11.11	10.26	9.42
Wood	7.15	7.27	7.48

Table F.4: Fuel prices [EUR20/GJ] [24].

G Energy system capacities

	2030	2040	2050
Bio and waste	43	48	45
Electric storage	61	134	282
Pumped hydro storage	31	33	36
Natural gas	282	270	267
Other fossil fuels	36	15	13
Hydro	127	126	127
Nuclear	87	80	57
Offshore wind	150	305	457
Onshore wind	333	416	514
Solar PV	656	857	1240
Total	1803	2284	3036

Table G.1: Installed power generation capacity [GW].

		2030	2040	2050
Electrolyzer capacity	GW	127	294	582
Hydrogen storage	TWh	34	80	148
District heating heat pumps	GW	13	22	29
District heating storage	TWh	1.4	1.6	1.7
Individual heating heat pumps	GW	315	318	321
Individual heating electric boiler	GW	138	139	141
Individual heating storage	GWh	224	323	424

Table G.2: Other installed energy infrastructure.

In fig. G.1, the installed generation capacities in 2050 for solar pv, onshore wind and offshore wind are given in absolute terms (GW) in blue coloured text for each country. The position of the blue dots indicate how the capacities relative to the assumed minimum and maximum capacity constraints on a normalized scale from 0% to 100%. The maximum and minimum constraints are written in absolute terms (GW) above and below the dashed lines. Note that in some cases (such as onshore wind in Germany), the installed capacity exceeds the maximum. This is due to the installation taking place in a year before the constraint becomes binding.

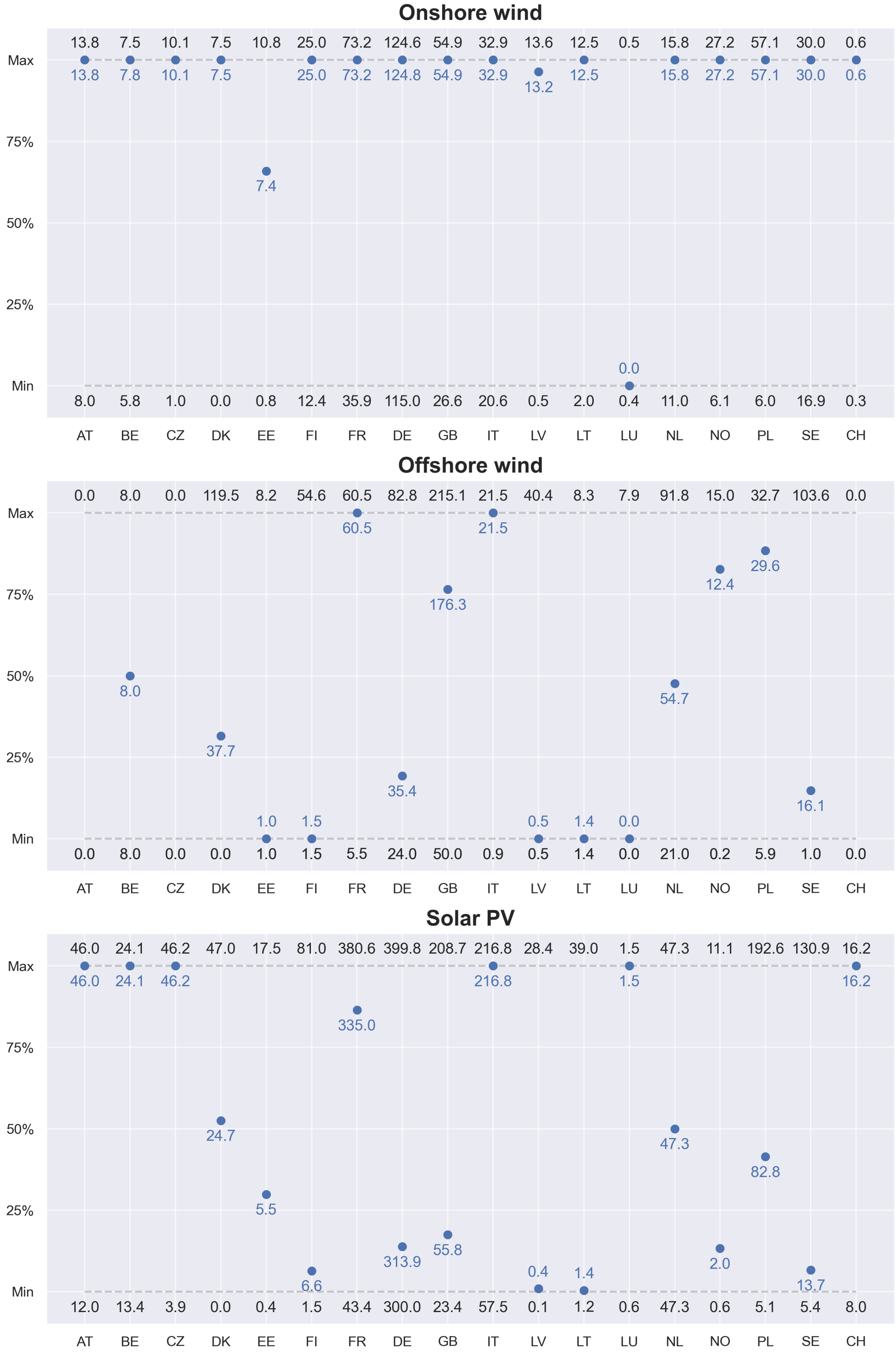


Figure G.1: Installed generation capacities in individual countries [GW] in 2050 relative to the assumed capacity potential.

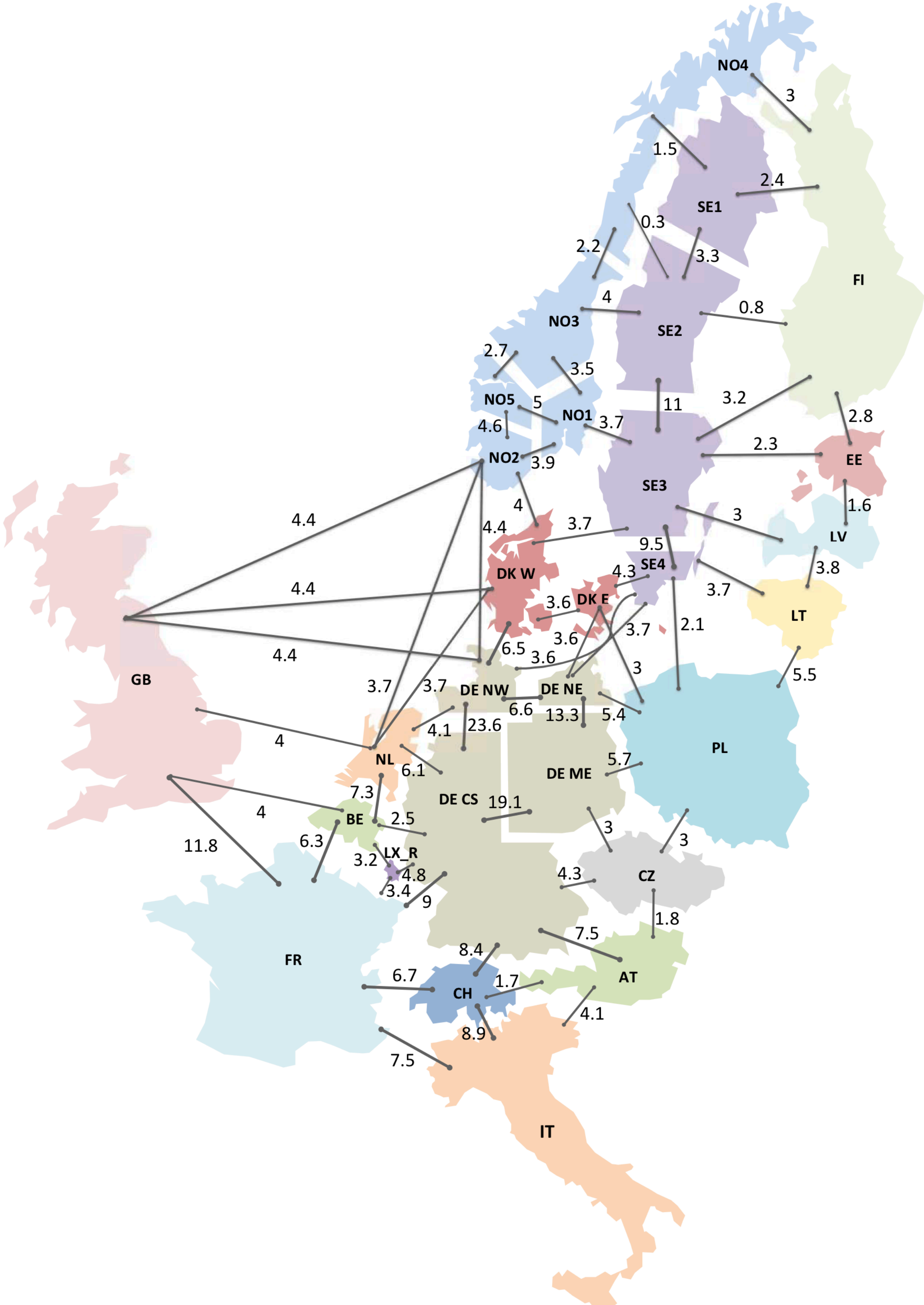


Figure G.2: Installed transmission capacity [GW] in 2050.

H Inter-annual flexibility from natural gas and nuclear

	Natural gas		Nuclear	
	Generation	Full load hours	Generation	Full load hours
Avg year	219	820	299	5236
1982	329	1229	290	5066
1983	246	918	261	4565
1984	292	1093	297	5197
1985	352	1316	301	5260
1986	217	810	276	4834
1987	376	1405	304	5324
1988	214	802	266	4655
1989	234	875	293	5120
1990	261	977	267	4676
1991	296	1106	299	5220
1992	219	817	270	4729
1993	243	908	282	4939
1994	251	937	265	4629
1995	278	1040	264	4624
1996	335	1254	324	5663
1997	344	1287	299	5228
1998	161	601	266	4646
1999	210	787	281	4921
2000	226	847	278	4859
2001	277	1037	292	5103
2002	295	1103	287	5026
2003	302	1131	304	5314
2004	244	911	283	4950
2005	163	611	301	5263
2006	314	1175	279	4884
2007	240	897	264	4618
2008	241	901	286	4996
2009	218	814	309	5399
2010	378	1414	334	5838
2011	180	671	277	4844
2012	210	785	300	5243
2013	270	1010	298	5207
2014	291	1089	295	5151
2015	154	577	277	4849
2016	282	1054	320	5601

Table H.1: Inter-annual flexibility from natural gas and nuclear plants given as generation [TWh] and full load hours [h].

I Backstop capacity and generation

	Backstop generation	**Backstop capacity**
Avg year	0.5	8.2
1982	2.3	22.6
1983	1.2	11.1
1984	17.3	147.2
1985	0.4	10.0
1986	0.8	6.7
1987	0.6	10.9
1988	0.9	21.6
1989	0.0	1.1
1990	1.2	27.7
1991	7.8	102.1
1992	0.6	6.4
1993	2.7	21.4
1994	1.7	23.1
1995	3.6	33.5
1996	1.1	20.1
1997	1.6	34.8
1998	0.1	1.3
1999	0.1	6.0
2000	0.9	16.5
2001	11.4	134.3
2002	8.9	89.6
2003	0.0	0.0
2004	0.3	4.7
2005	0.1	1.6
2006	11.4	91.6
2007	0.0	0.0
2008	0.3	3.2
2009	0.0	0.5
2010	1.9	35.1
2011	0.0	2.6
2012	0.0	0.0
2013	1.8	22.3
2014	2.3	21.1
2015	0.0	0.0
2016	0.0	0.2

Table I.1: Overview of backstop generation [TWh] and capacity [GW] in all weather years

J Demand correction factors

On the following pages, the demand correction factors for classic electricity and low temperature heat is given for each region.

J.1 Low temperature heat demand correction factors

	AT	BE	CH	CZ	DE_CS	DE_ME	DE_NE	DE_NW	DK_W	DK_E	EE	FI	FR	GB	IT	LT	LU
1982	1.022	1.028	1.023	1.008	1.019	1.019	1.019	1.019	1.040	1.043	1.030	1.034	1.012	1.022	1.050	1.027	1.025
1983	1.012	1.043	1.024	0.993	1.024	1.024	1.024	1.024	1.010	1.000	0.981	1.012	1.058	1.020	1.059	0.964	1.046
1984	1.088	1.084	1.093	1.065	1.095	1.095	1.095	1.095	1.041	1.032	1.012	0.999	1.095	1.040	1.108	1.027	1.094
1985	1.100	1.150	1.084	1.110	1.129	1.129	1.129	1.129	1.139	1.147	1.133	1.150	1.139	1.114	1.087	1.145	1.129
1986	1.071	1.122	1.061	1.057	1.102	1.102	1.102	1.102	1.115	1.114	1.061	1.067	1.108	1.133	1.071	1.071	1.107
1987	1.085	1.129	1.064	1.105	1.132	1.132	1.132	1.132	1.151	1.171	1.158	1.155	1.112	1.101	1.082	1.167	1.114
1988	1.026	0.985	1.002	1.001	0.987	0.987	0.987	0.987	0.989	1.002	1.026	1.030	0.993	1.038	1.026	1.030	0.993
1989	1.012	0.960	1.004	0.968	0.966	0.966	0.966	0.966	0.944	0.945	0.921	0.930	0.970	0.966	1.020	0.924	0.974
1990	1.018	0.971	1.001	0.981	0.966	0.966	0.966	0.966	0.927	0.921	0.943	0.968	0.968	0.969	1.002	0.929	0.982
1991	1.093	1.074	1.054	1.075	1.070	1.070	1.070	1.070	1.024	1.032	0.979	0.996	1.093	1.064	1.122	0.993	1.062
1992	1.006	1.007	1.020	0.997	0.997	0.997	0.997	0.997	0.959	0.969	0.973	0.988	1.031	1.027	1.020	0.986	1.000
1993	1.042	1.031	1.026	1.038	1.039	1.039	1.039	1.039	1.064	1.060	1.047	1.025	1.049	1.060	1.042	1.041	1.035
1994	0.942	0.963	0.940	0.964	0.964	0.964	0.964	0.964	1.004	1.004	1.055	1.042	0.949	0.994	0.957	1.028	0.960
1995	1.034	0.993	1.019	1.032	1.028	1.028	1.028	1.028	1.030	1.030	0.984	0.995	0.999	0.989	1.025	1.006	1.004
1996	1.107	1.143	1.068	1.139	1.157	1.157	1.157	1.157	1.145	1.145	1.085	1.049	1.099	1.088	1.038	1.113	1.122
1997	1.014	1.002	0.984	1.039	1.017	1.017	1.017	1.017	1.019	1.033	1.021	1.007	0.968	0.964	0.974	1.028	1.004
1998	1.018	0.990	1.013	1.004	0.995	0.995	0.995	0.995	1.018	1.018	1.025	1.034	1.012	0.970	1.010	1.016	1.009
1999	1.001	0.960	1.004	0.971	0.962	0.962	0.962	0.962	0.967	0.972	0.977	0.994	0.969	0.954	1.005	0.968	0.972
2000	0.954	0.937	0.965	0.927	0.925	0.925	0.925	0.925	0.940	0.937	0.934	0.936	0.948	0.982	0.948	0.925	0.935
2001	1.014	0.997	1.000	1.030	1.004	1.004	1.004	1.004	1.030	1.021	1.009	1.017	0.995	1.011	0.974	1.007	0.992
2002	0.947	0.933	0.966	0.965	0.957	0.957	0.957	0.957	0.966	0.977	0.989	1.004	0.931	0.949	0.944	0.972	0.937
2003	0.997	0.987	0.985	1.002	1.000	1.000	1.000	1.000	0.998	1.008	1.019	1.017	0.983	0.964	1.013	1.018	0.978
2004	1.018	1.002	1.015	1.013	1.010	1.010	1.010	1.010	0.998	1.011	1.007	0.996	1.015	0.967	1.007	1.020	1.016
2005	1.033	0.978	1.031	1.028	0.999	0.999	0.999	0.999	0.986	0.986	0.999	0.965	1.010	0.966	1.066	1.015	0.985
2006	0.998	0.962	0.977	1.004	0.970	0.970	0.970	0.970	0.940	0.948	0.968	0.965	0.965	0.938	0.991	0.991	0.963
2007	0.940	0.917	0.959	0.943	0.920	0.920	0.920	0.920	0.930	0.922	0.953	0.956	0.938	0.942	0.939	0.961	0.930
2008	0.953	0.984	0.988	0.948	0.964	0.964	0.964	0.964	0.927	0.924	0.920	0.936	0.994	1.000	0.964	0.924	0.986
2009	0.966	0.982	0.977	0.975	0.979	0.979	0.979	0.979	0.977	0.988	1.003	1.001	0.982	0.986	0.984	0.998	0.974
2010	1.049	1.104	1.056	1.085	1.107	1.107	1.107	1.107	1.138	1.138	1.104	1.091	1.095	1.094	1.035	1.082	1.080
2011	0.950	0.899	0.930	0.959	0.929	0.929	0.929	0.929	0.958	0.957	0.959	0.948	0.882	0.926	0.949	0.967	0.913
2012	0.971	1.000	0.983	0.992	0.990	0.990	0.990	0.990	1.023	1.008	1.050	1.028	0.994	1.030	0.991	1.023	0.990
2013	0.995	1.060	1.028	1.018	1.034	1.034	1.034	1.034	1.013	1.004	0.966	0.949	1.044	1.039	0.974	0.977	1.051
2014	0.892	0.880	0.930	0.891	0.885	0.885	0.885	0.885	0.886	0.887	0.971	0.946	0.877	0.904	0.865	0.961	0.889
2015	0.928	0.960	0.950	0.928	0.942	0.942	0.942	0.942	0.952	0.936	0.910	0.910	0.934	0.968	0.929	0.920	0.958
2016	0.946	0.979	0.970	0.958	0.966	0.966	0.966	0.966	0.951	0.940	0.977	0.970	0.987	0.972	0.923	0.974	0.984

	LV	NL	NO_SE	NO_SW	NO_M	NO_N	NO_MW	PL	SE_N1	SE_N2	SE_M	SE_S
1982	1.028	1.021	1.051	1.013	1.027	1.029	1.013	1.011	1.009	1.026	1.035	1.045
1983	0.970	1.030	0.994	1.003	1.016	1.036	1.010	0.973	1.019	1.006	0.992	1.001
1984	1.016	1.092	1.005	1.016	1.028	1.009	1.025	1.055	1.004	1.007	0.999	1.012
1985	1.136	1.158	1.158	1.113	1.091	1.090	1.085	1.131	1.138	1.146	1.164	1.145
1986	1.058	1.129	1.084	1.085	1.077	1.048	1.079	1.079	1.050	1.066	1.086	1.098
1987	1.158	1.140	1.159	1.096	1.074	1.067	1.074	1.141	1.093	1.116	1.161	1.164
1988	1.023	0.979	1.021	1.007	1.006	1.046	1.004	1.012	1.025	1.009	1.017	1.004
1989	0.929	0.959	0.942	0.961	0.976	0.974	0.994	0.939	0.943	0.942	0.932	0.941
1990	0.931	0.955	0.926	0.958	0.956	0.963	0.979	0.943	0.957	0.950	0.921	0.925
1991	0.982	1.076	1.007	1.002	1.005	0.999	1.012	1.055	1.006	0.992	1.002	1.022
1992	0.984	0.990	0.973	0.987	0.998	1.003	1.004	1.011	0.976	0.974	0.967	0.976
1993	1.040	1.042	1.037	1.037	1.050	1.017	1.048	1.040	1.014	1.015	1.035	1.048
1994	1.042	0.983	1.039	1.012	1.049	1.029	1.030	0.984	1.029	1.043	1.026	1.003
1995	0.998	1.008	1.019	1.001	1.023	1.028	1.030	1.031	1.012	1.017	1.031	1.026
1996	1.097	1.173	1.086	1.071	1.062	1.030	1.066	1.143	1.023	1.055	1.084	1.116
1997	1.028	1.020	0.974	0.983	0.984	1.006	0.997	1.044	0.983	0.970	0.999	1.022
1998	1.025	0.985	0.999	1.012	1.010	1.042	1.010	1.012	1.047	1.021	1.030	1.035
1999	0.969	0.946	0.982	0.979	0.986	1.017	0.980	0.959	1.008	0.996	0.975	0.975
2000	0.924	0.932	0.908	0.954	0.969	0.979	0.969	0.907	0.946	0.951	0.927	0.929
2001	1.007	0.988	1.035	1.026	1.024	1.019	1.036	1.023	1.011	1.022	1.020	1.016
2002	0.982	0.946	1.000	0.975	0.963	1.000	0.956	0.965	0.994	0.985	0.990	0.979
2003	1.020	0.995	0.993	0.980	0.962	0.985	0.977	1.018	0.984	0.990	1.006	1.009
2004	1.017	0.992	0.990	0.982	0.976	0.977	0.970	1.003	1.003	0.992	1.006	1.019
2005	1.012	0.962	0.940	0.969	0.965	0.965	0.959	1.015	0.962	0.966	0.979	0.996
2006	0.977	0.948	0.943	0.938	0.931	0.957	0.939	1.000	0.957	0.943	0.952	0.955
2007	0.955	0.901	0.960	0.968	0.984	0.965	0.982	0.948	0.969	0.968	0.956	0.939
2008	0.920	0.974	0.956	0.970	0.971	0.984	0.971	0.933	0.979	0.969	0.941	0.936
2009	0.998	0.980	1.007	0.990	0.981	0.986	0.976	0.989	0.998	1.008	1.002	0.988
2010	1.089	1.124	1.124	1.101	1.120	1.058	1.093	1.097	1.077	1.107	1.139	1.121
2011	0.965	0.920	0.965	0.959	0.946	0.934	0.943	0.964	0.946	0.944	0.950	0.954
2012	1.033	1.007	1.022	1.021	1.038	1.025	1.023	1.010	1.026	1.019	1.021	1.024
2013	0.982	1.061	1.010	1.036	0.997	0.947	1.022	1.004	0.968	0.978	0.988	0.999
2014	0.969	0.861	0.901	0.921	0.908	0.946	0.907	0.917	0.948	0.936	0.929	0.904
2015	0.923	0.959	0.928	0.977	0.943	0.941	0.970	0.920	0.930	0.943	0.932	0.938
2016	0.976	0.969	0.954	0.985	0.974	0.950	0.973	0.952	0.976	0.977	0.957	0.956

J.2 Classic electricity demand correction factors

	AT	BE	CH	CZ	DE_CS	DE_ME	DE_NE	DE_NW	DK_W	DK_E	EE	FI	FR	GB	IT	LT	LU
1982	1.0000	0.9992	1.0017	0.9995	1.0027	1.0027	1.0027	1.0027	1.0014	1.0021	1.0005	0.9984	0.9983	0.9989	0.9986	0.9990	0.9990
1983	1.0001	0.9993	1.0031	0.9996	1.0024	1.0024	1.0024	1.0024	0.9999	0.9992	0.9962	0.9989	1.0029	0.9998	0.9985	0.9981	1.0002
1984	1.0031	1.0025	1.0096	1.0022	1.0060	1.0060	1.0060	1.0060	1.0021	1.0028	1.0024	1.0019	1.0047	1.0029	0.9919	1.0001	1.0001
1985	1.0042	0.9996	1.0092	0.9996	1.0038	1.0038	1.0038	1.0038	1.0040	1.0107	1.0159	0.9991	1.0083	0.9988	1.0033	1.0063	0.9977
1986	1.0023	0.9990	1.0060	0.9996	1.0026	1.0026	1.0026	1.0026	1.0016	1.0062	1.0053	0.9989	1.0058	0.9986	0.9962	1.0022	0.9980
1987	1.0011	0.9990	1.0048	0.9990	1.0027	1.0027	1.0027	1.0027	1.0011	1.0086	1.0142	0.9974	1.0045	0.9980	0.9984	1.0037	0.9970
1988	1.0010	1.0010	0.9998	1.0016	1.0042	1.0042	1.0042	1.0042	1.0008	1.0018	1.0050	1.0029	0.9991	1.0011	0.9989	1.0036	0.9994
1989	0.9973	0.9995	0.9988	0.9997	1.0016	1.0016	1.0016	1.0016	0.9963	0.9937	0.9883	0.9991	0.9965	1.0002	0.9884	0.9936	0.9993
1990	0.9988	0.9997	0.9978	0.9996	1.0005	1.0005	1.0005	1.0005	0.9949	0.9918	0.9906	0.9987	0.9968	0.9996	0.9932	0.9907	0.9993
1991	1.0027	0.9995	1.0061	0.9996	0.9990	0.9990	0.9990	0.9990	0.9996	1.0006	0.9954	0.9988	1.0056	0.9997	1.0014	0.9973	0.9998
1992	1.0028	1.0021	1.0031	1.0018	1.0014	1.0014	1.0014	1.0014	1.0011	1.0008	0.9975	1.0017	1.0030	1.0013	0.9980	1.0028	1.0025
1993	0.9993	0.9988	1.0003	0.9990	0.9992	0.9992	0.9992	0.9992	0.9989	1.0017	1.0023	0.9981	1.0003	0.9980	0.9988	0.9980	0.9981
1994	0.9975	0.9990	0.9927	0.9996	0.9976	0.9976	0.9976	0.9976	1.0004	0.9991	1.0047	0.9994	0.9960	0.9992	1.0027	1.0004	1.0005
1995	0.9990	0.9998	0.9997	0.9994	0.9987	0.9987	0.9987	0.9987	1.0023	1.0023	0.9986	0.9992	0.9968	1.0007	0.9918	1.0005	1.0004
1996	1.0055	1.0025	1.0067	1.0024	1.0032	1.0032	1.0032	1.0032	1.0077	1.0130	1.0123	1.0018	1.0037	1.0024	0.9948	1.0071	1.0012
1997	0.9989	0.9992	0.9961	0.9992	0.9981	0.9981	0.9981	0.9981	1.0023	1.0028	1.0023	1.0005	0.9962	1.0000	0.9968	1.0020	0.9995
1998	0.9987	0.9988	1.0000	0.9984	0.9978	0.9978	0.9978	0.9978	0.9958	0.9971	0.9997	0.9979	0.9993	0.9981	1.0051	0.9974	0.9983
1999	0.9976	0.9991	0.9986	0.9991	0.9986	0.9986	0.9986	0.9986	0.9985	0.9975	0.9973	0.9996	0.9973	0.9991	0.9995	1.0003	0.9997
2000	0.9993	1.0015	0.9968	1.0018	0.9995	0.9995	0.9995	0.9995	0.9967	0.9942	0.9920	1.0014	0.9974	1.0018	0.9994	0.9949	1.0006
2001	0.9999	1.0000	0.9985	0.9993	0.9982	0.9982	0.9982	0.9982	1.0001	0.9999	1.0015	0.9996	0.9988	0.9992	1.0013	1.0002	0.9996
2002	0.9983	0.9991	0.9936	1.0001	0.9979	0.9979	0.9979	0.9979	1.0006	0.9986	1.0019	1.0010	0.9925	0.9995	0.9949	1.0037	0.9995
2003	1.0030	0.9998	1.0025	0.9999	0.9979	0.9979	0.9979	0.9979	1.0011	1.0009	1.0009	1.0001	1.0033	1.0005	1.0166	1.0009	1.0032
2004	1.0011	1.0020	1.0022	1.0016	1.0019	1.0019	1.0019	1.0019	1.0012	1.0012	1.0011	1.0016	1.0027	1.0018	1.0019	0.9995	1.0019
2005	0.9995	0.9992	1.0025	0.9989	0.9983	0.9983	0.9983	0.9983	0.9988	0.9985	0.9998	0.9995	1.0022	0.9996	0.9978	0.9989	1.0006
2006	0.9993	1.0000	0.9976	0.9994	0.9983	0.9983	0.9983	0.9983	1.0007	0.9976	0.9979	1.0005	0.9993	1.0010	1.0010	1.0014	1.0017
2007	0.9980	0.9994	0.9936	0.9996	0.9972	0.9972	0.9972	0.9972	0.9953	0.9921	0.9948	0.9995	0.9956	0.9987	1.0031	0.9982	0.9989
2008	1.0015	1.0023	0.9999	1.0023	1.0010	1.0010	1.0010	1.0010	0.9999	0.9964	0.9898	1.0018	1.0005	1.0022	1.0042	0.9966	1.0020
2009	0.9980	0.9992	0.9971	0.9982	0.9980	0.9980	0.9980	0.9980	0.9979	0.9978	0.9980	0.9991	0.9998	0.9988	1.0055	0.9976	0.9996
2010	1.0001	0.9995	1.0047	0.9987	1.0005	1.0005	1.0005	1.0005	1.0061	1.0107	1.0132	1.0003	1.0062	0.9988	1.0003	1.0069	0.9993
2011	0.9974	0.9987	0.9919	0.9990	0.9975	0.9975	0.9975	0.9975	0.9977	0.9963	0.9953	1.0006	0.9930	0.9991	1.0056	0.9990	0.9992
2012	1.0026	1.0028	1.0011	1.0028	1.0012	1.0012	1.0012	1.0012	1.0022	1.0024	1.0078	1.0015	1.0039	1.0025	1.0148	1.0038	1.0023
2013	1.0010	0.9998	1.0027	1.0001	0.9987	0.9987	0.9987	0.9987	1.0005	1.0001	0.9979	1.0005	1.0027	1.0001	1.0012	1.0007	0.9998
2014	0.9934	0.9986	0.9882	0.9993	0.9962	0.9962	0.9962	0.9962	0.9954	0.9902	0.9949	1.0007	0.9893	0.9997	0.9887	0.9992	0.9990
2015	0.9981	0.9989	0.9948	0.9986	0.9971	0.9971	0.9971	0.9971	0.9950	0.9919	0.9849	0.9980	0.9974	0.9982	1.0078	0.9935	1.0004
2016	0.9996	1.0018	0.9983	1.0017	1.0006	1.0006	1.0006	1.0006	1.0020	0.9996	0.9999	1.0021	1.0001	1.0022	0.9996	1.0017	1.0023

	LV	NL	NO_SE	NO_SW	NO_M	NO_N	NO_MW	PL	SE_N1	SE_N2	SE_M	SE_S
1982	0.9995	1.0000	1.0167	1.0038	1.0027	1.0044	1.0021	1.0004	0.9999	1.0035	0.9999	0.9998
1983	0.9987	1.0004	0.9969	1.0012	0.9998	1.0045	1.0006	0.9990	1.0016	0.9994	0.9989	0.9995
1984	1.0021	0.9972	1.0033	1.0044	1.0042	1.0030	1.0055	1.0016	1.0026	1.0031	1.0023	1.0024
1985	1.0061	0.9951	1.0576	1.0192	1.0096	1.0184	1.0131	1.0031	1.0161	1.0268	1.0053	1.0022
1986	1.0016	0.9952	1.0283	1.0160	1.0076	1.0096	1.0140	1.0015	1.0051	1.0108	1.0020	1.0003
1987	1.0034	0.9933	1.0537	1.0152	1.0065	1.0119	1.0112	1.0030	1.0091	1.0182	1.0038	1.0004
1988	1.0043	0.9965	1.0099	1.0030	1.0032	1.0116	1.0023	1.0018	1.0061	1.0044	1.0025	1.0021
1989	0.9954	1.0008	0.9750	0.9916	0.9946	0.9927	0.9972	0.9962	0.9926	0.9892	0.9968	0.9983
1990	0.9925	0.9988	0.9703	0.9894	0.9924	0.9908	0.9947	0.9956	0.9929	0.9890	0.9969	0.9985
1991	0.9967	0.9984	1.0025	1.0001	0.9995	0.9974	1.0016	0.9995	0.9999	0.9979	0.9995	0.9999
1992	1.0006	1.0032	0.9936	0.9984	1.0012	1.0010	1.0010	1.0040	0.9987	0.9971	1.0007	1.0016
1993	0.9978	0.9946	1.0076	1.0036	1.0029	1.0024	1.0059	0.9994	1.0000	1.0011	1.0000	0.9993
1994	1.0002	1.0010	1.0125	1.0036	1.0061	1.0056	1.0056	0.9986	1.0031	1.0078	0.9999	0.9996
1995	1.0000	1.0036	1.0055	1.0023	1.0011	1.0037	1.0054	1.0009	1.0009	1.0020	1.0002	1.0001
1996	1.0066	0.9994	1.0354	1.0155	1.0095	1.0083	1.0138	1.0054	1.0052	1.0123	1.0059	1.0048
1997	1.0015	1.0008	0.9937	0.9996	1.0015	1.0023	1.0018	1.0006	0.9986	0.9961	0.9991	0.9997
1998	0.9972	0.9954	0.9930	0.9977	0.9986	1.0073	0.9986	0.9989	1.0049	1.0006	0.9992	0.9982
1999	0.9991	1.0009	0.9903	0.9942	0.9967	1.0028	0.9946	0.9979	1.0000	0.9988	0.9982	0.9986
2000	0.9959	1.0001	0.9623	0.9891	0.9957	0.9968	0.9938	0.9981	0.9942	0.9906	0.9991	1.0003
2001	1.0012	1.0010	1.0109	1.0035	1.0013	1.0028	1.0048	0.9994	1.0004	1.0033	1.0003	1.0000
2002	1.0031	1.0003	1.0038	0.9974	0.9991	0.9994	0.9938	0.9991	1.0011	0.9988	0.9994	1.0000
2003	1.0001	1.0052	0.9979	0.9962	0.9961	0.9970	0.9953	1.0018	0.9979	0.9974	0.9993	0.9993
2004	1.0005	1.0017	0.9949	0.9970	0.9990	0.9981	0.9959	1.0010	1.0020	0.9992	1.0019	1.0019
2005	0.9995	1.0015	0.9753	0.9916	0.9938	0.9920	0.9905	0.9999	0.9947	0.9925	0.9984	0.9990
2006	1.0007	1.0073	0.9820	0.9910	0.9941	0.9908	0.9899	1.0013	0.9956	0.9906	0.9979	0.9990
2007	0.9990	0.9990	0.9825	0.9919	0.9978	0.9922	0.9958	0.9976	0.9955	0.9940	0.9976	0.9983
2008	0.9965	1.0028	0.9823	0.9971	0.9992	0.9979	0.9975	0.9994	0.9987	0.9944	1.0001	1.0015
2009	0.9973	0.9999	0.9999	0.9963	0.9970	0.9963	0.9937	0.9994	0.9989	1.0003	0.9987	0.9985
2010	1.0064	0.9999	1.0488	1.0180	1.0143	1.0117	1.0161	1.0021	1.0091	1.0204	1.0041	1.0014
2011	0.9989	0.9988	0.9845	0.9893	0.9918	0.9858	0.9876	0.9977	0.9924	0.9888	0.9975	0.9982
2012	1.0038	1.0025	1.0069	1.0042	1.0051	1.0054	1.0052	1.0033	1.0047	1.0046	1.0027	1.0023
2013	1.0011	1.0009	1.0040	1.0059	0.9994	0.9903	1.0027	0.9993	0.9959	0.9960	0.9996	0.9996
2014	0.9985	1.0007	0.9610	0.9844	0.9906	0.9894	0.9818	0.9960	0.9935	0.9868	0.9958	0.9970
2015	0.9926	0.9977	0.9689	0.9913	0.9908	0.9854	0.9912	0.9968	0.9896	0.9868	0.9961	0.9971
2016	1.0015	1.0063	0.9882	0.9973	0.9973	0.9909	0.9957	1.0003	0.9986	0.9974	1.0007	1.0012

K Full load hours

On the following pages, the full load hours for wind, solar PV and hydro power are given for each region.

K.1 Solar PV full load hours

	AT	BE	CH	CZ	DE_CS	DE_ME	DE_NE	DE_NW	DK_W	DK_E	EE	FI	FR	GB	IT	LT	LU
1982	1.022	1.028	1.023	1.008	1.019	1.019	1.019	1.019	1.040	1.043	1.030	1.034	1.012	1.022	1.050	1.027	1.025
1983	1.012	1.043	1.024	0.993	1.024	1.024	1.024	1.024	1.010	1.000	0.981	1.012	1.058	1.020	1.059	0.964	1.046
1984	1.088	1.084	1.093	1.065	1.095	1.095	1.095	1.095	1.041	1.032	1.012	0.999	1.095	1.040	1.108	1.027	1.094
1985	1.100	1.150	1.084	1.110	1.129	1.129	1.129	1.129	1.139	1.147	1.133	1.150	1.139	1.114	1.087	1.145	1.129
1986	1.071	1.122	1.061	1.057	1.102	1.102	1.102	1.102	1.115	1.114	1.061	1.067	1.108	1.133	1.071	1.071	1.107
1987	1.085	1.129	1.064	1.105	1.132	1.132	1.132	1.132	1.151	1.171	1.158	1.155	1.112	1.101	1.082	1.167	1.114
1988	1.026	0.985	1.002	1.001	0.987	0.987	0.987	0.987	0.989	1.002	1.026	1.030	0.993	1.038	1.026	1.030	0.993
1989	1.012	0.960	1.004	0.968	0.966	0.966	0.966	0.966	0.944	0.945	0.921	0.930	0.970	0.966	1.020	0.924	0.974
1990	1.018	0.971	1.001	0.981	0.966	0.966	0.966	0.966	0.927	0.921	0.943	0.968	0.968	0.969	1.002	0.929	0.982
1991	1.093	1.074	1.054	1.075	1.070	1.070	1.070	1.070	1.024	1.032	0.979	0.996	1.093	1.064	1.122	0.993	1.062
1992	1.006	1.007	1.020	0.997	0.997	0.997	0.997	0.997	0.959	0.969	0.973	0.988	1.031	1.027	1.020	0.986	1.000
1993	1.042	1.031	1.026	1.038	1.039	1.039	1.039	1.039	1.064	1.060	1.047	1.025	1.049	1.060	1.042	1.041	1.035
1994	0.942	0.963	0.940	0.964	0.964	0.964	0.964	0.964	1.004	1.004	1.055	1.042	0.949	0.994	0.957	1.028	0.960
1995	1.034	0.993	1.019	1.032	1.028	1.028	1.028	1.028	1.030	1.030	0.984	0.995	0.999	0.989	1.025	1.006	1.004
1996	1.107	1.143	1.068	1.139	1.157	1.157	1.157	1.157	1.145	1.145	1.085	1.049	1.099	1.088	1.038	1.113	1.122
1997	1.014	1.002	0.984	1.039	1.017	1.017	1.017	1.017	1.019	1.033	1.021	1.007	0.968	0.964	0.974	1.028	1.004
1998	1.018	0.990	1.013	1.004	0.995	0.995	0.995	0.995	1.018	1.018	1.025	1.034	1.012	0.970	1.010	1.016	1.009
1999	1.001	0.960	1.004	0.971	0.962	0.962	0.962	0.962	0.967	0.972	0.977	0.994	0.969	0.954	1.005	0.968	0.972
2000	0.954	0.937	0.965	0.927	0.925	0.925	0.925	0.925	0.940	0.937	0.934	0.936	0.948	0.982	0.948	0.925	0.935
2001	1.014	0.997	1.000	1.030	1.004	1.004	1.004	1.004	1.030	1.021	1.009	1.017	0.995	1.011	0.974	1.007	0.992
2002	0.947	0.933	0.966	0.965	0.957	0.957	0.957	0.957	0.966	0.977	0.989	1.004	0.931	0.949	0.944	0.972	0.937
2003	0.997	0.987	0.985	1.002	1.000	1.000	1.000	1.000	0.998	1.008	1.019	1.017	0.983	0.964	1.013	1.018	0.978
2004	1.018	1.002	1.015	1.013	1.010	1.010	1.010	1.010	0.998	1.011	1.007	0.996	1.015	0.967	1.007	1.020	1.016
2005	1.033	0.978	1.031	1.028	0.999	0.999	0.999	0.999	0.986	0.986	0.999	0.965	1.010	0.966	1.066	1.015	0.985
2006	0.998	0.962	0.977	1.004	0.970	0.970	0.970	0.970	0.940	0.948	0.968	0.965	0.965	0.938	0.991	0.991	0.963
2007	0.940	0.917	0.959	0.943	0.920	0.920	0.920	0.920	0.930	0.922	0.953	0.956	0.938	0.942	0.939	0.961	0.930
2008	0.953	0.984	0.988	0.948	0.964	0.964	0.964	0.964	0.927	0.924	0.920	0.936	0.994	1.000	0.964	0.924	0.986
2009	0.966	0.982	0.977	0.975	0.979	0.979	0.979	0.979	0.977	0.988	1.003	1.001	0.982	0.986	0.984	0.998	0.974
2010	1.049	1.104	1.056	1.085	1.107	1.107	1.107	1.107	1.138	1.138	1.104	1.091	1.095	1.094	1.035	1.082	1.080
2011	0.950	0.899	0.930	0.959	0.929	0.929	0.929	0.929	0.958	0.957	0.959	0.948	0.882	0.926	0.949	0.967	0.913
2012	0.971	1.000	0.983	0.992	0.990	0.990	0.990	0.990	1.023	1.008	1.050	1.028	0.994	1.030	0.991	1.023	0.990
2013	0.995	1.060	1.028	1.018	1.034	1.034	1.034	1.034	1.013	1.004	0.966	0.949	1.044	1.039	0.974	0.977	1.051
2014	0.892	0.880	0.930	0.891	0.885	0.885	0.885	0.885	0.886	0.887	0.971	0.946	0.877	0.904	0.865	0.961	0.889
2015	0.928	0.960	0.950	0.928	0.942	0.942	0.942	0.942	0.952	0.936	0.910	0.910	0.934	0.968	0.929	0.920	0.958
2016	0.946	0.979	0.970	0.958	0.966	0.966	0.966	0.966	0.951	0.940	0.977	0.970	0.987	0.972	0.923	0.974	0.984

	LV	FI	NO_N	NO_M	NO_MW	NO_SE	NO_SW	SE_N1	SE_N2	SE_M	SE_S	NL
1982	981	906	766	914	889	1058	1059	908	953	999	1014	982
1983	921	845	684	747	772	971	976	804	873	948	961	960
1984	927	862	742	870	905	961	983	836	893	938	924	904
1985	941	890	817	890	865	1020	1019	883	947	979	970	927
1986	952	871	780	909	861	1059	1041	851	952	1000	993	970
1987	1000	857	797	871	881	997	994	836	900	963	957	929
1988	959	874	831	936	873	992	991	864	938	964	976	886
1989	943	887	767	872	819	1036	1069	896	960	990	1014	989
1990	954	919	810	869	825	1033	1027	885	934	971	1020	993
1991	937	841	787	854	894	1051	1071	846	926	971	953	995
1992	961	856	801	905	864	1013	1020	877	919	974	1026	962
1993	987	893	800	889	933	1064	1081	889	962	1011	988	941
1994	994	954	834	938	891	1091	1030	1006	1061	1065	1024	947
1995	985	898	765	868	906	1068	1115	902	975	1016	1037	1027
1996	1049	943	828	935	929	1054	1035	944	1002	1011	991	977
1997	1017	969	859	898	901	1096	1109	984	1026	1081	1053	974
1998	949	870	805	838	800	919	926	814	887	877	907	871
1999	987	901	762	895	862	992	947	858	944	963	974	983
2000	976	909	770	855	828	944	935	870	927	964	962	913
2001	964	900	774	889	886	995	1036	862	936	977	969	944
2002	1068	982	831	948	901	1046	1036	954	1021	1048	1026	949
2003	1000	917	829	953	904	1077	1066	933	1010	1043	1066	1109
2004	974	898	809	906	839	1028	1041	878	968	1012	1019	976
2005	1054	937	776	882	844	1030	1065	906	970	1017	1093	1013
2006	1058	948	827	963	909	1021	1035	939	966	1005	1030	991
2007	1002	901	777	853	807	1027	1035	901	970	984	974	950
2008	941	834	814	951	909	1032	1078	876	952	980	1024	973
2009	963	923	814	892	856	1010	1024	934	938	984	1047	974
2010	972	870	787	886	913	1022	1072	893	945	977	981	963
2011	1037	893	767	856	754	1009	965	847	964	1018	1003	992
2012	977	839	763	831	833	991	1020	840	886	957	1005	964
2013	1025	936	833	940	896	1049	1059	904	1020	1046	1043	952
2014	990	885	832	932	867	931	958	914	924	931	970	976
2015	995	854	737	854	821	1021	1071	845	921	981	1001	1002
2016	960	830	765	917	870	1006	1001	858	912	961	1018	1006

K.2 Existing onshore wind full load hours

	DK_E	DK_W	GB	IT	CZ	AT	CH	FR	BE	LU	PL	PL	DE_CS	DE_ME	DE_NE	DE_NW
1982	2094	1997	2373	1832	2185	2038	2600	2238	1879	2412	2171	2171	2221	1727	1617	1809
1983	2536	2415	2462	1957	2642	2461	2737	2396	2087	2709	2759	2759	2541	2119	2025	2149
1984	2293	2165	2108	2103	2348	2319	2734	2272	1857	2346	2394	2394	2249	1814	1820	1946
1985	2119	1916	2139	1870	2445	2275	2737	2180	1877	2453	2329	2329	2353	1927	1746	1842
1986	2406	2219	2717	1830	2445	2218	2651	2375	2118	2610	2553	2553	2425	1974	1861	2015
1987	2122	1978	1952	1973	2263	2391	2637	2142	1706	2323	2351	2351	2223	1685	1645	1763
1988	2474	2235	2320	1991	2541	2379	2755	2394	2064	2655	2562	2562	2529	2064	1934	2148
1989	2319	2285	2337	1640	2246	2119	2468	2074	1714	2140	2477	2477	2106	1796	1750	1916
1990	2555	2426	2749	1817	2469	2189	2673	2303	2092	2532	2701	2701	2416	2083	2034	2222
1991	2244	2181	2218	1966	2216	2172	2458	2181	1753	2265	2342	2342	2168	1734	1722	1905
1992	2418	2214	2475	1896	2505	2342	2712	2235	1930	2440	2540	2540	2369	1970	1913	2046
1993	2454	2257	2335	1863	2531	2279	2674	2286	1944	2558	2565	2565	2409	1976	1876	1991
1994	2586	2368	2605	1879	2512	2134	2724	2332	2047	2546	2614	2614	2480	2053	2002	2119
1995	2403	2218	2305	2097	2521	2353	2756	2301	1889	2509	2507	2507	2432	1975	1876	1985
1996	2002	1926	2202	2089	2136	2288	2485	2160	1674	2257	2012	2012	2096	1566	1493	1712
1997	2204	2090	2107	1958	2223	2219	2506	2111	1740	2281	2357	2357	2165	1756	1716	1826
1998	2599	2341	2468	2041	2707	2377	2936	2403	2117	2673	2673	2673	2552	2130	1980	2132
1999	2198	2077	2424	2004	2429	2323	2890	2441	2064	2677	2337	2337	2486	1915	1730	1951
2000	2343	2308	2297	1935	2330	2392	2657	2313	2090	2558	2338	2338	2353	1893	1805	2073
2001	2031	1929	2061	2207	2240	2398	2913	2333	1883	2543	2241	2241	2357	1772	1659	1760
2002	2271	2068	2186	1911	2353	2226	2535	2448	1935	2532	2412	2412	2333	1847	1745	1900
2003	2063	1859	2070	1928	2079	2112	2363	2050	1577	2199	2209	2209	2091	1573	1544	1645
2004	2357	2145	2250	1999	2402	2262	2619	2205	1829	2419	2411	2411	2303	1842	1728	1898
2005	2222	2116	2353	1914	2254	2198	2429	2093	1676	2241	2186	2186	2147	1721	1640	1825
2006	2074	1929	2213	1842	2178	2047	2474	2213	1887	2436	2096	2096	2287	1734	1589	1836
2007	2528	2372	2304	1970	2602	2269	2771	2351	1958	2627	2600	2600	2508	2078	1961	2098
2008	2494	2224	2469	1938	2381	2278	2622	2233	1905	2412	2482	2482	2299	1878	1856	2055
2009	2223	2003	2252	1996	2204	2174	2623	2148	1779	2331	2135	2135	2214	1717	1635	1810
2010	2101	1903	1813	2133	2167	2281	2542	2073	1563	2167	2252	2252	2038	1642	1599	1659
2011	2530	2289	2328	1786	2166	2067	2276	2033	1775	2199	2425	2425	2177	1847	1866	2028
2012	2408	2242	2124	2094	2280	2326	2779	2252	1782	2318	2306	2306	2229	1789	1736	1900
2013	2188	2048	2349	1983	2141	2252	2507	2194	1748	2225	2136	2136	2110	1677	1607	1813
2014	2360	2192	2245	1918	2001	2165	2366	2148	1779	2131	2174	2174	1988	1587	1606	1860
2015	2652	2501	2532	1803	2299	2224	2454	2289	1980	2405	2515	2515	2229	1884	1897	2094
2016	2112	2018	2098	2070	2012	2094	2290	2062	1686	2120	2122	2122	2009	1583	1543	1726

	LT	EE	LV	FI	NO_N	NO_M	NO_MW	NO_SE	NO_SW	SE_N1	SE_N2	SE_M	SE_S	NL
1982	2775	2389	1685	3044	3147	2342	2826	2826	2930	2508	2726	2627	2434	2224
1983	3251	2617	2025	2815	3082	2558	2949	2949	3120	2444	2851	3046	2974	2502
1984	2872	1954	1507	2461	3117	2029	2846	2846	3206	2049	2312	2326	2553	2162
1985	2785	2016	1470	2566	2899	1948	2499	2499	2595	2172	2405	2323	2389	2198
1986	3085	2306	1750	2865	3042	1991	2711	2711	2967	2283	2707	2748	2763	2521
1987	2923	2224	1631	2668	2992	2051	2670	2670	2863	2235	2509	2387	2459	2034
1988	3022	2431	1809	2742	2917	2033	2718	2718	3040	2246	2473	2524	2611	2505
1989	2968	2414	1733	2955	3133	2556	2921	2921	3020	2448	2898	2845	2642	2168
1990	3197	2365	1915	2893	3408	2455	3045	3045	3191	2502	2899	3001	2857	2574
1991	2854	2194	1649	2717	3131	2089	2809	2809	3071	2254	2545	2634	2543	2180
1992	2984	2398	1786	3105	3195	2335	2778	2778	2789	2632	2800	2782	2615	2354
1993	3188	2369	1866	2737	3136	2114	2833	2833	3106	2357	2591	2763	2788	2267
1994	2997	2231	1737	2643	2960	2076	2797	2797	3167	2183	2494	2616	2862	2407
1995	3008	2470	1811	2966	3100	2462	2880	2880	3009	2425	2867	2852	2710	2272
1996	2629	2083	1430	2606	2943	1804	2624	2624	2954	2239	2373	2277	2274	2046
1997	2890	2233	1700	2798	3104	2392	2881	2881	3055	2437	2825	2528	2402	2089
1998	2978	2203	1669	2806	2925	2085	2751	2751	3077	2124	2441	2619	2798	2482
1999	2720	2095	1542	2608	3024	2088	2662	2662	2800	2136	2445	2617	2459	2367
2000	2914	2298	1648	2882	3033	2217	2869	2869	3192	2423	2812	2560	2559	2474
2001	2575	2080	1431	2661	2941	1941	2469	2469	2501	2214	2448	2405	2244	2146
2002	2977	2014	1612	2367	2779	1905	2539	2539	2799	1880	2124	2419	2617	2199
2003	2748	2136	1566	2787	2918	2118	2535	2535	2554	2267	2488	2434	2322	1858
2004	2789	2019	1586	2559	2998	2130	2666	2666	2799	2112	2454	2538	2597	2188
2005	2618	2110	1517	2857	3130	2193	2793	2793	2963	2401	2629	2546	2425	2053
2006	2622	2068	1476	2638	3063	2061	2679	2679	2830	2201	2511	2377	2259	2214
2007	2992	2283	1714	2777	3080	2395	2855	2855	3009	2234	2573	2730	2716	2365
2008	3098	2465	1858	2665	2868	2130	2615	2615	2767	2100	2472	2655	2736	2365
2009	2615	1869	1466	2449	3055	2072	2742	2742	2975	2047	2295	2307	2411	2125
2010	2673	1944	1431	2421	2792	1737	2480	2480	2763	2069	2308	2247	2410	1832
2011	3115	2395	1877	2833	3203	2409	2961	2961	3164	2459	2797	2854	2789	2255
2012	2904	2269	1665	2710	3076	2292	2839	2839	3042	2224	2460	2625	2628	2113
2013	2641	2050	1511	2734	2894	2081	2615	2615	2782	2322	2632	2535	2432	2128
2014	2774	2020	1538	2603	3000	2003	2823	2823	3250	2167	2371	2494	2677	2145
2015	3069	2384	1823	3076	3209	2498	2992	2992	3175	2512	2927	3057	3077	2420
2016	2713	2086	1563	2460	2689	1873	2498	2498	2786	2060	2342	2598	2472	1995

K.3 Future onshore wind full load hours

	DK_E	DK_W	GB	IT	CZ	AT	CH	FR	BE	LU	PL	DE_CS	DE_ME	DE_NE	DE_NW
1982	3651	3687	4367	1964	2740	2472	2084	3248	3518	2879	2957	2874	3236	3305	3489
1983	4163	4218	4445	2039	3257	2973	2252	3443	3855	3256	3680	3310	3877	3964	4093
1984	3813	3944	4011	2254	2995	2762	2221	3354	3373	2771	3300	2894	3427	3659	3781
1985	3595	3605	4321	1989	3091	2804	2166	3161	3510	2966	3226	3060	3614	3461	3614
1986	4118	4085	4855	1969	3021	2654	2161	3335	3750	3100	3524	3127	3684	3802	3883
1987	3601	3670	3963	2066	2946	2880	2081	3141	3214	2783	3397	2888	3271	3411	3482
1988	4045	4031	4463	2039	3225	2994	2289	3421	3699	3109	3580	3273	3875	3863	4101
1989	3927	4078	4292	1680	2837	2559	1930	3086	3171	2512	3435	2725	3396	3624	3716
1990	4180	4216	4754	1871	3053	2630	2183	3271	3750	3007	3643	3123	3824	4037	4134
1991	3871	4044	4166	2006	2833	2667	1942	3214	3240	2672	3265	2780	3273	3554	3741
1992	4098	4071	4593	1959	3181	2891	2214	3249	3586	2908	3477	3093	3665	3899	4018
1993	4039	4037	4325	2039	3207	2935	2142	3281	3508	3027	3534	3085	3618	3700	3806
1994	4223	4194	4750	1972	3085	2724	2237	3306	3591	2990	3472	3158	3667	3832	3895
1995	4016	3995	4348	2105	3203	2977	2295	3345	3436	2956	3397	3129	3595	3687	3790
1996	3484	3635	4215	2159	2777	2665	1890	3210	3179	2732	2927	2713	3078	3100	3352
1997	3750	3795	4012	2085	2804	2715	1985	3109	3257	2714	3263	2817	3291	3519	3575
1998	4284	4256	4678	2119	3353	2987	2443	3479	3811	3138	3712	3295	3928	3943	4106
1999	3698	3811	4472	2128	3038	2794	2382	3511	3744	3177	3263	3201	3594	3468	3733
2000	3875	4081	4297	2005	2922	2798	2043	3371	3786	3002	3224	3062	3550	3606	3898
2001	3457	3651	4133	2262	2850	2815	2385	3436	3550	3061	3105	3066	3391	3360	3486
2002	3879	3908	4229	2009	3011	2799	2044	3493	3484	3034	3351	3001	3416	3464	3616
2003	3600	3553	4125	2096	2656	2573	1816	3069	3097	2670	3078	2714	3023	3307	3343
2004	3977	3934	4276	2099	2983	2775	2084	3195	3344	2876	3305	2967	3502	3607	3704
2005	3816	3885	4441	1938	2898	2795	1878	3162	3234	2665	3045	2796	3308	3454	3603
2006	3630	3693	4240	1910	2814	2579	1940	3215	3548	2936	2966	2993	3337	3371	3622
2007	4131	4158	4342	2043	3217	2955	2374	3372	3573	3133	3503	3254	3819	3898	3999
2008	4071	3932	4590	2052	3010	2727	2098	3225	3494	2888	3378	2974	3487	3737	3893
2009	3821	3770	4309	2130	2808	2670	1988	3162	3339	2799	2920	2879	3352	3419	3602
2010	3597	3647	3690	2179	2769	2730	2007	3119	2986	2591	3150	2635	3166	3333	3328
2011	4229	4142	4427	1861	2720	2563	1715	2973	3361	2604	3214	2827	3422	3842	3923
2012	4093	4130	4169	2148	2862	2715	2235	3322	3371	2798	3135	2898	3439	3605	3768
2013	3715	3775	4381	2052	2722	2601	1883	3258	3279	2670	2980	2721	3208	3340	3529
2014	4004	3992	4196	1940	2581	2466	1710	3176	3254	2517	3018	2559	2992	3325	3548
2015	4448	4439	4618	1938	2861	2619	1816	3289	3621	2862	3359	2875	3468	3847	3930
2016	3697	3765	4094	2146	2560	2511	1708	3048	3209	2539	2962	2606	3040	3256	3439

	LT	EE	LV	FI	NO_N	NO_M	NO_MW	NO_SE	NO_SW	SE_N1	SE_N2	SE_M	SE_S	NL
1982	3381	3441	3311	3631	4667	4440	4655	3286	4226	3378	3577	3401	3321	3637
1983	3951	3600	3727	3416	4675	4418	4280	3571	4426	3329	3732	3832	3914	4100
1984	3510	2939	3141	2965	4644	4322	4260	3027	4427	2899	3160	3027	3395	3542
1985	3364	2928	2995	3123	4320	4019	3620	2787	3786	2983	3167	3105	3323	3622
1986	3754	3265	3379	3416	4552	4396	4584	3528	4460	3144	3616	3543	3720	4013
1987	3606	3306	3329	3257	4427	4193	3811	2972	4030	3062	3304	3154	3367	3365
1988	3713	3435	3467	3288	4352	4142	4081	3134	4270	2972	3286	3298	3475	4016
1989	3685	3391	3416	3524	4668	4503	4594	3596	4439	3352	3764	3582	3514	3578
1990	3821	3240	3468	3454	4943	4576	4569	3777	4574	3459	3821	3725	3753	4039
1991	3462	3121	3183	3251	4503	4177	4163	3160	4324	3017	3387	3406	3480	3579
1992	3640	3348	3395	3667	4696	4224	4487	3387	4181	3414	3587	3565	3577	3899
1993	3858	3385	3528	3287	4528	4234	4078	3212	4346	3082	3371	3521	3712	3666
1994	3606	3207	3354	3186	4425	4294	4321	3243	4469	2978	3311	3347	3702	3739
1995	3728	3496	3522	3566	4590	4493	4086	3558	4374	3286	3735	3647	3643	3654
1996	3259	3053	3009	3162	4308	3896	3942	2822	4073	2979	3145	2973	3114	3363
1997	3601	3149	3353	3309	4489	4390	4102	3264	4222	3271	3676	3209	3255	3483
1998	3701	3120	3344	3305	4334	4171	4127	3128	4445	2835	3203	3372	3717	4021
1999	3317	2963	3031	3125	4449	4229	4086	3205	4077	2902	3267	3337	3309	3789
2000	3532	3167	3196	3429	4504	4472	4468	3489	4488	3267	3653	3258	3397	3944
2001	3185	2887	2924	3258	4357	3991	3719	2969	3739	3014	3250	3117	3092	3546
2002	3551	2937	3198	2882	4033	3886	3892	2768	4130	2539	2895	3188	3590	3516
2003	3414	3051	3136	3324	4205	4030	3919	2994	3806	2976	3271	3165	3224	3252
2004	3363	2883	3073	3065	4575	4339	4134	3201	4153	2888	3306	3290	3476	3531
2005	3194	3099	3086	3384	4550	4344	4508	3536	4298	3102	3451	3269	3286	3453
2006	3244	2986	3018	3158	4477	4171	4165	3184	4111	3020	3358	3101	3137	3687
2007	3651	3228	3349	3336	4560	4428	4379	3381	4415	3026	3416	3480	3609	3834
2008	3820	3524	3604	3190	4293	4142	4027	3160	4023	2821	3281	3372	3581	3819
2009	3107	2663	2877	2907	4556	4337	4267	3072	4189	2868	3104	2983	3258	3580
2010	3258	2816	2942	2926	4212	3868	3623	2884	4070	2806	3083	2963	3314	3085
2011	3669	3411	3483	3374	4696	4491	4514	3447	4495	3255	3681	3658	3771	3736
2012	3530	3264	3282	3302	4528	4279	4227	3219	4382	3019	3294	3423	3593	3532
2013	3155	2867	2911	3257	4492	4082	4209	3200	4177	3155	3452	3222	3311	3504
2014	3274	2837	2990	3026	4434	4416	4451	3246	4488	2878	3220	3233	3556	3428
2015	3637	3344	3363	3664	4699	4612	4723	3807	4731	3370	3849	3874	4044	3899
2016	3341	2972	3091	2981	4131	4000	4048	3114	4143	2790	3151	3328	3380	3411

K.4 Existing offshore wind full load hours

	BE	DE_KF	DE_NE	DE_NW	DK_E	DK_W	FI	NL	SE_S	GB
1982	3552	3138	3259	3572	2678	3497	3408	3578	2563	3711
1983	3897	3707	3878	4130	3231	4063	3540	4038	3103	3872
1984	3376	3456	3598	3901	2979	3818	2663	3671	2755	3468
1985	3611	3265	3395	3733	2753	3480	2829	3664	2584	3613
1986	4038	3677	3862	4039	3098	3900	3428	4042	2973	4196
1987	3231	3214	3444	3528	2735	3446	3039	3424	2596	3313
1988	3840	3547	3702	4243	3183	3977	3396	4167	2911	3827
1989	3306	3409	3602	3924	2969	3926	3584	3742	2771	3630
1990	3893	3698	3885	4151	3275	4074	3397	4069	3054	4084
1991	3344	3281	3457	3828	2838	3812	3184	3660	2682	3522
1992	3732	3624	3804	4116	3156	3814	3572	3963	2865	3903
1993	3556	3670	3807	3853	3133	3818	3208	3736	2977	3677
1994	3703	3832	3936	3952	3276	4000	3102	3819	3157	4021
1995	3655	3516	3645	3905	3064	3851	3469	3813	2943	3817
1996	3405	3063	3187	3690	2523	3504	2825	3609	2450	3659
1997	3233	3257	3407	3616	2824	3591	3279	3519	2636	3398
1998	3886	3873	4003	4299	3341	4143	3305	4179	3107	4047
1999	3820	3219	3346	3964	2803	3687	3097	3908	2615	3882
2000	3846	3348	3495	4154	2983	3970	3475	4038	2727	3742
2001	3661	3011	3222	3636	2632	3470	3171	3611	2404	3526
2002	3504	3537	3683	3760	2924	3673	2729	3631	2797	3633
2003	3087	3161	3331	3389	2658	3314	3169	3265	2548	3454
2004	3405	3546	3706	3769	3049	3742	3074	3648	2823	3641
2005	3393	3283	3456	3946	2867	3790	3284	3763	2618	3777
2006	3580	3150	3293	3772	2705	3533	3103	3717	2453	3651
2007	3715	3737	3903	4127	3284	3939	3296	3962	2985	3729
2008	3762	3768	3890	4175	3245	3764	3144	4069	2999	3985
2009	3381	3401	3522	3804	2857	3635	2857	3686	2681	3585
2010	3104	3222	3443	3464	2735	3459	2688	3267	2609	3115
2011	3614	3756	3895	4088	3250	3992	3277	3907	3019	3778
2012	3441	3551	3729	3975	3083	3935	3266	3751	2881	3555
2013	3552	3322	3486	3781	2822	3600	3174	3701	2620	3694
2014	3403	3608	3662	4014	2997	3911	3054	3795	2943	3653
2015	3809	3894	4001	4079	3300	4174	3597	3960	3279	3942
2016	3372	3236	3364	3586	2714	3595	2957	3481	2595	3459

K.5 Future offshore wind full load hours

	BE	DE_NE	DE_NW	DK_E	DK_W	EE	FI	FR	IT	LT	LV	NL
1982	4215	3750	4195	3650	4452	4236	4245	4086	2577	4033	4133	4301
1983	4653	4320	4758	4180	4982	4783	4540	4143	2688	4738	4753	4678
1984	4051	4066	4657	3903	4869	3657	3474	4095	2803	4186	3987	4461
1985	4371	3876	4317	3686	4421	3976	3747	3997	2547	4132	4079	4343
1986	4708	4418	4601	4193	4879	4304	4224	4274	2684	4594	4506	4769
1987	3910	3907	4110	3659	4400	4183	3969	4026	2735	4243	4262	4093
1988	4541	4167	4831	4075	4870	4349	4204	4243	2794	4363	4389	4846
1989	4040	4071	4676	3971	5010	4423	4386	3881	2379	4386	4358	4485
1990	4623	4378	4769	4215	4943	4403	4283	4008	2481	4408	4412	4785
1991	3978	3947	4557	3842	4842	4134	3995	4157	2603	4198	4212	4402
1992	4461	4325	4778	4154	4795	4357	4312	4080	2572	4368	4363	4714
1993	4253	4263	4562	4089	4763	4405	4129	4087	2697	4435	4416	4459
1994	4370	4391	4590	4268	4861	4122	3977	4200	2701	4167	4154	4573
1995	4380	4083	4493	4013	4758	4605	4431	4089	2824	4311	4447	4578
1996	4123	3642	4343	3507	4534	3893	3867	4159	2929	3728	3792	4405
1997	3943	3887	4296	3771	4530	4303	4137	3835	2660	4192	4242	4221
1998	4619	4464	4924	4336	5022	4140	4001	4363	2760	4374	4312	4947
1999	4465	3832	4562	3746	4493	4090	3922	4287	2826	4027	4075	4557
2000	4480	3993	4717	3933	4849	4104	4122	4123	2703	4200	4144	4661
2001	4314	3660	4224	3520	4388	3941	3931	4210	2888	3822	3861	4305
2002	4205	4194	4399	3977	4679	3917	3623	4231	2612	4423	4288	4366
2003	3854	3823	4015	3617	4160	4027	3988	3849	2686	3979	3970	4052
2004	3985	4214	4407	4033	4632	3927	3789	4023	2713	4244	4209	4326
2005	4170	3987	4682	3854	4820	3960	3829	4098	2600	3970	4006	4685
2006	4241	3816	4344	3686	4533	3992	3890	4004	2502	3899	3963	4427
2007	4411	4375	4721	4214	4921	4168	4003	4074	2654	4329	4281	4646
2008	4523	4406	4647	4210	4531	4409	4050	4173	2542	4450	4483	4798
2009	4103	4031	4460	3901	4528	3915	3603	4045	2760	3998	4042	4437
2010	3800	3871	4183	3641	4605	3779	3500	4066	2971	3898	3895	4019
2011	4357	4447	4777	4294	4919	4428	4116	3955	2462	4541	4569	4670
2012	4175	4224	4718	4119	4981	4343	4054	4080	2783	4255	4297	4516
2013	4291	3993	4402	3807	4604	3820	3810	4355	2785	3901	3872	4515
2014	4068	4166	4649	4095	4772	4069	3826	4065	2674	4175	4162	4520
2015	4587	4557	4802	4444	5078	4371	4221	4202	2483	4508	4463	4776
2016	4111	3836	4271	3746	4649	4010	3798	3963	2854	3950	4034	4309

	NO_N	NO_M	NO_MW	NO_SE	NO_SW	PL	SE_N1	SE_N2	SE_M	SE_S	GB
1982	4321	5010	5038	4461	4685	3970	4289	4242	4073	4012	4784
1983	4288	5031	5018	4683	4945	4662	3911	4364	4728	4722	4793
1984	4105	4355	4450	4778	5019	4182	3380	3658	4097	4206	4461
1985	4157	4109	4133	4160	4415	4157	3557	3643	4123	4238	4439
1986	4186	4804	4832	4553	4828	4619	4121	4587	4591	4696	4997
1987	4051	4226	4262	4293	4493	4201	3656	3974	4210	4309	4353
1988	3956	4341	4366	4582	4838	4258	3907	4177	4300	4271	4811
1989	4213	4974	4964	4644	4911	4406	4161	4467	4391	4410	4830
1990	4416	4902	4941	4712	4960	4528	4040	4285	4453	4521	4999
1991	4280	4304	4329	4620	4871	4242	3853	3963	4246	4350	4565
1992	4286	4850	4815	4385	4683	4388	4322	4351	4375	4399	4962
1993	4269	4282	4309	4671	4905	4480	3694	4020	4475	4587	4687
1994	3957	4399	4448	4704	4956	4356	3724	3869	4236	4413	5031
1995	4240	4505	4467	4618	4860	4306	4048	4368	4407	4394	4750
1996	4042	4090	4148	4448	4704	3703	3672	3796	3764	3816	4651
1997	4129	4622	4614	4494	4694	4113	3911	4144	4054	4101	4430
1998	4103	4398	4438	4783	5051	4523	3843	4025	4435	4578	5003
1999	4069	4538	4519	4286	4523	3925	3699	3888	4021	3955	4804
2000	4090	4734	4772	4552	4775	4249	4094	4208	4216	4284	4545
2001	4022	4169	4162	3903	4163	3803	3623	3987	3815	3791	4365
2002	3812	3905	3950	4366	4637	4497	3240	3598	4426	4567	4587
2003	4010	4542	4518	3995	4201	4042	3931	4110	4002	4142	4557
2004	3974	4451	4407	4307	4566	4407	3543	3933	4327	4485	4701
2005	4264	4979	4973	4613	4910	4016	4060	4194	4064	4102	4955
2006	4248	4496	4474	4334	4578	3881	3689	3910	3908	3948	4632
2007	4196	4892	4860	4648	4915	4495	3764	4080	4411	4537	4714
2008	3928	4313	4364	4216	4473	4445	3570	3868	4406	4507	4853
2009	4128	4481	4506	4368	4582	4017	3521	3634	4050	4133	4612
2010	3808	3613	3646	4359	4648	3981	3382	3502	3947	4070	4101
2011	4426	4814	4851	4725	4971	4595	4039	4210	4613	4657	4855
2012	4101	4565	4567	4632	4876	4255	3539	3893	4329	4389	4599
2013	3884	4424	4417	4365	4655	4002	4055	4077	3973	4104	4650
2014	3955	4339	4473	4694	4928	4230	3705	3886	4231	4316	4648
2015	4227	4692	4708	4760	4994	4678	4124	4433	4691	4818	5008
2016	3768	4296	4300	4302	4585	3943	3439	3803	4060	4047	4505

K.6 Hydro run-of-river full load hours

	GB	IT	CZ	AT	CH	FR	BE	LU	PL	DE_CS	DE_ME	DE_NE	DE_NW
1982	2015	3422	2779	5347	4504	4465	3470	3471	2599	3982	3982	3982	3982
1983	2274	3704	1894	4776	4508	4044	3426	3434	2276	3560	3560	3560	3560
1984	2176	3884	1859	4599	4283	3898	3852	3877	2012	3482	3482	3482	3482
1985	1836	3890	3054	4756	4363	3267	2872	2957	2076	3676	3676	3676	3676
1986	2000	4088	2715	4898	4462	3578	3345	3571	2042	3715	3715	3715	3715
1987	1929	3958	3324	5590	4472	3540	3526	3822	2416	4247	4247	4247	4247
1988	2185	3533	3142	5224	4562	4331	3522	3172	3035	4181	4181	4181	4181
1989	2314	3271	1919	5001	3883	2492	2858	2833	1980	3572	3572	3572	3572
1990	2846	3050	1956	4652	4093	2785	2743	2880	2012	3322	3322	3322	3322
1991	2070	3432	1819	4445	3832	2717	2629	2409	1643	3363	3363	3363	3363
1992	2206	3490	2540	5070	4192	3351	3171	2953	2344	3742	3742	3742	3742
1993	2172	3461	1970	5049	4249	3256	2933	2710	2401	3913	3913	3913	3913
1994	2629	3827	2100	4684	4508	4203	3371	3235	3400	3787	3787	3787	3787
1995	2470	3424	3058	5090	4325	4162	3243	3021	3040	3938	3938	3938	3938
1996	1751	3062	3436	5283	3720	3853	2533	2436	1896	3767	3767	3767	3767
1997	1918	3620	3854	5040	3958	3186	2670	3130	1924	3793	3793	3793	3793
1998	2217	3476	2704	4986	4139	3475	3548	3522	2439	3782	3782	3782	3782
1999	2460	3629	2957	5313	4554	4256	3333	3233	3092	4260	4260	4260	4260
2000	2227	3513	3082	5354	4712	4145	3493	3890	3130	4242	4242	4242	4242
2001	2401	3855	2219	4909	4735	4691	3734	3685	1974	3732	3732	3732	3732
2002	1935	3552	5218	5570	4686	3493	3415	3189	2643	4342	4342	4342	4342
2003	2185	3498	2662	4634	4133	3326	2595	2267	1461	3566	3566	3566	3566
2004	1997	3468	3079	5143	4298	3427	2867	2900	3338	3985	3985	3985	3985
2005	2216	3093	3104	4809	4063	2914	2603	2436	2638	3680	3680	3680	3680
2006	2093	3158	4310	5364	4208	2998	3065	3315	3917	4042	4042	4042	4042
2007	2148	2738	2942	5174	4390	3242	3133	3027	4394	3983	3983	3983	3983
2008	2095	3695	2249	4739	4408	3727	3081	3326	3876	3850	3850	3850	3850
2009	2146	3520	2991	5556	4265	2938	2816	2803	2697	4263	4263	4263	4263
2010	1847	3512	3223	4883	4229	3327	3205	3075	3906	3878	3878	3878	3878
2011	2412	3257	2681	4350	3797	2724	2596	2061	3082	3487	3487	3487	3487
2012	1838	3209	2616	5416	4503	3352	3001	3051	2338	4261	4261	4261	4261
2013	2225	4475	3211	5269	4496	3908	3110	3733	3224	4131	4131	4131	4131
2014	2715	5050	2634	4936	4389	3540	2867	3199	2647	3936	3936	3936	3936
2015	2938	3982	2608	4542	4225	2962	2871	3129	2206	3622	3622	3622	3622
2016	3004	3646	2744	4969	4230	3375	2991	3274	2572	3933	3933	3933	3933

	LT	LV	FI	NO_N	NO_M	NO_MW	NO_SE	NO_SW	SE_N1	SE_N2	SE_M	SE_S	NL
1982	4093	814	4029	3279	3774	3774	3080	3080	2667	3310	4001	4835	3416
1983	4323	723	4317	3807	4673	4673	3783	3783	3446	3933	3825	5259	3373
1984	3468	620	4030	3156	3869	3869	3300	3300	3039	3748	4444	5257	3793
1985	3977	639	3980	3158	3809	3809	3261	3261	3188	3994	4952	5483	2793
1986	4087	901	3993	2821	3618	3618	3079	3079	2420	3232	4499	4817	3293
1987	3362	750	4275	2783	4040	4040	3331	3331	2900	4229	5046	5459	3471
1988	4064	555	3758	3173	4114	4114	3689	3689	3027	3477	4700	6154	3467
1989	4177	755	4070	4304	4908	4908	4005	4005	3501	4101	4020	4214	2779
1990	4457	1135	3154	3750	4862	4862	4207	4207	3274	4357	4508	4968	3217
1991	3548	725	4177	3437	3940	3940	3120	3120	2841	3764	3906	5134	1733
1992	4000	591	4810	3480	4248	4248	3440	3440	3090	3917	3877	4996	3122
1993	4522	767	3974	3368	3863	3863	3132	3132	3178	4098	4408	5206	2943
1994	5013	851	3656	2925	3884	3884	3573	3573	2401	3077	3810	5521	3319
1995	4523	858	3972	3683	4077	4077	3245	3245	2681	3181	4021	4532	3192
1996	3438	346	3968	3064	3265	3265	2487	2487	2618	2988	3523	3487	2020
1997	3879	776	3556	3597	4369	4369	3206	3206	2919	3364	3889	4000	1760
1998	4703	1232	4972	3230	4389	4389	3630	3630	3285	4613	5110	6120	3494
1999	4106	759	4027	3358	4155	4155	3824	3824	2923	3517	4496	5809	3281
2000	4060	724	4750	3527	4363	4363	4583	4583	3325	4537	5470	5218	3439
2001	3491	735	3855	3617	4175	4175	3523	3523	3408	4575	4917	5070	3677
2002	4138	759	3116	3504	3899	3899	2937	2937	2847	2940	4030	4743	3362
2003	3614	617	3154	3420	3945	3945	3123	3123	2606	3240	3861	4037	1711
2004	4492	766	4756	3501	4195	4195	3346	3346	3159	3631	3992	6066	3363
2005	4621	913	4457	4175	4685	4685	3797	3797	3368	4160	4552	4644	1716
2006	3833	781	3581	3503	4176	4176	3495	3495	2765	3627	4662	4986	3188
2007	4213	938	4659	4059	4851	4851	3888	3888	3540	3632	4093	6587	3448
2008	4218	1085	5261	3078	3984	3984	3661	3661	2686	3100	4877	5517	3390
2009	4086	1005	3672	3509	4288	4288	3636	3636	3031	4020	4923	4506	3302
2010	4455	1060	3852	2715	3394	3394	3076	3076	2479	3237	4957	5146	3155
2011	3965	936	4103	3945	5140	5140	4507	4507	3794	4374	5044	5905	1710
2012	3597	1153	5252	3133	4372	4372	3937	3937	3088	4170	5552	5320	3122
2013	4419	915	3899	3280	3960	3960	3284	3284	2810	3514	4009	4088	3422
2014	4036	609	4253	2983	3792	3792	3870	3870	2469	3241	5513	5438	3362
2015	3728	581	4997	4012	4696	4696	4468	4468	3554	4388	5230	5235	2792
2016	4703	769	4396	3217	4225	4225	3398	3398	3152	3822	4617	5369	3001

K.7 Hydro reservoir full load hours

	IT	CZ	AT	CH	FR	PL	DE_CS	DE_ME	DE_NE	DE_NW
1982	1761	1008	1225	1910	2534	996	411	411	411	411
1983	1727	699	1109	1938	2593	831	417	417	417	417
1984	1750	702	1180	1866	2302	715	386	386	386	386
1985	1840	1103	1277	1866	2296	1076	356	356	356	356
1986	1960	1001	1109	1782	2277	799	351	351	351	351
1987	1966	1197	1225	1823	2056	804	318	318	318	318
1988	1731	1121	1451	1798	2697	1013	311	311	311	311
1989	1700	716	1138	1823	1610	1028	512	512	512	512
1990	1519	719	954	1782	1859	730	432	432	432	432
1991	1521	661	1248	1494	1809	623	449	449	449	449
1992	1645	925	1180	1590	2227	929	445	445	445	445
1993	1772	707	1212	1592	2283	869	321	321	321	321
1994	1779	774	1331	1592	2849	1018	259	259	259	259
1995	1663	1134	1225	1334	2568	1229	286	286	286	286
1996	1438	1236	1036	1334	2363	918	459	459	459	459
1997	1711	1399	1178	1400	2058	1057	380	380	380	380
1998	1561	968	1199	1761	2202	1309	363	363	363	363
1999	1711	1082	1378	1783	2436	1054	240	240	240	240
2000	1625	1140	1384	1682	2665	1256	286	286	286	286
2001	1751	795	1298	1683	2909	920	421	421	421	421
2002	1728	1880	1354	1636	2059	1029	302	302	302	302
2003	1680	977	1174	1636	2203	543	316	316	316	316
2004	1544	1128	1277	1645	2565	2027	310	310	310	310
2005	1374	1129	1223	1691	2110	1536	355	355	355	355
2006	1471	1593	1218	1560	1886	1906	352	352	352	352
2007	1317	1077	1161	1560	2062	2766	270	270	270	270
2008	1728	825	1256	1560	2537	2753	191	191	191	191
2009	1767	1084	1319	1539	2108	1252	357	357	357	357
2010	1778	1070	1238	1539	2235	1521	238	238	238	238
2011	1632	746	1138	1539	1653	854	203	203	203	203
2012	1437	859	1451	1608	1983	903	346	346	346	346
2013	2071	1189	1332	1608	2619	963	304	304	304	304
2014	2360	698	1328	1626	2219	860	272	272	272	272
2015	1896	607	1221	1627	1917	705	204	204	204	204
2016	1768	722	1183	1593	2121	909	226	226	226	226

	FI	NO_N	NO_M	NO_MW	NO_SE	NO_SW	SE_N1	SE_N2	SE_M	SE_S
1982	4398	3858	4349	4349	3510	3510	2981	3983	4327	5252
1983	4627	4081	5454	5454	4583	4583	3762	4952	4194	5422
1984	4299	3934	4671	4671	3814	3814	3559	4675	4707	5411
1985	4175	3411	4366	4366	3701	3701	3403	4940	5440	5922
1986	4169	3245	4127	4127	3466	3466	2858	4127	5033	5147
1987	4404	3036	4648	4648	3656	3656	3410	5260	5674	5810
1988	3931	3363	4801	4801	4245	4245	3327	4424	5151	6513
1989	4463	4967	5665	5665	4280	4280	4142	5009	4209	4369
1990	3243	4120	5618	5618	4771	4771	3757	4994	4563	5238
1991	4213	3845	4231	4231	3129	3129	3451	4217	4100	5646
1992	5106	4207	5241	5241	3870	3870	3649	4858	4160	5202
1993	4379	4037	4543	4543	3528	3528	3918	5137	4651	5696
1994	3830	3070	4219	4219	3942	3942	2608	3683	4085	5843
1995	4306	4564	5128	5128	4037	4037	3584	4346	4503	4543
1996	4149	3524	3459	3459	2487	2487	2903	3249	3523	3643
1997	3906	4505	5620	5620	3533	3533	3767	4474	4249	4276
1998	5284	3603	4839	4839	3865	3865	3895	5600	5509	6676
1999	4140	3640	4678	4678	4308	4308	3586	4269	4718	6146
2000	5067	4338	5492	5492	5137	5137	4067	5468	5945	5354
2001	4096	3716	4406	4406	3971	3971	3729	5383	5253	5172
2002	3356	3827	4493	4493	3504	3504	3074	3653	4319	4945
2003	3273	3780	4292	4292	3436	3436	2808	3874	3901	4267
2004	4991	3756	4668	4668	3700	3700	3672	4207	4141	6555
2005	4726	5033	5728	5728	4123	4123	3952	5068	4565	4779
2006	3768	3627	4413	4413	3729	3729	2916	4086	5126	5316
2007	4755	4344	5563	5563	4418	4418	3922	4392	4093	6724
2008	5531	3233	4656	4656	4388	4388	3007	3909	5209	5621
2009	3902	3700	4749	4749	3755	3755	3142	4603	5225	4682
2010	4001	3145	3789	3789	3390	3390	2917	4172	5083	5452
2011	4131	4540	6001	6001	4887	4887	4203	5243	5241	6284
2012	5567	3480	5224	5224	4288	4288	3532	4906	5666	5511
2013	4186	3817	4664	4664	3970	3970	3302	4202	4090	4213
2014	4361	3532	4268	4268	4519	4519	2950	3917	5802	5822
2015	5381	4248	5118	5118	4772	4772	4250	5236	5485	5418
2016	4673	3336	4648	4648	3760	3760	3465	4517	4757	5371