OSMOSE

OPTIMAL SYSTEM-MIX OF FLEXIBILITY SOLUTIONS FOR EUROPEAN ELECTRICITY

Optimal Mix of Flexibility - Appendixes

D1.3

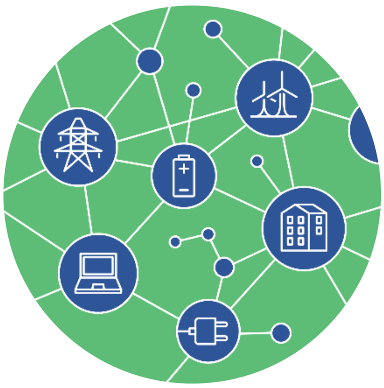

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Table of content

1 List of acronyms and abbreviations

aFRR	Automated Frequency Restoration Reserves
AT	Accelerated Transformation
BESS	Battery Energy Storage System
CAPEX	Capital expenditures
CCGT	Combined cycle gas turbine
CCS	Carbon capture and storage
CExM	Capacity Expansion Model
CGA	Current Goals Achieved
DC	Discrete current
DSM	Demand-side management
DSO	Distribution System Operator
ENS	Energy not served
EV	Electric vehicle
FCR	Frequency Containment Reserves
FRR	Frequency Restoration Reserves
FSCD	Flexibility Solution Contribution Distribution
FSMS	Flexibility Solution Modulation Stack
GTC	Grid Transfer Capability
IAM	Integrated Assessment Model
LCA	Life-cycle analysis
LOLD	Loss-of-load duration
LOLE	Loss-of-load expectation
MAF	Mid-Term Adequacy Forecast
mFRR	Manual Frequency Restoration Reserves
NCA	Neglected Climate Act
NTC	Net transfer capacity
OCGT	Open cycle gas turbine
OPEX	Operational expenditure
OPF	Optimal power flow
P2G	Power-to-gas
PCM	Production Cost Models
PECD	Pan-European Climate Database
PEM	Polymer electrolyte membrane (electrolysis)
PSP	Pump storage plant
PV	Photo-voltaic
RES	Renewable energy source
RoR	Run-of-river (hydro unit)
TOTEX	Total expenditure
TSO	Transmission System Operator
TYNDP	Ten-year network development plan
VRES	Variable Renewable Energy Source

2 Purpose of the document

This document is intended to provide the appendixes to D1.3 deliverable:

- Appendix A: AntaresSimulator modelling description
- Appendix B: Dataset and weather dependent variable generation
- Appendix C: Environmental impact indicators - proof-of-concept studies

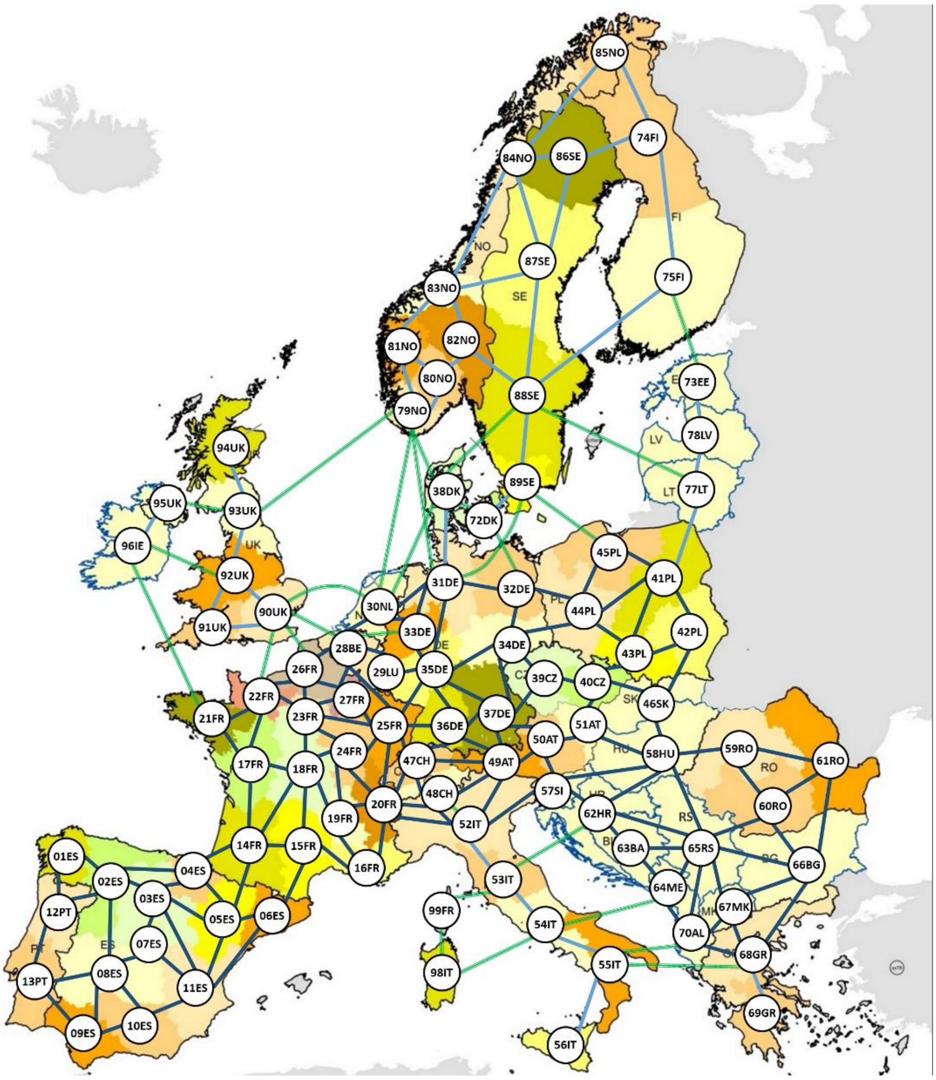
3 Appendix A - AntaresSimulator modelling description

The present section focuses on describing the set-up of the ANTARES simulations run within Task 1.2 with a particular emphasis on the modelling of the flexibilities.

3.1 Grid model

The grid model used in the simulation comes from the e-Highway2050 project (see [e-Highway 2050]). It is made of 99 nodes representing the 33 European countries of the study (see figure below).

Exchange capacities between countries and within country nodes are modelled via NTC which come from T1.1 results. Impedances of links and Kirchhoff laws are currently not taken into account.



3.2 Generation capacities

Except otherwise stated, installed capacities are given by the results of Task 1.1.

3.2.1 Thermal clusters[1]

In order to identify the number of thermal units that are actually available in each cluster, thermal capacities are split into a number of identical units, which characteristics depend on the technology. The capacities are rounded to the closest integer number of units. Technical parameters used for each thermal cluster technology are given in the table below:

Cluster technology	Nominal capacity (MW)	Min up time (h)	Min down time (h)	Min stable power (MW)	Market bid (€)		CO_2 emissions (tCO_2/MWh)
					2030	2050	
ocgt	250	0	0	120	129	172	0,488
ccgt	500	3	3	150	110	118	0,327
nuclear	800	168	168	500	14	14	0
hard_coal	800	6	6	320	79	N/A	0,75
lignite	800	24	24	320	77	N/A	0,91

Thermal cluster availability is defined by forced and planned outage rates, common to all technologies, which are season dependent.

Months	Forced outage duration	Planned outage duration	Forced outage rate	Planned outage rate	MTBF Forced outage	MTBF Planned outage
JAN - FEB	7	7	0,05	0	133	N/A
MARCH	7	7	0,05	0,1	133	63
APR. – OCT	7	7	0,05	0,23	133	23,6
NOV	7	7	0,05	0,1	133	63
DEC	7	7	0,05	0	133	N/A

3.2.2 Renewable energies

Power generation from wind (onshore and offshore) and solar is directly given by 35 capacity factor time-series for each country or cluster. These capacity factors are multiplied by the installed capacities and these technologies are modelled as must run units.

3.2.3 Bio-energies

Power generation from bio-energies (biomass, geothermal and waste) is modelled as must run units. Installed capacities are multiplied by a capacity factor of 40% to retrieve the same annual energy as the initial GENeSYS-MOD results.

3.2.4 Hydro generation

For all countries, run-of-river generation is given by one time-series of daily energy for each country and for each Monte-Carlo year (see details on the hydro generation time series in section 4.4). Run-of-river units are modelled as must-run generation.

Inflows are given by one time series of weekly energy for each country and for each Monte-Carlo year (see details on the hydro generation time series in section 4.4). For all countries, reservoir generation is managed using ANTARES "reservoir management heuristic"[2]. This heuristic adapts reservoir generation on an annual basis, with respect to annual inflows and

[1] "thermal clusters" in Antares wording refers to a set of thermal plants located in the same area and having the same technical and economical parameters.

[2] More details in ANTARES documentation. See [AntaresSimulator].

net load (load minus non-dispatchable generation). This means, the heuristic will allocate more hydro energy to months and weeks with higher net load, respecting the overall annual energy. The allocated weekly energy is then optimised by ANTARES within the hours of the week.

3.2.5 Modelling of reserves requirements

The built-in "day-ahead reserves[3]" functionality of ANTARES is used to take into account reserve requirements. This piece of functionality makes it possible to indifferently model some kind of FCR, aFRR and mFRR (i.e. generation available in less than 30 min).

In practice ANTARES fictitiously increases the demand during the first phase of its optimisation so as to start a higher number of generators than the real demand would require. During the second phase of the optimisation, ANTARES adjusts the generation of these running generators to match the real demand, but it is not allowed to turn off generators. The reserves requirements assigned to each country and their calculation principles are described in D1.3.

Due to generators technical constraints (minimum generation capacity and minimum up and down time), this can therefore lead to some additional spillage. Also reserve requirements may not be entirely fulfilled in case of unsupplied energy. It is worth noting that a part of the reserves can be provided by neighbouring countries, but in such cases the first phase ensures exchange capacities are available.

Reserve restoration is currently not modelled: the power system is assumed to globally have enough capacity to restore generation after 1 hour.

3.3 Flexibility modelling

3.3.1 Flexibility list

Power system flexibilities modelled in ANTARES simulations as part of T1.2 work consist of:

- Pump Storage Plants (PSP)
- Batteries (BAT) hosted within the grid
- Power-to-gas (P2G) facilities producing gas intended both for power generation (power-out/power-in) as well as other usages leaving the power system realm (power-to-x, in particular for synthetic fuel)
- Management of electric vehicles load
- Management of heat-pump load

Flexibility provided by biogas, geothermal and waste units is currently out of scope. Such generators are considered as must-run units.

3.3.2 Naming convention

The following naming convention is used throughout this document:

- Fictive nodes [4]are prefixed with node number "00"
- Fictive storage flexibilities are suffixed with label "_STO"
- Flexibilities generation are suffixed with label "_gen" (ex. p2g_gen)

[3] More details in ANTARES documentation. See [AntaresSimulator].

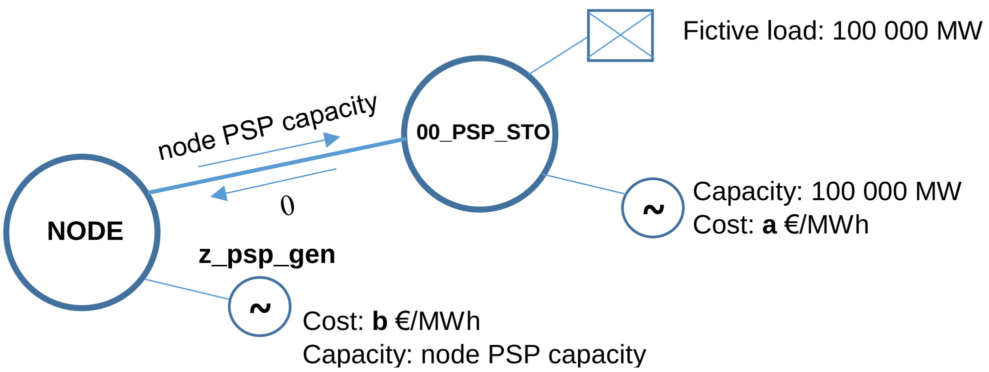
[4] Fictive nodes are necessary in Antares to model advanced flexibilities or constraints, they do not represent a real geographical area contrary to other nodes.

- Fictive thermal generators, used for modelling purposes are prefixed with label “z_” (ex. z_hpl_gen)

3.3.3 Pump Storage Plants modelling

Closed Pump Storage Plant generation is managed on a weekly basis. It is modelled via a fictitious node “00_PSP_STO” which is connected to all nodes via a fictitious link. A fictitious generator “z_psp_gen” is added to each node with capacity that correspond to PSP generation capacity.

The capacity of the fictitious link between the real node and the fictitious node corresponds to the node PSP storage capacity (pumping capacity). Capacity of the link is set to 0 in the opposite direction (from the fictitious node to the real node).



Note: The value of the load and the capacity of the generator in the fictitious node must be greater than the sum of installed PSP capacities for all nodes.

During the optimisation, it will be cost-effective to store energy on hour H1 and generate on hour H2 if:

$$marginalCost_{H2} \quad - b \geq (marginalCost_{H1} - a)/efficiency_{ratio}$$

with efficiency_ratio=0.75

Generation costs “a” and “b” can therefore be chosen with $b = a/0.75$, so that the formula above simplifies:

$$marginalCost_{H2} \geq marginalCost_{H1}/0.75$$

A weekly binding constraint ensures that all energy stored within a week is given back to the system within the same time period (using a 75% efficiency ratio):

$$\sum 0{,}75 * flow(NODE \rightarrow OO\_PSP\_STO) - z\_psp\_gen = 0$$

In order to enforce reservoir capacity constraints, two additional fictitious generators are used (“z_NODE_psp_1” and “z_NODE_psp_1”). These generators are located in a fictitious node called “00_xtra”, which is not linked to any real node. Their generation represents reservoir level and are linked via hourly binding constraints:

$$z\_NODE\_psp\_1(H) = z\_NODE\_psp\_2(H)$$

$$z\_NODE\_psp\_1(H+1) = z\_NODE\_psp\_2(H) + flow(NODE \rightarrow 00\_PSP\_STO) - z\_psp\_gen/0{,}75$$

To ensure continuity between the different weeks of the year, a third binding constraint imposes that the reservoir level equals to 50% of the capacity at the beginning and at the end of the optimisation period (i.e. the week).

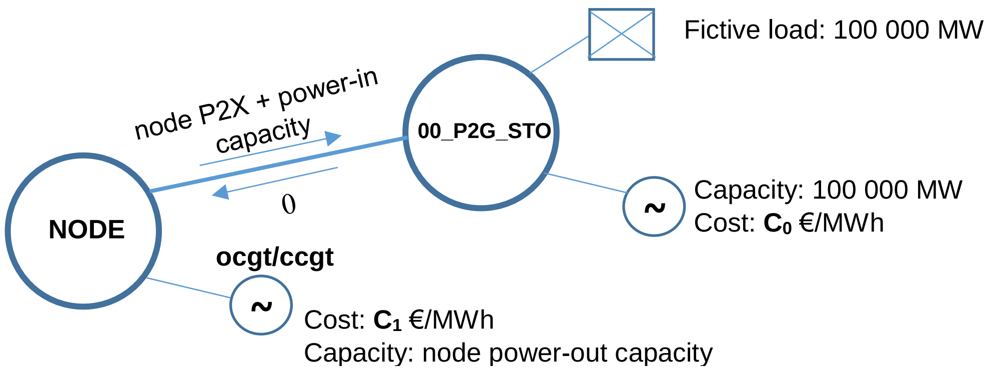
3.3.4 Grid batteries modelling

Grid batteries use the exact same modelling as PSP with an efficiency ratio of 90% and daily (instead of weekly) cycle (and hence a daily binding constraint).

3.3.5 Power-to-gas modelling

Power-to-gas storage is mainly used for seasonal or annual flexibility, so the modelling techniques applied for batteries or PSP (hourly, daily or weekly binding constraints) cannot be used. The modelling approach is derived from management principles of hydro power units.

Power-to-gas is modelled via a single fictitious node which represents both gas produced for future electricity generation (power-in) as well as for other usages (power-to-x). A gas generator in each "real" node is used to model power-out flexibility.



Note: The value of the load and the capacity of the generator in the fictitious node must be greater than the sum of installed capacities for all real nodes.

The control loop is achieved in a heuristic manner, thanks to judicious choice of C_0 and C_1 costs. Obviously, $C_0 < C_1$. Additionally, if C_f is the smallest cost of power generation from fossil fuels, one shall also consider to set $C_0 < C_f$ in order not to produce "green gas" from fossil fuel and to actually "de-carbonate" power generation.

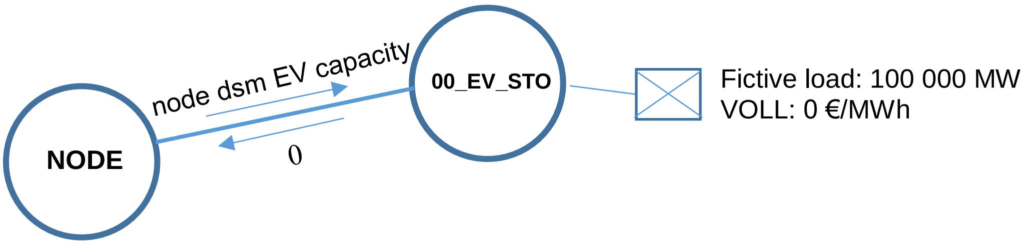
According to known characteristics, on one hand, of electrolysis and methanation processes, and on the other hand, of CCGTs and OCGTs, the efficiency of the power_to_gas_in to power_to_gas_out cycle is expected to be lower than 40%. In our simulations, the observed efficiency of this cycle cannot be put as a constraint in the simulation, but is computed and checked ex-post. If this efficiency appears to be greater than 40%, CO_2 emissions are corrected (using CCGT emission factors) to consider that a part of the power_to_gas_out generation will actually have to run on fossil gas.

3.3.6 Electric vehicles load management

In accordance with the current dominant use of cars, a daily cycle is assumed for electric vehicle charging. A given percentage of the daily electric vehicle load profile (6% in 2030 and

2050) can be optimally placed by ANTARES. This is achieved via a fictive node with a loss-of-load cost (VOLL) of 0 €, enforcing that the daily flow on the link equals to the optimised load value. Charging capacity is decreased by 2/3 between 9 am and 6pm on working days to reflect a lower vehicle connection rate to charging stations during working hours.

Note: Vehicle-to-grid flexibility (i.e. ability for EV to actually inject power into the grid) is not considered at this stage.



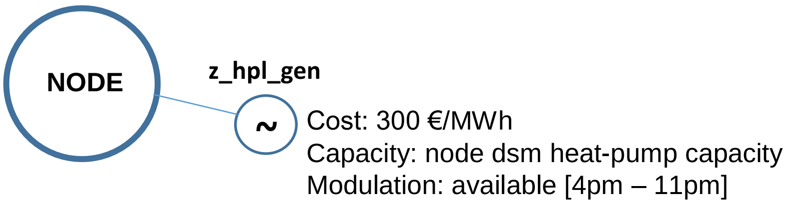
The daily binding constraint that ensures the pilotable electric vehicle load is actually consumed writes:

$$\sum_{day} flow(NODE \rightarrow 00\_EV\_STO) = A * \sum_{day} electric\ vehicule\ load$$

where A = 0.06 in 2050 and 2030.

3.3.7 Heat-pump load management

Heat-pump flexibility is currently simply modelled as a peak generator, with a high cost (to date, the threshold is set to 300 €/MWh) and an availability of 8 hours, centred on European peak load (currently set at 7pm). Load transfer and rebound effect are currently not taken into account as this flexibility is not expected to be widely used. This could be reconsidered based on results, as well as the option to switch to net load when determining the peak hours.



4 Appendix B - dataset and weather dependent variable generation

4.1 Summary of the weather dependent data published by OSMOSE WP1

In the first simulations run by the OSMOSE project, only 1 time-series of hydro and load data and 11 time-series of renewables hourly capacity-factors have been used. There was therefore no suitable correlation between the load and the meteorological conditions driving VRES generation, although this may have a significant impact on the Security of Supply Assessment. This document describes the work done by the project team to enhance this aspect, which is crucial for the relevance of the results.

Data collection and model development represented more than 90% of the work and is a common barrier for prospective studies on the power system. To promote transparency on the assumptions, constructive criticism, and facilitate reuse and additional studies, RTE, EKC and TUB aimed from the very beginning of the project to make public all the data develop. Special attention was therefore paid to the licensing scheme of the data used to fuel the process, especially for the climate-dependent variables, which have a major impact on the Security-of-Supply assessment:

- When the first OSMOSE simulation was run, the most easily reusable data source that met this criterion was the e-highway 2050 dataset[5]. Unfortunately, this dataset only contained 1 time-series of load and hydro data and 11 time-series of renewables hourly capacity-factors. There was therefore no suitable correlation between the load and the meteorological conditions driving VRES generation. It was used as a starting point, but an action plan was immediately put in place to find a replacement dataset.
- For the second simulation run, a dataset composed of 35 years of data (spatially and meteorologically coherent) was prepared and used. These data are available at two geographical scales (33 countries and 99 clusters[6]) and include:
    - RES capacity factors (onshore wind, offshore wind and solar PV)
    - Load profiles (non-thermosensitive, heating and electric vehicles)
    - Hydro time-series (run-of-river generation and reservoir inflows).

In order to prepare these data, several open sources have been used:

- The main source is the dataset produced by the Plan4Res H2020 project[7]. This data is available at the geographical resolution of the OSMOSE 99 clusters. Additionally, the Plan4Res project released demand data for most of the 33 EU countries modelled in OSMOSE. This demand data provides a single profile for the non-thermo-sensitive usages and the charging of electric vehicles, in addition to weather-dependent profiles for heating and air-conditioning.
- The Plan4RES dataset relies in turn on the PECD v3 dataset (Pan-European Climate Database). The PECD dataset has also been used in ENTSO-E Mid-Term Adequacy Forecast (MAF) 2019 and 2020 provides 42 years of temperatures, RES capacity-factors (onshore and offshore wind and solar) and hydro time-series (both run-of-river –RoR- and inflows) which are correlated from the geographical and meteorological point of view. Whilst the non-thermo-sensitive data has been reused without modifications in OSMOSE, the thermo-sensitive profiles have been reprocessed after

[5] See [e-highway2050]

[6] The same geographical clusters as the ones used in [e-highway2050].

[7] See [Plan4RES]

some inconsistencies were discovered (ex. peak load in Italy being twice the one of France for 1985).
- The PECD v3 and the Plan4RES are based on a reanalysis of years 1981-2016 and therefore does not account for future effects of climate change.

New electric vehicle charging profiles have also been created by OSMOSE to better reflect the expected natural charging patterns as found in the literature and to include thermo-sensitivity, which may account for up to 35% of the consumption of the vehicle in winter. Air-conditioning profiles have been discarded due to lack of information to accurately build them. Details of the building of these profiles are available in [appendix B]. Removing incomplete years, the OSMOSE data finally comprises 35 years of consistent data. This number may still not be seen ideal for an adequacy assessment but is already a significant step forward.

Besides, hydro is modelled using more time series (35 instead of 1). Also, hydro parameters in 2030 and 2050 have been updated based on TYNDP2020:

- Run-of-river generation capacities from TYNDP2020 for 2040 have been taken as expected in 2050. Generation capacities in 2030 have been scaled between current values and the ones expected in 2050. Daily generation from PECD have been scaled with respect to capacities.
- Pumped storages and corresponding reservoir capacities (volumes in GWh) have been modelled as closed cycle with same generation capacities in 2030 and 2050 based on data from e-Highway2050 scenario Big&market (see [e-Highway 2050]) which are the same as data from the initial CGA scenario.
- Reservoir generation capacities took into account the total hydro capacities from TYNDP2020 and run-of-river and PSP capacities determined as described above. Annual generation and reservoir capacities (volumes in GWh) have been taken from PECD (see [PECD]) and scaled to determined capacities.

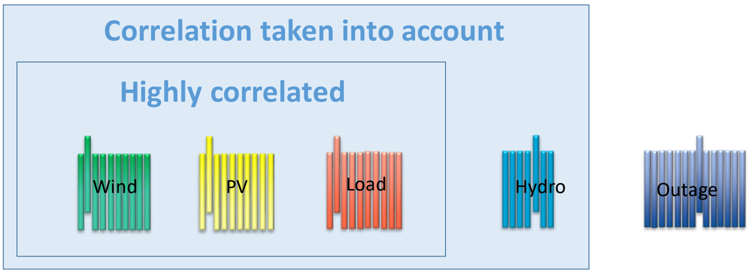


Figure 1: correlation between weather-dependent variables in OSMOSE WP1 dataset

4.2 Load data

4.2.1 Context and objectives

As mentioned above, the single Monte-Carlo year of load time series published by e-highway was clearly insufficient to capture variability, which is crucial to assess flexibility requirements. In addition, the weather-dependent part of the load could not be easily identified in this dataset, although the energy transition is expected to foster the development of heat pumps throughout Europe, while today most European countries rely on natural gas for heating. As an aside, air conditioning is expected to increase at the same time, since climate change leads more frequent heat waves.

The question about profiles is also relevant because new uses are emerging (heat pumps, electric vehicle), for which little is known, although they could represent a significant part of the consumption in 2050.

The H2020 project Plan4RES made public a large dataset in 2020 with promising technical coverage in these respects:

- 4 load profiles per country, for
    - Non-thermosensitive load (1 time series)
    - Electric heating (1 time series per Monte Carlo year)
    - Air conditioning (1 time series per Monte Carlo year)
    - Electric vehicle (1 time series)
- All weather-dependent time series are based on a re-analysis over 1979-2018 of Copernicus Climate Change Service (C3S) data[8]).

A key limitation of using this dataset is that reanalysis cannot properly capture climate change. However, Copernicus has recently provided scenarios corresponding to RCP 4.5 or RCP 8.5. Due to time constraints, waiting for their availability was not an option for OSMOSE WP1[9].

A first attempt to use the coefficients of this dataset on OSMOSE WP1 data revealed some limitations, which led the project to set up ad hoc alternatives.

A first issue affected the winter peak of the Italian load. After analysis, the coefficients for the thermosensitive load of Italy were found particularly volatile within the day. The project opted for a reassessment of the thermosensitive part of the Plan4RES load (see section 4.2.2).

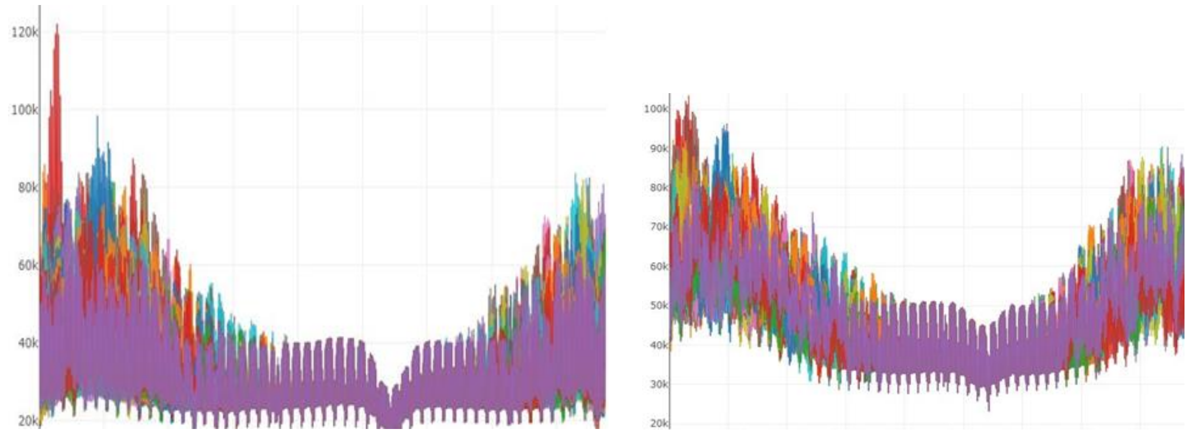


Figure 2: load time series for Italy (left) and France (right) with annual load computed by OSMOSE WP1 for 2050 - Extreme values for the 1985 Monte Carlo tiem series (red)

A second issue affected the summer peak of Norway. It was found to be the result of an inaccurate air conditioning coefficient. Under the current climate conditions, there is no obvious reason why the volume of air conditioning in 2050 should increase compared to today. Fine-grained air conditioning modeling only makes sense when used in conjunction with weather scenarios compatible with RCP 4.5 or RCP 8.5, and is very complex and speculative in countries with almost no air conditioning today. The project decided to omit the air conditioning coefficient for all countries.

[8] See [C3S]. As the same C3S weather years are used by PECD for VRES generation, the proper correlation between load and VRES generation time series is ensured.

[9] Although the RCP 4.5 and RCP 8.5 compatible datasets have been published by Copernicus before the end of OSMOSE, time constraints prevented WP1 to rerun the simulation with these new data. It is worth noting that the proposed methodology could be applied to them in a straightforward way.

Plan4RES electric vehicle time series were a “natural” candidate for OSMOSE WP1. Unfortunately, some characteristics of this dataset were found inaccurate for a study focused on assessing flexibility requirements and provisions:

- EV profiles were found identical for all countries, and for all weeks along the year (no seasonal variation).
- No thermosensitivity was considered.
- The maximum charging load took place during the weekend, which contradicts reference data (see below profiles published by [JRC]).

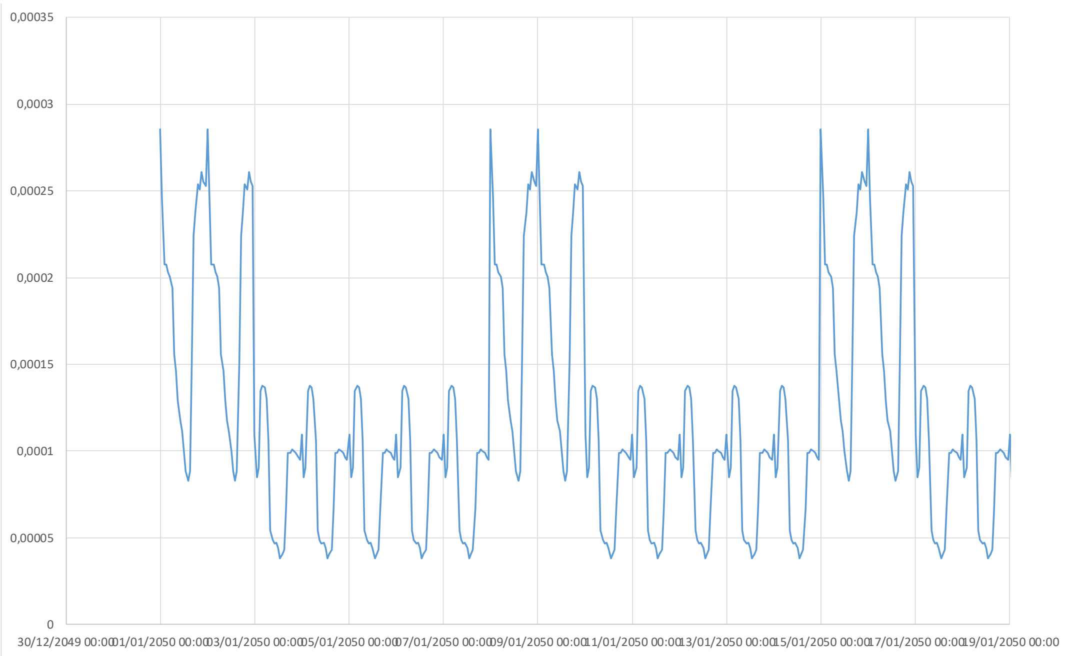


Figure 3: EV charging time series from the Plan4RES dataset – source [P4R])

Faced with this situation, OSMOSE WP1 decided to generate its own EV charging dataset.

Finally, non-thermosensitive load were also missing for some countries in the Plan4RES dataset. A way to complement them had to be elaborated.

4.2.2 Adaptation of Plan4RES non-thermosensitive load

4.2.2.1 Methodology

A country-to-country mapping was discussed.

4.2.2.2 Data mapping

Countries	Profiles mapped from
AL	HR
AT	AT
BA	HR
BE	BE
BG	HU
CH	CH
CZ	CZ
DE	DE

Countries	Profiles mapped from
DK	DE
EE	LV
ES	ES
FI	NO
FR	FR
GR	HR
HR	HR
HU	HU

Countries	Profiles mapped from
IE	IE
IT	IT
LT	LV
LU	BE
LV	LV
ME	HR
MK	HR
NL	BE
NO	NO
PL	PL
PT	ES
RO	HU
RS	HR
SE	NO
SI	AT
SK	SK
UK	UK

Table 1: mapping for non-thermosensistive load time series

4.2.3 Adaptation of Plan4RES heating data

4.2.3.1 Methodology

The detailed analysis of Plan4RES time series showed that the load factor excursion primarily affected the short term time scale. Unfortunately, the detailed transfer function used by Plan4RES was not available to us. Since building a new model from scratch was a very complex task, OSMOSE WP1 decided to build upon the existing Plan4RES data and try to mitigate its most prominent side effects, while keeping the general logic.

A comparative time scale analysis[10] of the heating load published by Plan4RES and the temperature published by Copernicus (on which Plan4RES load is based) showed:

- Similarly for load and temperature
  - A strong dependency on the Monte-Carlo year for the medium term component.
  - Conversely, the short term component is lowly dependent on the Monte-Carlo year.
- However, the high similarity observed between countries in the temperature components is not reflected in the heating load components, especially for countries geographically close to each other like Czechia, Slovakia and Poland (see Figure 4:), or Italy and Croatia, or the Netherlands and United Kingdom (see Figure 5).
- This suggests that the transfer functions in the Plan4RES dataset are very varied across countries.

[10] Spectral resolution:
- The medium term time signal is computed based on filtering out wave lengths longer than 48 hours or shorter than 6 hours.
- The short term time signal is computed based on filtering out wave lengths longer than 6 hours.

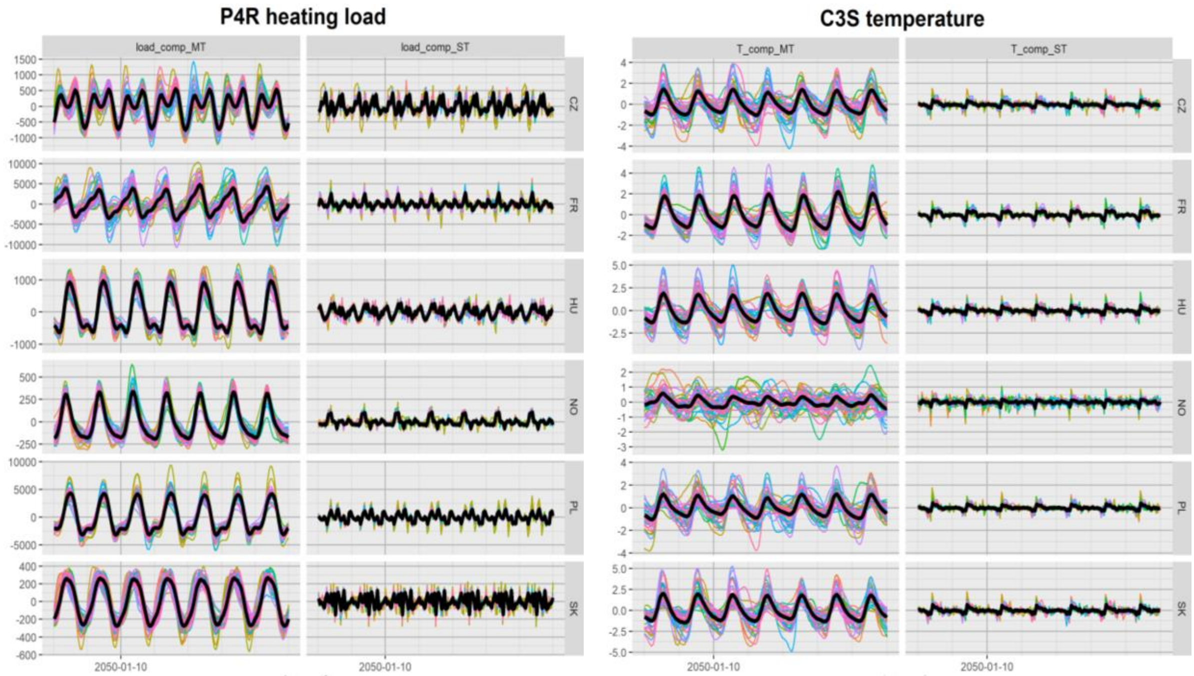


Figure 4: time scale analysis for Plan4RES load and Copernicus temperature - Czechia, France, Hungry Norway, Poland and Slovakia- January for 35 Monte-Carlo year

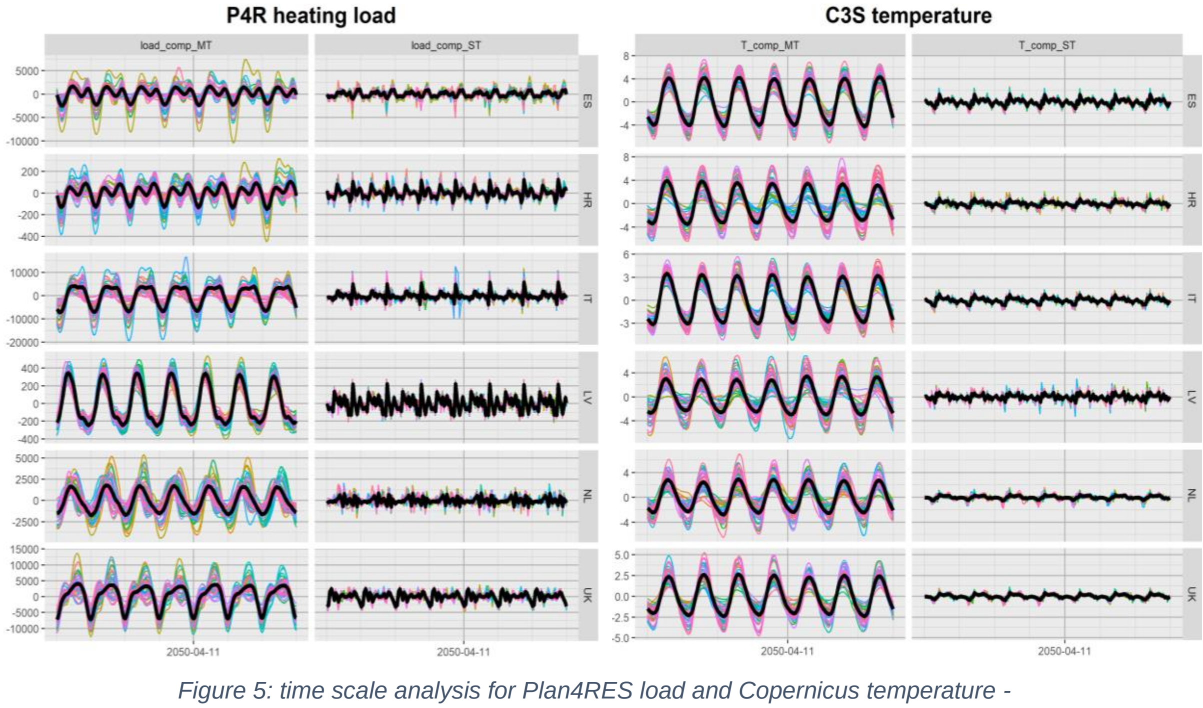


Figure 5: time scale analysis for Plan4RES load and Copernicus temperature - Spain, Croatia, Italy, Latvia, Netherlands and UK - April for 35 Monte-Carlo year

The transfer function between temperature and load is directly related to the specific socio-cultural habits of citizens and the architecture of buildings (housing, offices, factories…). Variations between countries are therefore very likely. However, one of the pillar of the energy transition is buildings insulation to reduce heating (in winter) and cooling (in summer). Higher buildings insulation will affect the transfer functions by increasing thermal inertia, which in turn should reduce the dependency to specific habits. Thus, even if a massive switch to electric heat pumps until 2050 will induce a huge increase of thermo-sensitivity in many European countries, transfer functions are expected to become rather similar. OSMOSE WP1 decided to setup the heating load dataset for 2030-2050 with this assumption in mind.

This assumption was implemented by fitting a transfer function for Czechia from the Plan4RES heating load time series and applying it to the 33 countries. An additional filter was applied to the results to avoid negative heating values or positive heating values when the daily average temperature was over 14.5° C. Czechia was selected because its bi-modal daily pattern was found to be a kind of average of the observed daily patterns.

A consistency check, the daily averaged heating coefficients in Plan4RES data and is the new model were compared, showing that the new fit introduced no bias at a daily time scale.

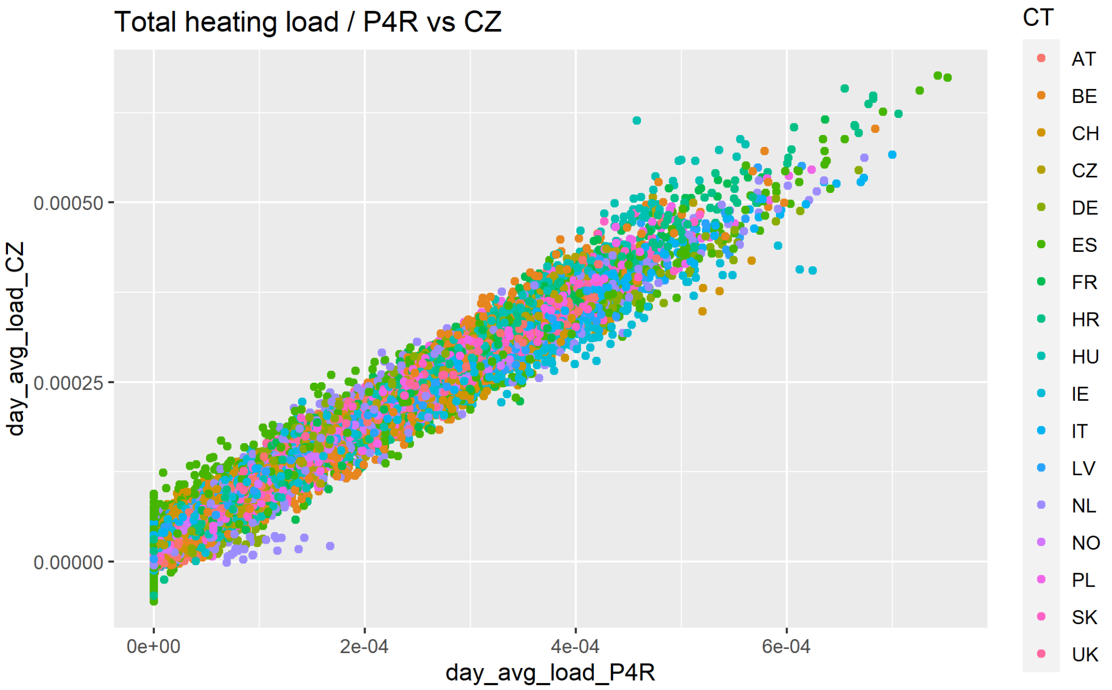


Figure 6: total heating load – WP1 regression vs P4R value

The load duration curves were also compared and found very similar.

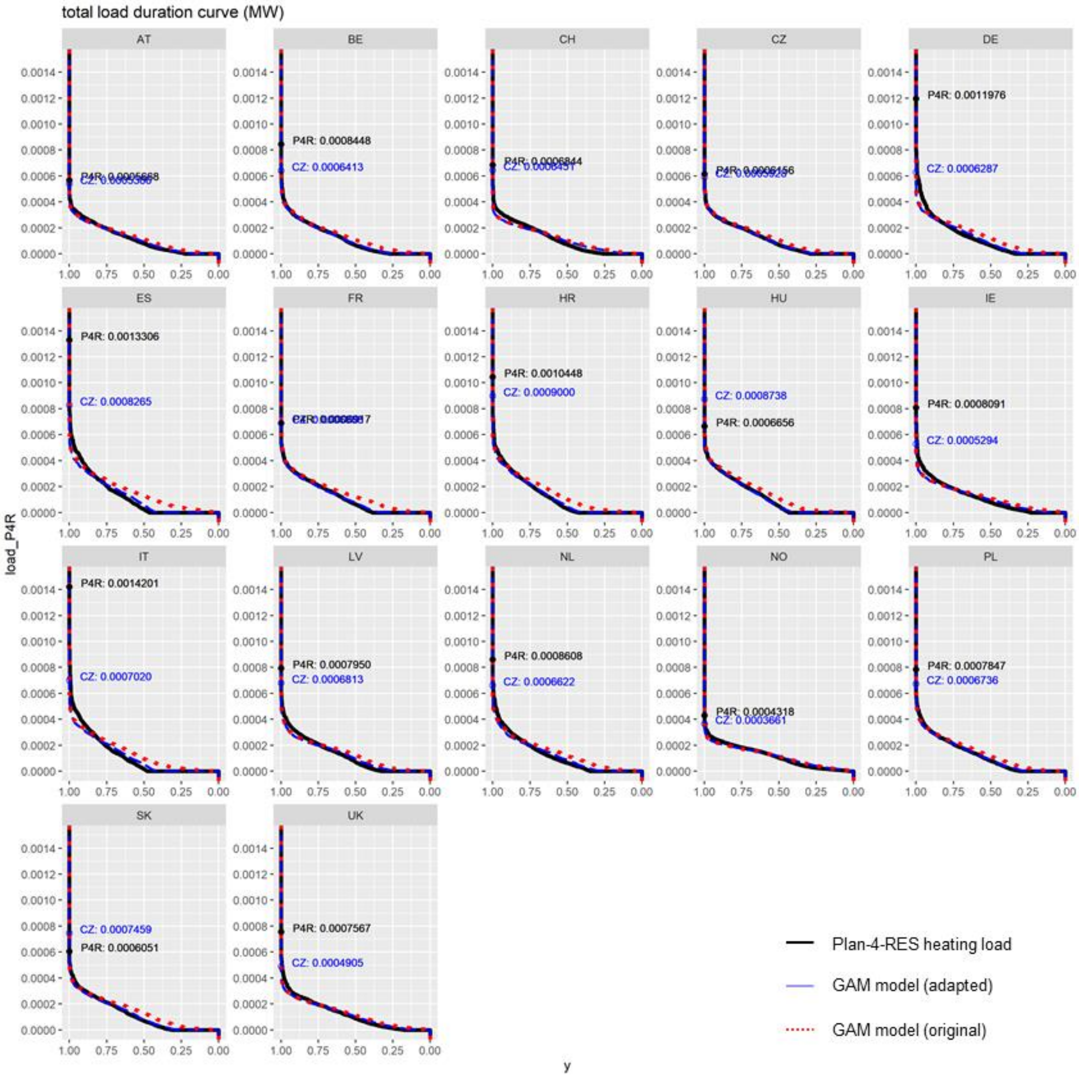


Figure 7: load duration curves- Plan4RES vs OSMOSE WP1 -
Plan4RES dataset (black) – New model before filtering (dotted) – New model after filtering (blue)

The figures below illustrate the comparison between the OSMOSE WP1 dataset and the Plan4RES dataset in terms of total load times series, assuming the shares of non-thermosensitive and thermosensitive annual energy obtained in the Current Goals Achieved scenario for 2050.

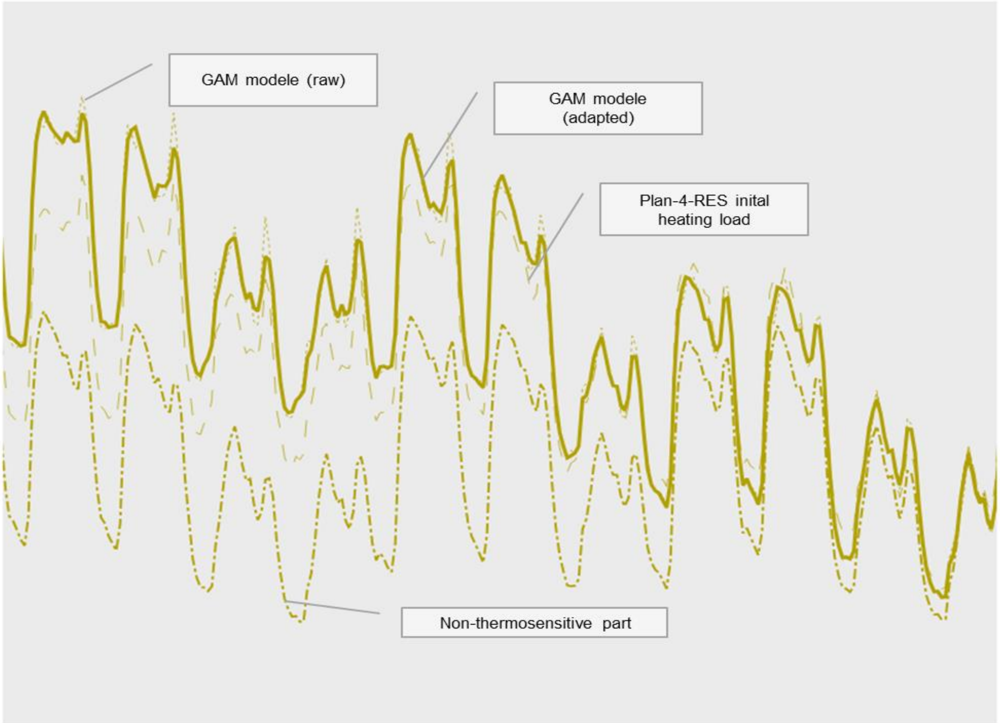


Figure 8: load time series- Plan4RES vs OSMOSE WP1 – Czech Republic (2050)

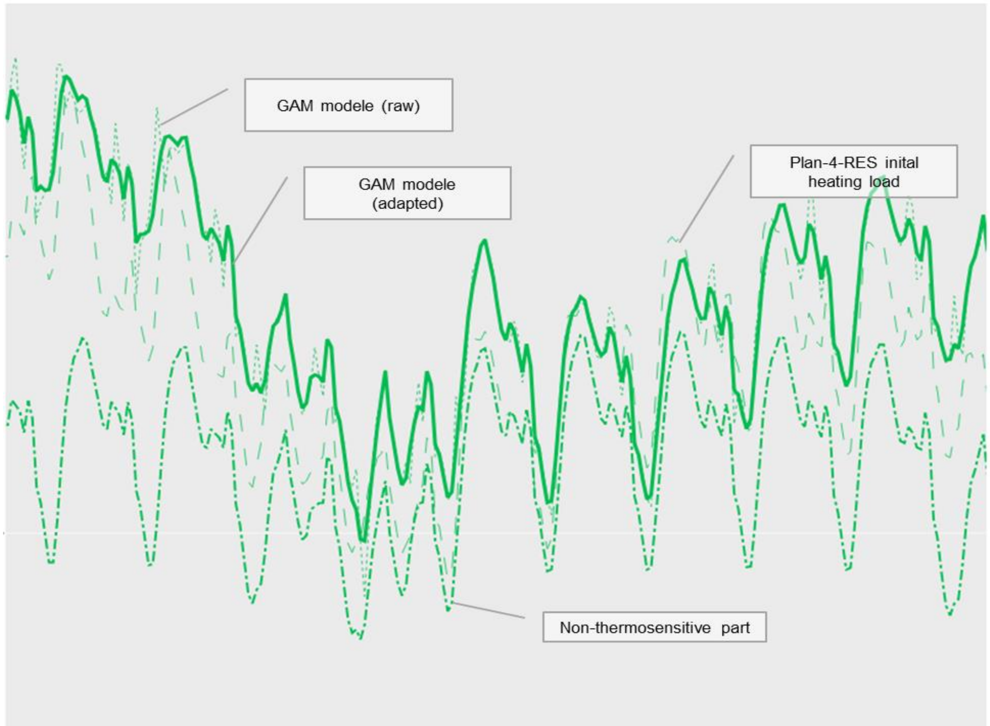


Figure 9: load time series- P4R vs OSMOSE WP1 – France (2050)

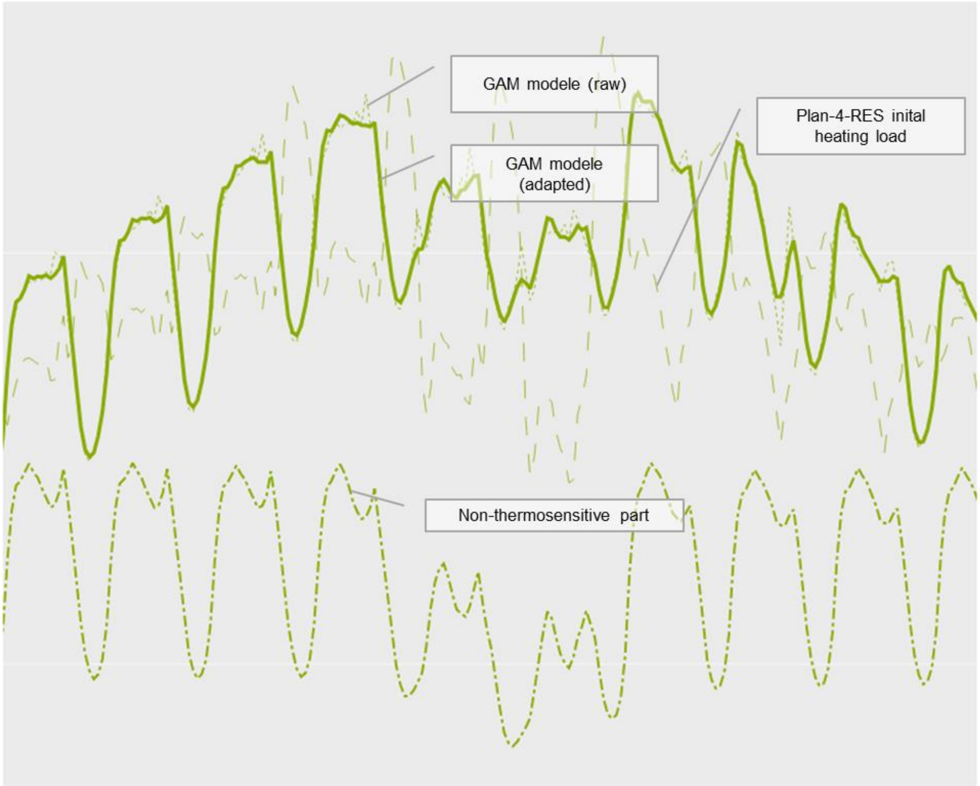


Figure 10: load time series- P4R vs OSMOSE WP1 – Germany (2050)

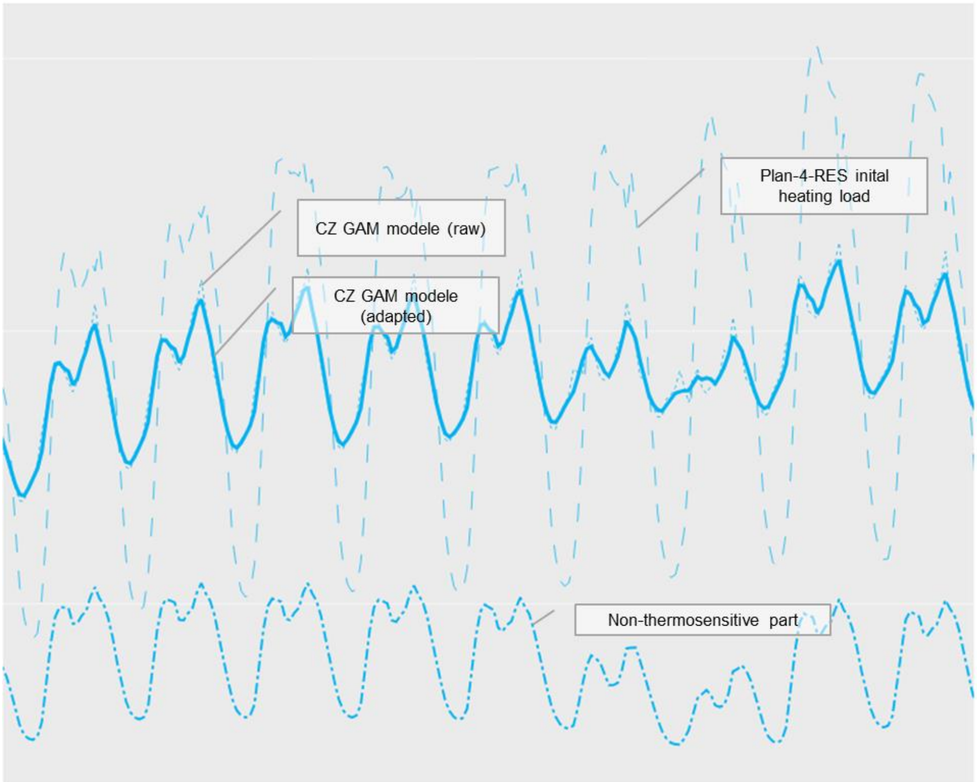


Figure 11: load time series- P4R vs OSMOSE WP1 – Italy (2050)

4.2.3.2 Data mapping

Since the principle of this step is to regenerate all thermosentive time series (except for Czechia), no question should be raised regarding mapping. However, there is an issue with

Bosnia-Herzegovina, for which Copernicus does not provide Hourly temperature time series. OSMOSE WP1 decided to match BA to RS for hourly temperature.

4.2.4 Electric vehicle

4.2.4.1 Methodology

The goal of this section is to produce “natural load” charging time series for each country and each Monte-Carlo year. Indeed, the thermo-sensitivity of electric vehicle charging may account for up to 35% of the consumption of the vehicle in winter and therefore cannot be neglected. Insofar as thermo-sensitivity comes into play, correlation with thermo-sensitive load time series must be ensured.

First, we must keep in mind that the charging profile differs is linked to the battery usage profile, with a certain delay. The use of the battery is mainly linked to the use of the vehicle (person.km or ton.km). Looking at the usage profile published by the Copernicus project [Copernicus Emission], we can distinguish for each country several time scales:

- Annual profile by month (see Figure 12:),
- Weekly profile by day (with the main difference stemming from the distinction between working days and weekends, see Figure 13:),
- Daily profile by hour (see Figure 14, Figure 15:, and Figure 16).

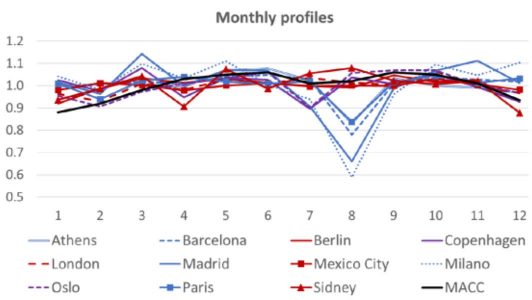


Figure 12: annual use profile in selected cities source [Copernicus]

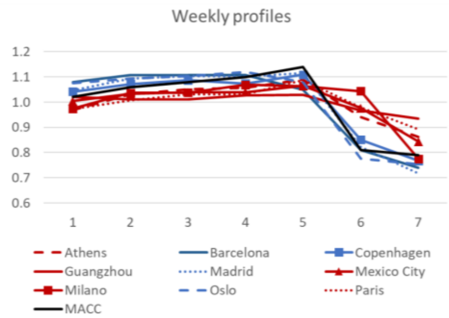


Figure 13: weekly use profile in selected cities source [Copernicus]

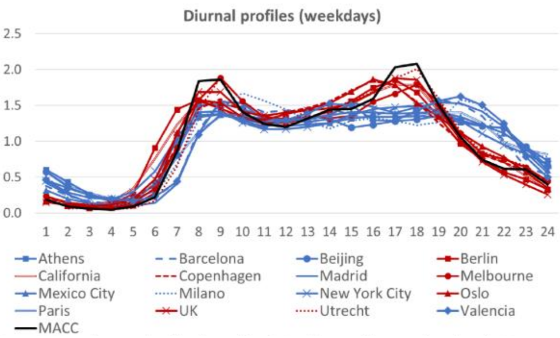


Figure 14: annual use profile in selected cities source [Copernicus]

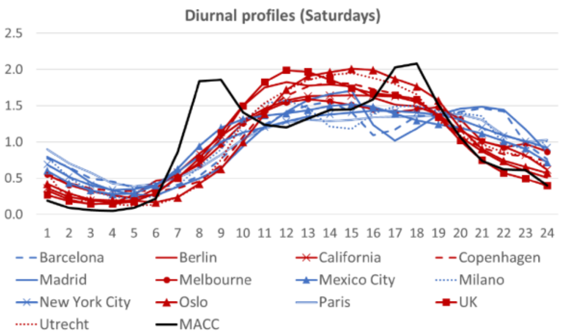


Figure 15: weekly use profile in selected cities source [Copernicus]

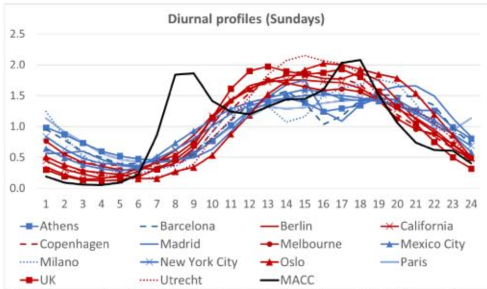


Figure 16: weekly use profile in selected cities source [Copernicus]

Due to the additional consumption for heating or cooling of the passenger cabin, but also to the reduced efficiency of the electric engine and the battery, the use of the battery is temperature-dependent[11], which leads to a “delayed” thermo-sensitivity. Data are available for the Nissan leaf that allow the calculation of a temperature-consumption transfer function over a wide temperature range. Moreover, as this vehicle is equipped with a reversible heat pump (instead of an electric convection heater), this transfer function is considered a viable and realistic technical solution in the medium term.

[11] EV consumption is also influenced by humidity, but this weather dependent variable is outside the scope of the variables directly available to OSMOSE WP1.

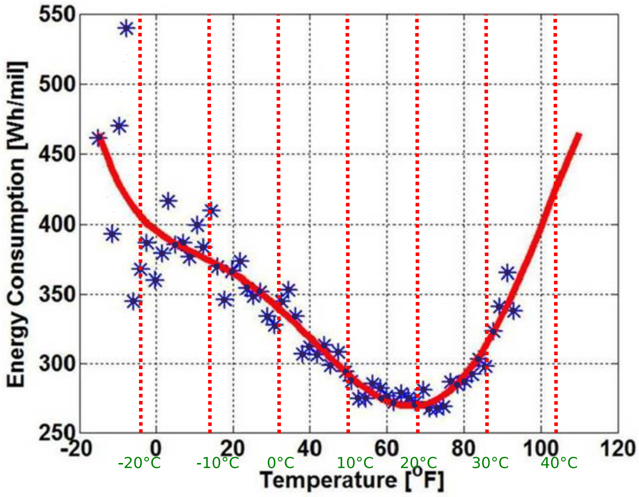


Figure 17: sensitivity of Nissan Leaf consumption to temperature source [NissanLeaf]

The time lag between the discharge of the battery due to the car motion and the recharging is a crucial assumption. In practice, the recharging cannot be delayed for more than a few days without deteriorating the mobility service provided.

As far as "natural" charging of EV (i.e. without centralized charging management) is concerned, a recent survey conducted by [JRC] showed a periodic behavior on a weekly basis, which most likely reflects the regularity of car owners' habits.

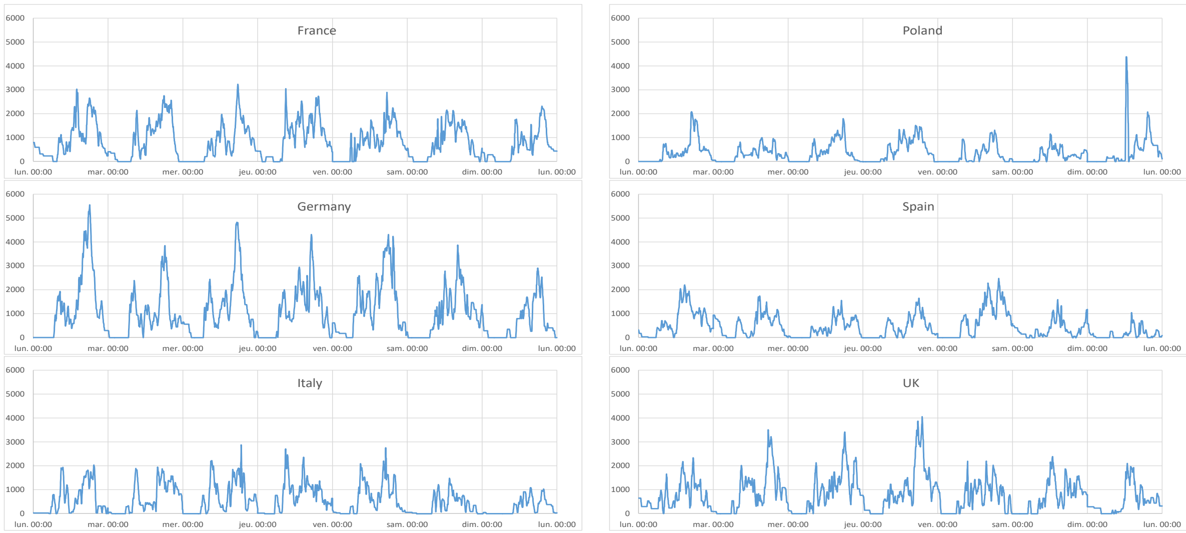


Figure 18: EV charging load profiles in Europe based on Travel Survey Data source [JRC]

These available datasets have driven us to implement the following data generation process:

- As charging cannot be delayed more than a few days, non thermosensitive yearly and weekly natural cycles for EV charging are expected to be aligned with EV battery use cycles.

- Non thermosensitive natural daily cycles for battery charging are based on JRC average data[12]. Three patterns are considered, one for weekdays, one for Saturdays, one for Sundays.
- A mapping is proposed for the non-thermosensitive profiles of the 6 JRC countries to all OSMOSE WP1 countries.
- The thermosensitive part of the daily profiles are computed to be correlated with Plan4RES data by using the historical hourly temperature time series, which were used to set up Plan4RES Heating and Air-conditioning datasets.
- The thermosensitive effect is defined by the ratio of the battery consumption in the last 24h in the current weather scenario, with respect to the "no effect" scenario. This coefficient is applied to the non-thermosensitive charging profile to get the thermosensitive charging profile.

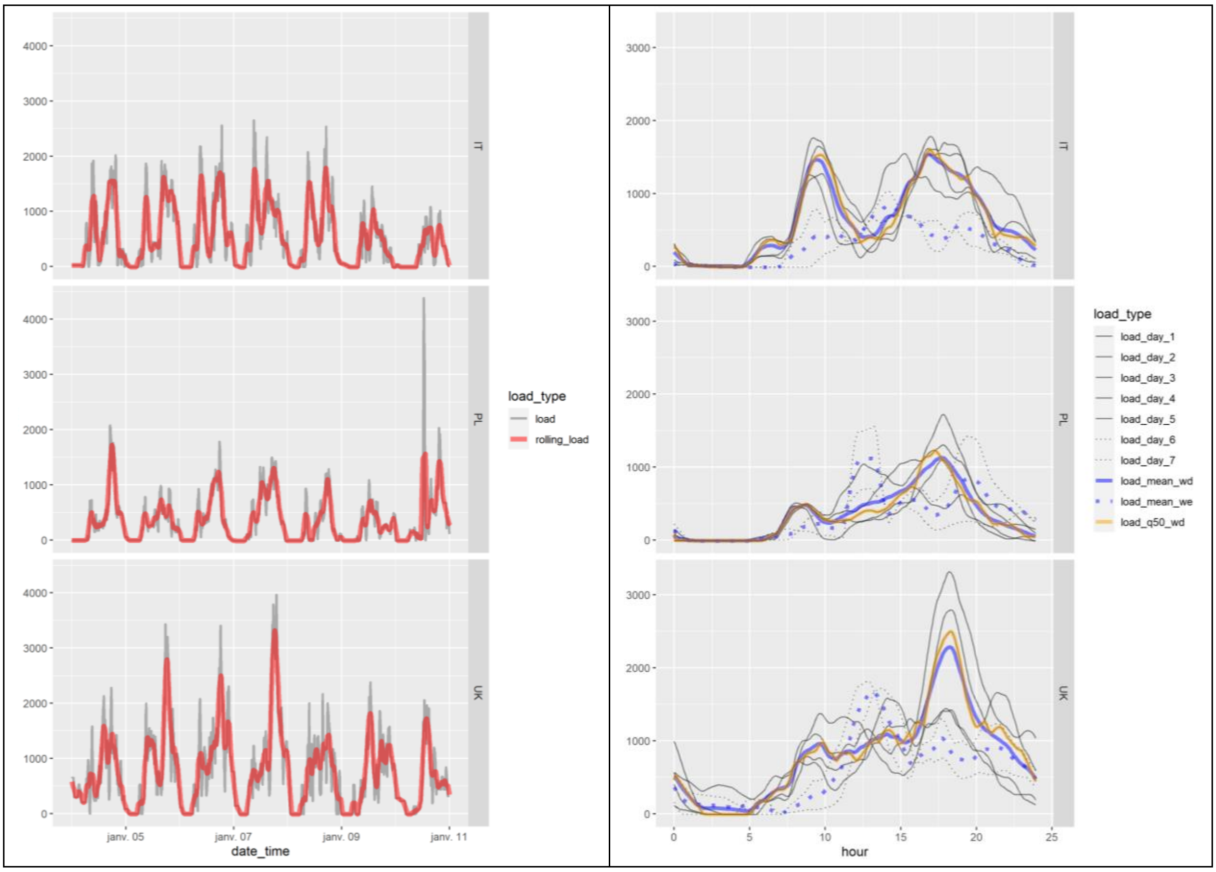


Figure 19: averaging process of JRC data to obtain more robust EV hourly profiles - JRC initial 90 sec time step data (left) vs identified hourly profiles (right)

[12] The JRC profile (time step around 90 sec) were first sampled to 5 min time steps, then smoothed using a rolling window of 2 hours. The resulting data could be visibly categorized into three types, working days, Saturdays and Sundays. Finally, all working days were grouped together and an hour-by-hour average was calculated.

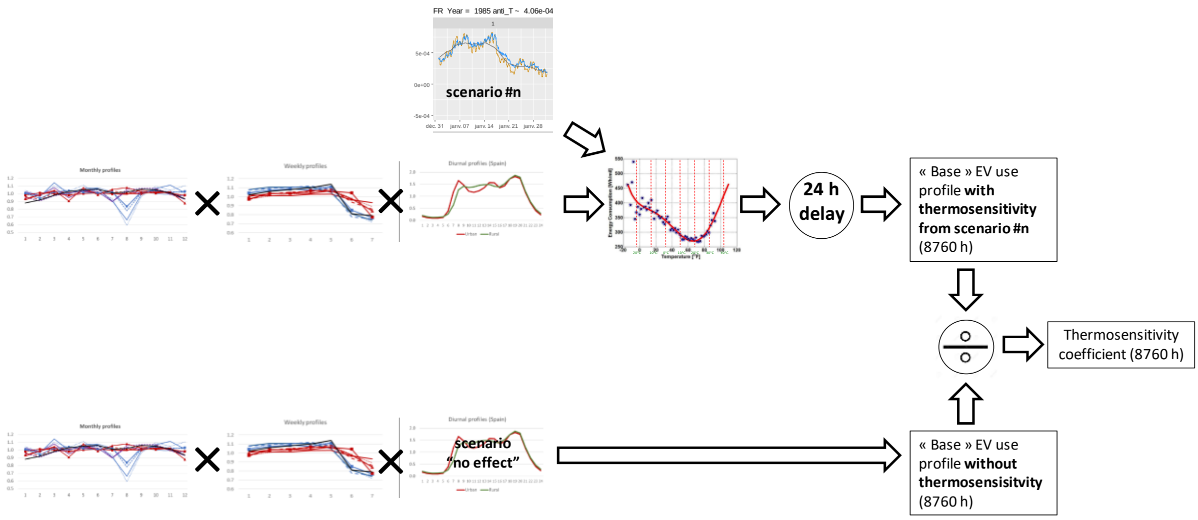


Figure 20: process for computing thermosensitive EV charging coefficient time series

Resulting time series exhibit a high level of thermosensitivity in winter (mainly heating) as well as in summer (cooling).

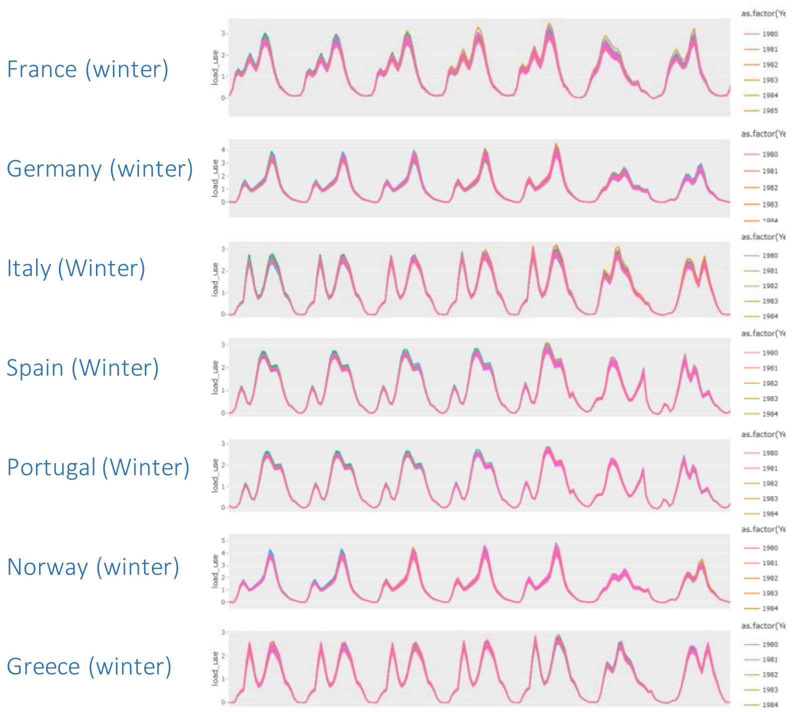


Figure 21: thermosensitive hourly time series of EV charging for 7 countries

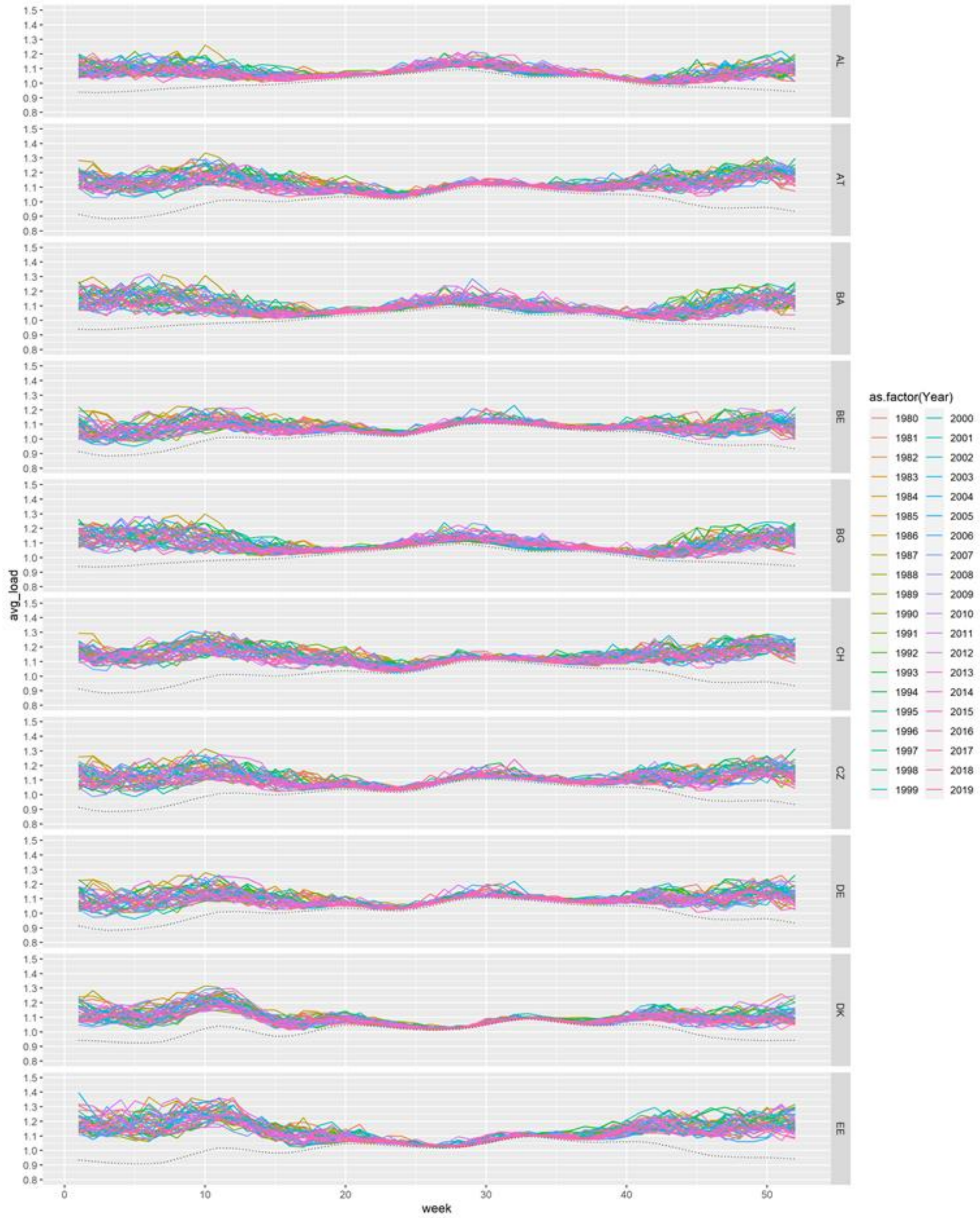


Figure 22: weekly average of total charging load (including heating and air-conditioning) for 10 countries

For the “base charging profile”, without thermo-sensitivity, it averages to 1 for each country: a reminder this part of the EV load directly reflects the traffic. Hence, they are represent the “footprint” of one EV over the year.

However, when thermo-sensitivity is applied, some countries (the colder ones in winter, the hotter ones in summer) will experience an additional load for heating and air conditioning.

CT	**AL**	**AT**	**BA**	**BE**	**BG**	**CH**	**CZ**	**DE**	**DK**
charging	1.077	1.127	1.099	1.085	1.095	1.141	1.113	1.100	1.098
CT	**EE**	**ES**	**FI**	**FR**	**GR**	**HR**	**HU**	**IE**	**IT**
charging	1.136	1.063	1.179	1.073	1.064	1.086	1.099	1.075	1.065
CT	**LT**	**LU**	**LV**	**ME**	**MK**	**NL**	**NO**	**PL**	**PT**

charging	1.126	1.099	1.131	1.099	1.097	1.081	1.181	1.111	1.052
CT	**RO**	**RS**	**SE**	**SI**	**SK**	**UK**			
charging	1.108	1.099	1.164	1.097	1.113	1.083			

Table 2: average additional load factor due to EV thermosensitivity

These results are consistent with the geographical intuition:

- Due to heating, a typical EV in Norway consumes more than a typical EV in Germany,
- Due to air conditioning, a typical EV in ES consumes more than a typical EV in PT (Portuguese temperature is less hot in summer than the Spanish one)

In line with the assumption made in GENeYS-Mod, 6% of the daily load is considered flexible (see details in section 3.3.6).

4.2.4.2 Data mapping

5 main types of data are to be used in the process of EV time series generation:

- Yearly road traffic profiles (in months)
- Weekly road traffic profiles (in days)
- Daily road traffic profiles (in hours)
- Daily battery charging profile (in hours)
- Temperature (1 year in hours)

A mapping is necessary to be able to model all European countries. Unfortunately, countries for which data are available differ from one category to another. Additionaly, a timeshift is necessary to reflect the activity shift due to dawn and sunset. As data source for daily traffic and charging may differ, so may the time shift. This time shift is understood like this:

New time (UTC) = Original data time (UTC) + timeshift

Given the shape of the daily road traffic profiles as well as of the daily charging profiles, we assume they correspond to local times. As a consequence, and due to the fact that summer time is not modelled in OSMOSE until now (and questioned in the EU), we consider a "base timeshift" corresponding to the shift between local winter time and UTC, i.e.:

- -1 for DE, DK, ES, FR, IT, NL and NO
- -2 for GR
- 0 for UK
- And so on…

Country	Traffic						Charging						T
	Monthly	Weekly	Hourly Work.days	Hourly Saturdays	Hourly Sundays	Timeshift (UTC)[13]	Monthly	Weekly	Hourly Work.days	Hourly Saturdays	Hourly Sundays	Timeshift (UTC)	Hourly Temperature
AL	GR	Other	GR	GR	GR	-1	*id. Tr Monthly*	*id. Tr Weekly*	IT	IT	IT	-1	AL
AT	DE	Other	DE	DE	DE	-1	*id. Tr Monthly*	*id. Tr Weekly*	DE	DE	DE	-1	AT
BA	GR	Other	GR	GR	GR	-1	*id. Tr Monthly*	*id. Tr Weekly*	IT	IT	IT	-1	RS
BE	DE	Other	NL	NL	NL	-1	*id. Tr Monthly*	*id. Tr Weekly*	FR	FR	FR	-1	BE
BG	GR	Other	GR	GR	GR	-1	*id. Tr Monthly*	*id. Tr Weekly*	IT	IT	IT	-1	BG
CH	DE	DE	DE	DE	DE	-1	*id. Tr Monthly*	*id. Tr Weekly*	DE	DE	DE	-1	CH
CZ	DE	DE	DE	DE	DE	-1	*id. Tr Monthly*	*id. Tr Weekly*	PL	PL	PL	-1	CZ
DE	DE	DE	DE	DE	DE	-1	*id. Tr Monthly*	*id. Tr Weekly*	DE	DE	DE	-1	DE
DK	DK	DK	DK	DK	DK	-1	*id. Tr Monthly*	*id. Tr Weekly*	DE	DE	DE	-1	DK
EE	FI	NO	NO	NO	NO	-2	*id. Tr Monthly*	*id. Tr Weekly*	PL	PL	PL	-2	EE
ES	ES	ES	ES	ES	ES	-1	*id. Tr Monthly*	*id. Tr Weekly*	ES	ES	ES	-1	ES
FI	FI	NO	NO	NO	NO	-2	*id. Tr Monthly*	*id. Tr Weekly*	DE	DE	DE	-2	FI
FR	FR	FR	FR	FR	FR	-1	*id. Tr Monthly*	*id. Tr Weekly*	FR	FR	FR	-1	FR
GR	GR	GR	GR	GR	GR	-2	*id. Tr Monthly*	*id. Tr Weekly*	IT	IT	IT	-2	GR
HR	GR	Other	GR	GR	GR	-1	*id. Tr Monthly*	*id. Tr Weekly*	IT	IT	IT	-1	HR

[13] New hour (UTC) = File hour (UTC) + timeshift

Country	Traffic						Charging						T
	Monthly	Weekly	Hourly Temperature	Hourly Saturdays	Hourly Sundays	Timeshift (UTC)[14]	Monthly	Weekly	Hourly Work.days	Hourly Saturdays	Hourly Sundays	Timeshift (UTC)	Hourly Temperature
HU	DE	Other	DE	DE	DE	-1	*id. Tr Monthly*	*id. Tr Weekly*	PL	PL	PL	-1	HU
IE	UK	UK	UK	UK	UK	0	*id. Tr Monthly*	*id. Tr Weekly*	UK	UK	UK	0	IE
IT	IT	IT	IT	IT	IT	-1	*id. Tr Monthly*	*id. Tr Weekly*	IT	IT	IT	-1	IT
LT	FI	NO	NO	NO	NO	-2	*id. Tr Monthly*	*id. Tr Weekly*	PL	PL	PL	-2	LT
LU	DE	DE	DE	DE	DE	-1	*id. Tr Monthly*	*id. Tr Weekly*	DE	DE	DE	-1	LU
LV	FI	NO	NO	NO	NO	-2	*id. Tr Monthly*	*id. Tr Weekly*	PL	PL	PL	-2	LV
ME	GR	Other	GR	GR	GR	-1	*id. Tr Monthly*	*id. Tr Weekly*	IT	IT	IT	-1	ME
MK	GR	Other	GR	GR	GR	-1	*id. Tr Monthly*	*id. Tr Weekly*	IT	IT	IT	-1	MK
NL	DE	Other	NL	NL	NL	-1	*id. Tr Monthly*	*id. Tr Weekly*	DE	DE	DE	-1	NL
NO	NO	NO	NO	NO	NO	-1	*id. Tr Monthly*	*id. Tr Weekly*	DE	DE	DE	-1	NO
PL	DE	DE	DE	DE	DE	-1	*id. Tr Monthly*	*id. Tr Weekly*	PL	PL	PL	-1	PL
PT	PT	ES	ES	ES	ES	0	*id. Tr Monthly*	*id. Tr Weekly*	ES	ES	ES	0	PT
RO	GR	Other	GR	GR	GR	-2	*id. Tr Monthly*	*id. Tr Weekly*	IT	IT	IT	-2	RO
RS	GR	Other	GR	GR	GR	-1	*id. Tr Monthly*	*id. Tr Weekly*	IT	IT	IT	-1	RS
SE	FI	NO	NO	NO	NO	-1	*id. Tr Monthly*	*id. Tr Weekly*	DE	DE	DE	-1	SE

[14] New hour (UTC) = File hour (UTC) + timeshift

Country	Traffic						Charging						T
	Monthly	Weekly	Hourly T	Hourly Saturdays	Hourly Sundays	Timeshift (UTC)[15]	Monthly	Weekly	Hourly Work.days	Hourly Saturdays	Hourly Sundays	Timeshift (UTC)	Hourly Temperature
SI	DE	Other	IT	IT	IT	-1	*id. Tr Monthly*	*id. Tr Weekly*	IT	IT	IT	-1	SI
SK	DE	DE	DE	DE	DE	-1	*id. Tr Monthly*	*id. Tr Weekly*	PL	PL	PL	-1	SK
UK	UK	UK	UK	UK	UK	0	*id. Tr Monthly*	*id. Tr Weekly*	UK	UK	UK	0	UK

Table 3: mappings used to build EV times series

4.2.4.3 Data mapping details – C3S monthly traffic profiles

Name	Sources and processing
DE_MT	Source C3S: • Germany – urban locations for urban Germany • Germany – rural locations for rural Germany OSMOSE: • average rural & urban
DK_MT	Source C3S: • Copenhagen for urban Denmark • Germany - rural locations for rural Denmark OSMOSE: • average rural & urban
ES_MT	Source C3S: • Madrid/Barcelone/Valencia for urban Spain • Spain – rural locations for rural Spain OSMOSE: • average rural & urban
FI_MT	Source C3S: • Oslo/Copenhagen for urban Finland • Germany – rural locations for rural Finland OSMOSE: • average rural & urban
FR_MT	Source C3S: • Paris for urban France • Germany – rural locations for rural France OSMOSE: • average rural & urban
GR_MT	Source C3S: • Athens for urban Greece • Spain - rural locations for rural Greece OSMOSE: • average rural & urban

[15] New hour (UTC) = File hour (UTC) + timeshift

Name	Sources and processing
IT_MT	Source C3S: • Milano for urban Italy, • Spain – rural locations for rural Italy OSMOSE: • average rural & urban
NO_MT	Source C3S: • Oslo for urban Norway • Germany - rural locations for rural Norway OSMOSE: • average rural & urban
PT_MT	Source C3S: • Madrid/Barcelona/Valencia/Athens for urban Portugal • Spain - rural locations for rural Portugal OSMOSE: • average rural & urban
UK_MT	Source C3S: • UK - urban locations for urban UK, • UK - rural locations for rural UK OSMOSE: • average rural & urban

4.2.4.4 Data mapping details – C3S weekly traffic profiles

Name	Sources and processing
DE_WT	Source C3S: • Germany – Urban for urban Germany • Germany – Rural for rural Germany OSMOSE: • average rural & urban
DK_WT	Source C3S: • Copenhagen for urban Denmark • Germany/UK/Spain - Rural for rural Denmark OSMOSE: • average rural & urban
ES_WT	Source C3S: • Madrid/Barcelona for urban Spain • rural Spain OSMOSE: • average rural & urban
FR_WT	Source C3S: • Paris for urban France • Germany/UK/Spain - Rural for rural France OSMOSE: • average rural & urban
GR_WT	Source C3S: • Athens for urban Greece • Germany/UK/Spain - Rural for rural Greece OSMOSE: • average rural & urban

Name	Sources and processing
IT_WT	Source C3S: • Milan for urban Italy • Germany/UK/Spain - Rural for rural Italy OSMOSE: • average rural & urban
NO_WT	Source C3S: • Oslo for urban Norway • Germany/UK/Spain - Rural for rural Norway OSMOSE: • average rural & urban
UK_WT	Source C3S: • UK - Urban for urban UK, • UK - Rural for rural UK OSMOSE: • average rural & urban
Other_WT	Source C3S: • MACC for urban Other, • Germany/UK/Spain – Rural for rural Other OSMOSE: • average rural & urban

4.2.4.5 Data mapping details – C3S daily traffic profiles for working days

Name	Sources and processing
DE_DTa	Source C3S: • Berlin diurnal profiles (weekday) / Monday to Friday OSMOSE: • average
DK_DTa	Source C3S: • Copenhagen diurnal profiles (weekdays) OSMOSE: • _[16]
ES_DTa	Source C3S: • Madrid diurnal profiles (weekday) / Monday to Friday OSMOSE: • average
FR_DTa	Source C3S: • Paris diurnal profiles (weekday) / Monday to Friday OSMOSE: • average
GR_DTa	Source C3S: • Athens diurnal profiles (weekdays) OSMOSE: • _[16]
IT_DTa	Source C3S: • Milan diurnal profiles (weekday) / Monday to Friday OSMOSE: • average

[16] Already published as an average

Name	Sources and processing
NL_DTa	Source C3S: • Utrecht diurnal profiles (weekday) / Monday to Friday OSMOSE: • average
NO_DTa	Source C3S: • Oslo diurnal profiles (weekday) / Monday to Friday OSMOSE: • average

4.2.4.6 Data mapping details – C3S daily traffic profiles for Saturdays

Name	Sources and processing
DE_DTb	Source C3S: • Berlin diurnal profiles (weekday) / Saturday OSMOSE: • _
DK_DTb	Source C3S: • Copenhagen diurnal profiles (Saturdays) OSMOSE: • _
ES_DTb	Source C3S: • Madrid diurnal profiles (weekday) / Saturday OSMOSE: • _
FR_DTb	Source C3S: • Paris diurnal profiles (weekday) / Saturday OSMOSE: • _
GR_DTb	Source C3S: • Paris, Milan and Madrid diurnal profiles (Saturdays) OSMOSE: • Average[17]
IT_DTb	Source C3S: • Milan diurnal profiles (weekday) / Saturday OSMOSE: • Average
NL_DTb	Source C3S: • Utrecht diurnal profiles (weekday) / Saturday OSMOSE: • Average
NO_DTb	Source C3S: • Oslo diurnal profiles (weekday) / Saturday OSMOSE: • Average

[17] Shapes published for these cities are very similar for the other days.

4.2.4.7 Data mapping details – C3S daily traffic profiles for Sundays

Name	Sources and processing
DE_DTc	Source C3S: • Berlin diurnal profiles (weekday) / Sunday OSMOSE: • _
DK_DTc	Source C3S: • Copenhagen diurnal profiles (Sundays) OSMOSE: • _[18]
ES_DTc	Source C3S: • Madrid diurnal profiles (weekday) / Sunday OSMOSE: • _
FR_DTc	Source C3S: • Paris diurnal profiles (weekday) / Sunday OSMOSE: • _
GR_DTc	Source C3S: • Athens diurnal profiles (Sundays) OSMOSE: • _[16]
IT_DTc	Source C3S: • Milan diurnal profiles (weekday) / Sunday OSMOSE: • _
NL_DTc	Source C3S: • Utrecht diurnal profiles (weekday) / Sunday OSMOSE: • _
NO_DTc	Source C3S: • Oslo diurnal profiles (weekday) / Sunday OSMOSE: • _

4.2.4.8 Data mapping details – JRC daily battery charging profiles for working days

Name	Sources and processing
DE_DCa	Source JRC: • High resolution profiles for Germany / Monday to Friday OSMOSE: • smoothing and average
ES_DCa	Source JRC: • High resolution profiles for Spain / Monday to Friday OSMOSE: • smoothing and average
FR_DCa	Source JRC: • High resolution profiles for France / Monday to Friday OSMOSE: • smoothing and average

[18] Already published as an average

Name	Sources and processing
IT_DCa	Source JRC: • High resolution profiles for Italy / Monday to Friday OSMOSE: • smoothing and average
PL_DCa	Source JRC: • High resolution profiles for Poland / Monday to Friday OSMOSE: • smoothing and average
UK_DCa	Source JRC: • High resolution profiles for UK / Monday to Friday OSMOSE: • smoothing and average

4.2.4.9 Data mapping details – JRC daily battery charging profiles for Saturdays

Name	Sources and processing
DE_DCb	Source JRC: • High resolution profiles for Germany, Spain, France, Italy, Poland, UK / Saturday OSMOSE: • smoothing and weighted average (**7***DE+1*ES+1*FR+1*IT+1*PL+1*UK)/12
ES_DCa	Source JRC: • High resolution profiles for Germany, Spain, France, Italy, Poland, UK / Saturday OSMOSE: • smoothing and weighted average (1*DE+**7***ES+1*FR+1*IT+1*PL+1*UK)/12
FR_DCa	Source JRC: • High resolution profiles for Germany, Spain, France, Italy, Poland, UK / Saturday OSMOSE: • smoothing and weighted average (1*DE+1*ES+**7***FR+1*IT+1*PL+1*UK)/12
IT_DCa	Source JRC: • High resolution profiles for Germany, Spain, France, Italy, Poland, UK / Saturday OSMOSE: • smoothing and weighted average (1*DE+1*ES+1*FR+**7***IT+1*PL+1*UK)/12
PL_DCa	Source JRC: • High resolution profiles for Germany, Spain, France, Italy, Poland, UK / Saturday OSMOSE: • smoothing and weighted average (1*DE+1*ES+1*FR+1*IT+**7***PL+1*UK)/12
UK_DCa	Source JRC: • High resolution profiles for Germany, Spain, France, Italy, Poland, UK / Saturday OSMOSE: • smoothing and weighted average (1*DE+1*ES+1*FR+1*IT+1*PL+**7***UK)/12

4.2.4.10 Data mapping details – JRC daily battery charging profiles for Sundays

Name	Sources and processing
DE_DCb	Source JRC: • High resolution profiles for Germany, Spain, France, Italy, Poland, UK / Sunday OSMOSE: • smoothing and weighted average (**7***DE+1*ES+1*FR+1*IT+1*PL+1*UK)/12
ES_DCa	Source JRC: • High resolution profiles for Germany, Spain, France, Italy, Poland, UK / Sunday OSMOSE: • smoothing and weighted average (1*DE+**7***ES+1*FR+1*IT+1*PL+1*UK)/12
FR_DCa	Source JRC: • High resolution profiles for Germany, Spain, France, Italy, Poland, UK / Sunday OSMOSE: • smoothing and weighted average (1*DE+1*ES+**7***FR+1*IT+1*PL+1*UK)/12
IT_DCa	Source JRC: • High resolution profiles for Germany, Spain, France, Italy, Poland, UK / Sunday OSMOSE: • smoothing and weighted average (1*DE+1*ES+1*FR+**7***IT+1*PL+1*UK)/12
PL_DCa	Source JRC: • High resolution profiles for Germany, Spain, France, Italy, Poland, UK / Sunday OSMOSE: • smoothing and weighted average (1*DE+1*ES+1*FR+1*IT+**7***PL+1*UK)/12
UK_DCa	Source JRC: • High resolution profiles for Germany, Spain, France, Italy, Poland, UK / Sunday OSMOSE: • smoothing and weighted average (1*DE+1*ES+1*FR+1*IT+1*PL+**7***UK)/12

4.3 Intermittent generation data

4.3.1 Context and objectives

In e-highway dataset, 11 Monte-Carlo years of RES time series were available. But this remained clearly insufficient to capture variability. In addition, it is essential to ensure time consistency between load and VRES time series, in order to guarantee a multivariate distribution in conformity with reality.

As for the load, the H2020 project Plan4RES was a very promising source for wind and PV generation factors: however, a detailed analysis showed some issues with the distribution for wind factors. It was therefore decided to compare its performance with the Pan European Climate Database (see [PECD]), which is based on Coperniucs reanalysis as well (see [C3S]).

The comparison presented in Figure 23 uses the wind speed / 20 as a consistency criterion. From this analysis, PECD was finally chosen over Plan4RES for VRES time series.

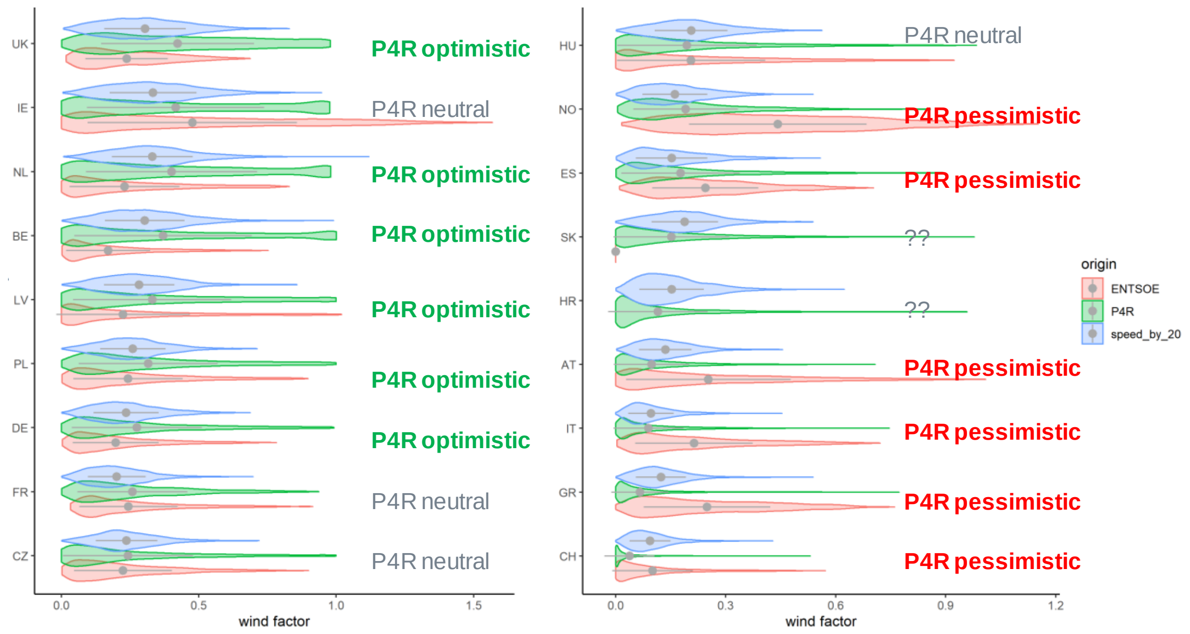


Figure 23: wind factor per data origin and Copernicus wind speed - 2018 data – Plan4RES (P4R) vs PECD (ENTSOE) vs wind speed / 20

NB: in the visual comparison of the time series (see Figure 24), the advantages of PECD are less obvious, but the identical origin of the weather data is well highlighted by the synchronicity of the curves.

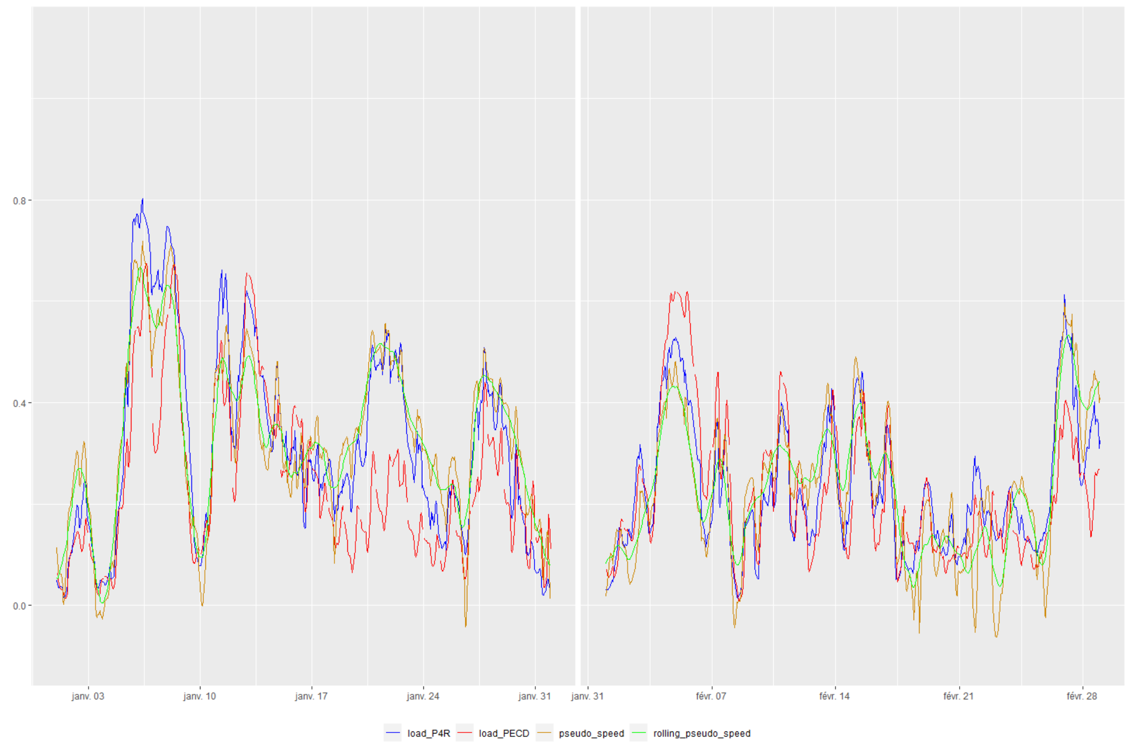


Figure 24: comparison of wind generation in Plan4RES (blue), and PECD (red) for 2012

Once PECD was selected for wind generation, it seemed convenient to use it for solar energy as well.

4.3.2 Onshore wind generation time series

4.3.2.1 Methodology

Onshore wind power-factor profiles are taken from [PECD].

Power-factor time series are provided in two “flavours”:

- 1 profile per country, 1 file per weather year
- 1 profile per cluster, 1 file per weather year).

4.3.2.2 Data mapping

The mapping between WP1 countries and clusters and PECD is as follows:

COUNTRY	CLUSTER	PECD
AL	70AL	AL00
AT	49AT	AT01
	50AT	AT02
	51AT	AT03
BA	63BA	BA00
BE	28BE	BE00
BG	66BG	BG00
CH	47CH	CH00
	48CH[19]	CH00
CZ	39CZ	CZ01
	40CZ	CZ02
DE	31DE	DE01
	32DE	DE02
	33DE	DE03
	34DE	DE04
	35DE	DE05
	36DE	DE06
	37DE	DE07
DK	38DK	DKW1
	72DK	DKE1
EE	73EE	EE00
	01ES	ES01
	02ES	ES02
	03ES	ES03
	04ES	ES04
	05ES	ES05
	06ES	ES06
	07ES	ES07
	08ES	ES08
	09ES	ES09
	10ES	ES10
	11ES	ES11
FI	74FI	FI01
	75FI	FI02
FR	14FR	FR01
	15FR	FR02

COUNTRY	CLUSTER	PECD
	16FR	FR03
	17FR	FR04
	18FR	FR05
	19FR	FR06
	20FR	FR07
	21FR	FR08
	22FR	FR09
	23FR	FR10
	24FR	FR11
	25FR	FR12
	26FR	FR13
	27FR	FR14
	99FR[20]	ITSA
GR	68GR	GR01
	69GR	GR02
HR	62HR	HR00
HU	58HU	HU00
IT	52IT	ITN1
	53IT	ITCN
	54IT	ITCS
	55IT	ITS1
	56IT	ITSI
	98IT	ITSA
LT	77LT	LT00
LU	29LU	LUB1
LV	78LV	LV00
ME	64ME	ME00
MK	67MK	MK00
NL	30NL	NL00
NO	79NO	NOS2
	80NO	NOS1
	81NO	NOS3
	82NO[21]	NOS1
	83NO	NOM1
	84NO	NON1
	85NO[22]	NON1

[19] Mapped with 47CH (PECD: CH00)

[20] Mapped with 98IT (PECD: ITSA)

[21] Mapped with 80NO (PECD: NOS1)

[22] Mapped with 84NO (PECD : NON1)

COUNTRY	CLUSTER	PECD
PL	41PL	PL01
	42PL	PL02
	43PL	PL03
	44PL	PL04
	45PL	PL05
PT	12PT	PT01
	13PT	PT02
RO	59RO	RO01
	60RO	RO02
	61RO	RO03
RS	65RS	RS00
SE	86SE	SE01
	87SE	SE02

COUNTRY	CLUSTER	PECD
	88SE	SE03
	89SE	SE04
SI	57SI	SI00
SK	46SK	SK00
UK	90UK	UK01
	91UK	UK02
	92UK	UK03
	93UK	UK04
	94UK	UK05
	95UK	UKNI
IE	96IE	IE00

Table 4: mappings used to build onshore wind times series

4.3.3 Offshore wind generation time series

4.3.3.1 Methodology

Offshore wind power-factor profiles are taken from [PECD].

Power-factor time series are provided in two “flavours”:

- 1 profile per country, 1 file per weather year
- 1 profile per cluster, 1 file per weather year).

NB: a special handling is applied for NL for the scenario Common Goals Achieved (CGA) and only for 2050. In 2050, GENeSYS-Mod (see [GENeSYS-MOD]) invests 50 GW of wind offshore capacity in the North Sea; as a side effects of the clustering, this new capacity was located only on the Dutch offshore cluster, which seemed too concentrated. A patch is applied to part this new capacity over BE, DE, DK, FR and NL.

Country	Before patch (MW)	After patch (MW)
BE	3 033	6 720
DE	16 497	36 554
DK	3 268	7 241
FR	7 875	17 449
NL	51 623	14 331

4.3.3.2 Data mapping

Offshore wind is located in the corresponding country or land cluster.

COUNTRY	CLUSTER	PECD	Offshore
AL	70AL	AL00	
AT	49AT	AT01	n.a.

COUNTRY	CLUSTER	PECD	Offshore
	50AT	AT02	n.a.
	51AT	AT03	n.a.

COUNTRY	CLUSTER	PECD	Offshore
BA	63BA	BA00	
BE	28BE	BE00	
BG	66BG	BG00	n.a.
CH	47CH	CH00	n.a.
	48CH[23]	CH00	n.a.
CZ	39CZ	CZ01	n.a.
	40CZ	CZ02	n.a.
DE	31DE	DE01	
	32DE	DE02	
	33DE	DE03	n.a.
	34DE	DE04	n.a.
	35DE	DE05	n.a.
	36DE	DE06	n.a.
	37DE	DE07	n.a.
DK	38DK	DKW 1	
	72DK	DKE1	
EE	73EE	EE00	
	01ES	ES01	
	02ES	ES02	
	03ES	ES03	n.a.
	04ES	ES04	
	05ES	ES05	n.a.
	06ES	ES06	
	07ES	ES07	n.a.
	08ES	ES08	n.a.
	09ES	ES09	
	10ES	ES10	
	11ES	ES11	
FI	74FI	FI01	
	75FI	FI02	
FR	14FR	FR01	
	15FR	FR02	
	16FR	FR03	
	17FR	FR04	
	18FR	FR05	n.a.
	19FR	FR06	n.a.
	20FR	FR07	n.a.
	21FR	FR08	
	22FR	FR09	
	23FR	FR10	n.a.

COUNTRY	CLUSTER	PECD	Offshore
	24FR	FR11	n.a.
	25FR	FR12	n.a.
	26FR	FR13	
	27FR	FR14	n.a.
	99FR[24]	ITSA	
GR	68GR	GR01	
	69GR	GR02	
HR	62HR	HR00	n.a.
HU	58HU	HU00	n.a.
IT	52IT	ITN1	
	53IT	ITCN	
	54IT	ITCS	
	55IT	ITS1	
	56IT	ITSI	
	98IT	ITSA	
LT	77LT	LT00	
LU	29LU	LUB1	n.a.
LV	78LV	LV00	
ME	64ME	ME00	
MK	67MK	MK00	n.a.
NL	30NL	NL00	
NO	79NO	NOS2	
	80NO	NOS1	n.a.
	81NO	NOS3	
	82NO[25]	NOS1	n.a.
	83NO	NOM 1	
	84NO	NON1	
	85NO[26]	NON1	
PL	41PL	PL01	n.a.
	42PL	PL02	n.a.
	43PL	PL03	n.a.
	44PL	PL04	
	45PL	PL05	
PT	12PT	PT01	
	13PT	PT02	
RO	59RO	RO01	n.a.
	60RO	RO02	n.a.
	61RO	RO03	
RS	65RS	RS00	n.a.
SE	86SE	SE01	

[23] Mapped with 47CH (PECD: CH00)
[24] Mapped with 98IT (PECD: ITSA)

[25] Mapped with 80NO (PECD: NOS1)
[26] Mapped with 84NO (PECD: NON1)

COUNTRY	CLUSTER	PECD	Offshore
	87SE	SE02	
	88SE	SE03	
	89SE	SE04	
SI	57SI	SI00	
SK	46SK	SK00	n.a.
UK	90UK	UK01	
	91UK	UK02	

COUNTRY	CLUSTER	PECD	Offshore
	92UK	UK03	
	93UK	UK04	
	94UK	UK05	
	95UK	UKNI	
IE	96IE	IE00	

Table 5: mappings used to build onshore wind times series

4.3.4 Solar generation times series

4.3.4.1 Methodology

Solar PV power-factor profiles are taken from [PECD].

Power-factor time series are provided in two “flavours”:

- 1 profile per country, 1 file per weather year
- 1 profile per cluster, 1 file per weather year).

4.3.4.2 Data mapping

The mapping for solar PV is identical to onshore wind (see section 4.3.2.2).

4.4 Hydro generation

4.4.1 Methodology

For all countries, run-of-river generation is given by 35 time-series of daily energy for each country, which are modelled as must-run generation.

Inflows are given by 35 time series weekly energy for each country. For all countries, reservoir generation is managed using ANTARES “reservoir management heuristic”[27]. This heuristic adapts reservoir generation on an annual basis, with respect to annual inflows and net load (load minus non-dispatchable generation). This means, the heuristic will allocate more hydro energy to months and weeks with higher net load, respecting the overall annual energy. The allocated weekly energy is then optimised by ANTARES within the hours of the week.

All data are publicly available. Reservoir capacities (volumes) are from MAF2019 data set.

4.4.2 Data mapping

Some mapping was needed as:

- Weekly inflow profiles reservoirs were only available for 13 countries.
- Daily generation profiles for run-of-river were only available for 11 countries only.

Then some adjustments and allocations were performed to ensure consistency between inflows, annual energy volumes, reservoir capacities and maximum power characteristics of each country.

[27] More details in ANTARES documentation.
See [AntaresSimulator]

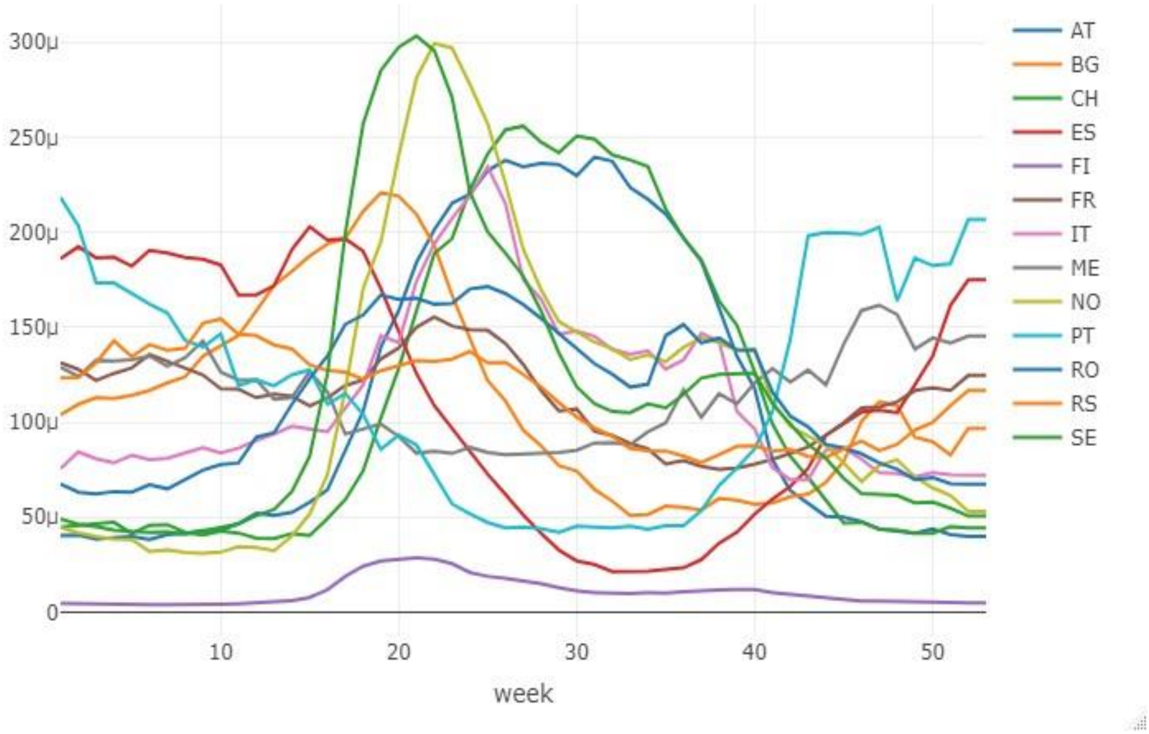


Figure 25: reservoirs - weekly inflow profiles available for 13 countries

Country	2018 reservoir (TWh)	2018 reservoir capacity (MW)	Reservoir 2050 (TYNDP)	Profile
AL	5,9	1534	2402	RS / ME
AT	10,1	8436	10843	**AT**
BA	6,1	2000	1120	RS
BE	0	0	2066	FR
BG	3,4	1591	2800	**BG**
CH	20,5	8152	15709	**CH**
CZ	0,7	753	1195	**AT**
DE	0,5	205	10864	AT
DK	0	0	0	N/A
EE	0	0	0	N/A
ES	27,5	15107	21070	**ES**
FI	0	0	3400	**NO**
FR	30,9	2455	13500	**FR**
GB	2,5	2830	8351	FR
GR	5	3169	4349	IT
HR	5,1	1669	2900	**RO / RS**
HU	0	28	0	N/A
IE	0	0	592	FR
IT	10,9	9177	16456	**IT**

LT	0	0	1125	FI
LU	0	17	1310	FR
LV	0	0	1619	FI
ME	0	0	1139	**ME**
MK	1,4	567	994	ME
NL	0	0	2500	FR
NO	138	26773	35817	**NO**
PL	0,6	555	2217	RO
PT	4,8	4335	8466	**PT**
RO	7,3	3566	4280	**RO**
RS	1,2	401	1763	**RS**
SE	61	16630	16184	**SE**
SI	0	0	600	**CH / AT**
SK	0,6	600	2292	**AT**

Table 6: reservoirs - mapping for missing countries

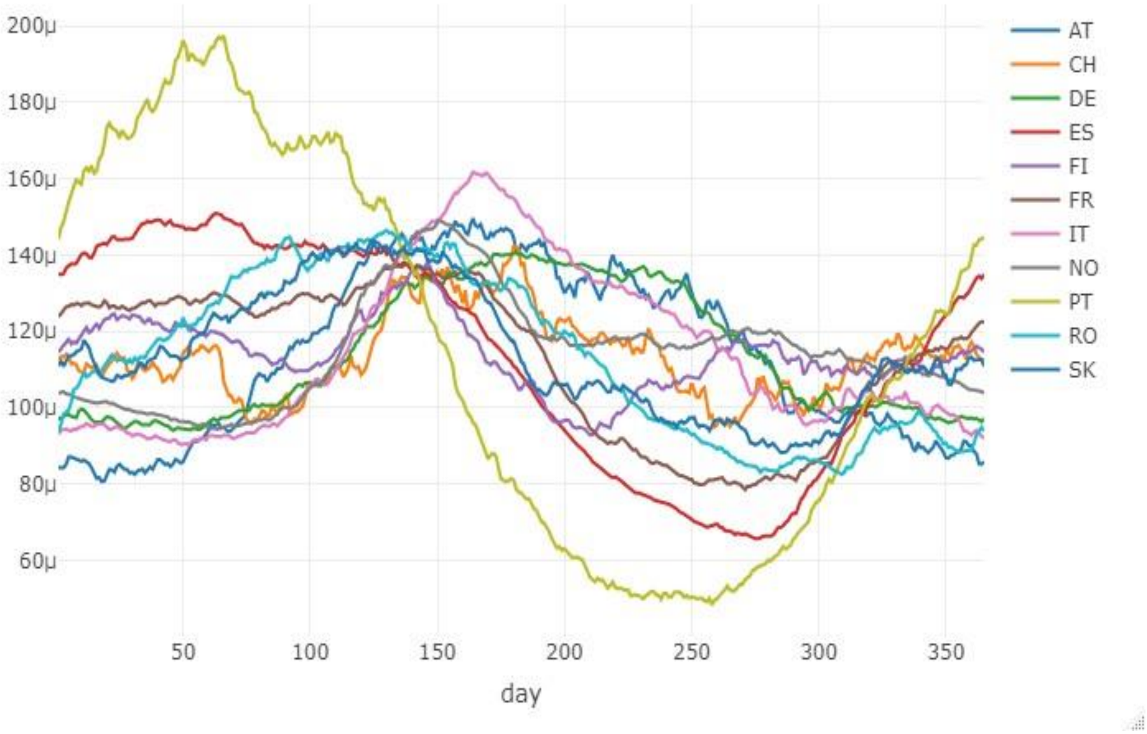


Figure 26: run-of-river - daily generation profiles available for 11 countries only

Country	RoR 2018 (TWh)	RoR 2018 (MW)	RoR capacity 2050 (TYNDP)	RoR profile
AL	2,2	301	468	RO / IT

AT	24	5714	4672	**AT**
BA			1144	RO
BE	0,3	125	117	DE
BG	1,6	600	600	RO
CH	16,9	4053	4139	**CH**
CZ	0,9	334	365	SK
DE	17,9	3781	4329	**DE**
DK	0	7	7	DE
EE	0,1	9	10	FI
ES	6,6	1942	3850	**ES**
FI	13,1	3148	0	**FI**
FR	32,3	21092	13600	**FR**
GB	3,4	963	142	FR
GR	0,7	230	275	IT
HR	1,8	426	500	RO
HU	0,2	28	60	RO
IE	0,7	238	216	FR
IT	36,2	12768	5637	**IT**
LT	0,4	127	138	FI
LU	0,1	15	34	DE
LV	2,4	1557	0, we should check this	FI
ME			132	SK / IT
MK	0,2	109	151	SK / IT
NL	0,1	38	38	DE
NO		5801	0	**NO**
PL	1,3	402	1033	SK
PT	7,3	2880	735	**PT**
RO	10,4	2763	3291	**RO**
RS	9,2	1990	2025	SK /RO
SE			0	N/A
SI	4,6	1122	1500	CH /AT
SK	2,9	1208	974	**SK**

Table 7: run-of-river - mapping for missing countries

4.5 Forecast data

4.5.1 Context and objectives

In order to assess the effect of look-ahead uncertainties on the operational processes, it was necessary to have at hand a dataset of “forecast data” consistent with the dataset used as “realised data”. Consistent means reflecting the probabilities of having a given forecast error between the forecast and the data we use as realised data with the given look-ahead. The variable affected by this issue are load, wind generation and PV generation[28].

In WP2, UDE developed a methodology (implemented as an R package) to perform this task (see [D2.1]) based on the idea of preparing pseudo forecast data by adding suitable errors to the pseudo realised data. In this process the key is to embed in the error time series the kind of correlations (inter-temporal, geographical and between-variables correlations) that we can expect from the operational reality.

However this module was designed by WP2 for market studies focused on Central Western Europe around 2035. Adaptations were necessary to use it for the 33 countries belonging to the geographical scope of WP1 over the whole 2020-2050 horizon, characterized by a strong increase in the share of VRES in all the considered countries.

Therefore, a methodology was developed, for load, and for onshore-wind and PV generation, to match the general behaviour observed in the realised and day-ahead forecast data published on the ENTSOE transparency web site, and then extrapolate to it to 2030 and 2050:

- Estimation of a target annual RMSE for each country, given the target share of renewables and load in 2030 and 2050,
- Recalibration of the error times series to match a target annual RMSE,
- Recalibration of the temporal autocorrelation by additional smoothing to match the regularity observe 2020 ENTSOE transparency reference data

4.5.2 Methodology

The general process for building forecast time series is as follows:

- Analysis of available observed data until 2020 (source ENTSOE transparency), for load, wind generation and PV generation,
- Determination of keys indicators summarising the behaviour of day-ahead forecast data for load, wind generation and PV generation with respect to realised data for each country until 2020,
- Estimation of a target annual RMSE for each country, given the target share of renewables and load in 2030 and 2050,
- Recalibration of the error times series to match a target annual RMSE,
- Recalibration of the temporal autocorrelation by additional smoothing to match the regularity observe 2020 ENTSOE transparency reference data

It should be noted that a thorough analysis of ENTSOE data led us to the conclusion that the country-to-country correlation for the day-ahead forecast errors are currently too low to be accounted for in the methodology (see Figure 30 for load, Figure 32 for PV generation, Figure 31 for onshore wind generation). For similar reason, inter-variable correlations for a given country (i.e. correlations between load and wind, load and solar and wind and solar forecast errors, as illustrated for Germany in Figure 33) were neglected.

Figure 34 to Figure 43 present the graphical comparison of ENTSOE forecast data and WP1 simulated data for 2020 and France, showing how the proposed methodology is able to reproduce the general behaviour of forecast time series.

[28] In theory, time series of hydro generation (especially run-of-river units) and thermal unit unavailability should also be taken into account. In OSMOSE WP1 the uncertainty effect of these two variables was considered to be of second order and neglected.

In the extrapolation step, rules for assessing the evolution of each country's RMSE[29] were derived, especially for countries that currently have little installed VRES capacity, or low thermo-sensitive part in their load. For all these weather-dependent variables, a trend can be observed on 2020 historical data (in log-log scale) between the RMSE and the annual energy. RMSE values for 2030 and 2050 have been obtained by extrapolating this trend[30].

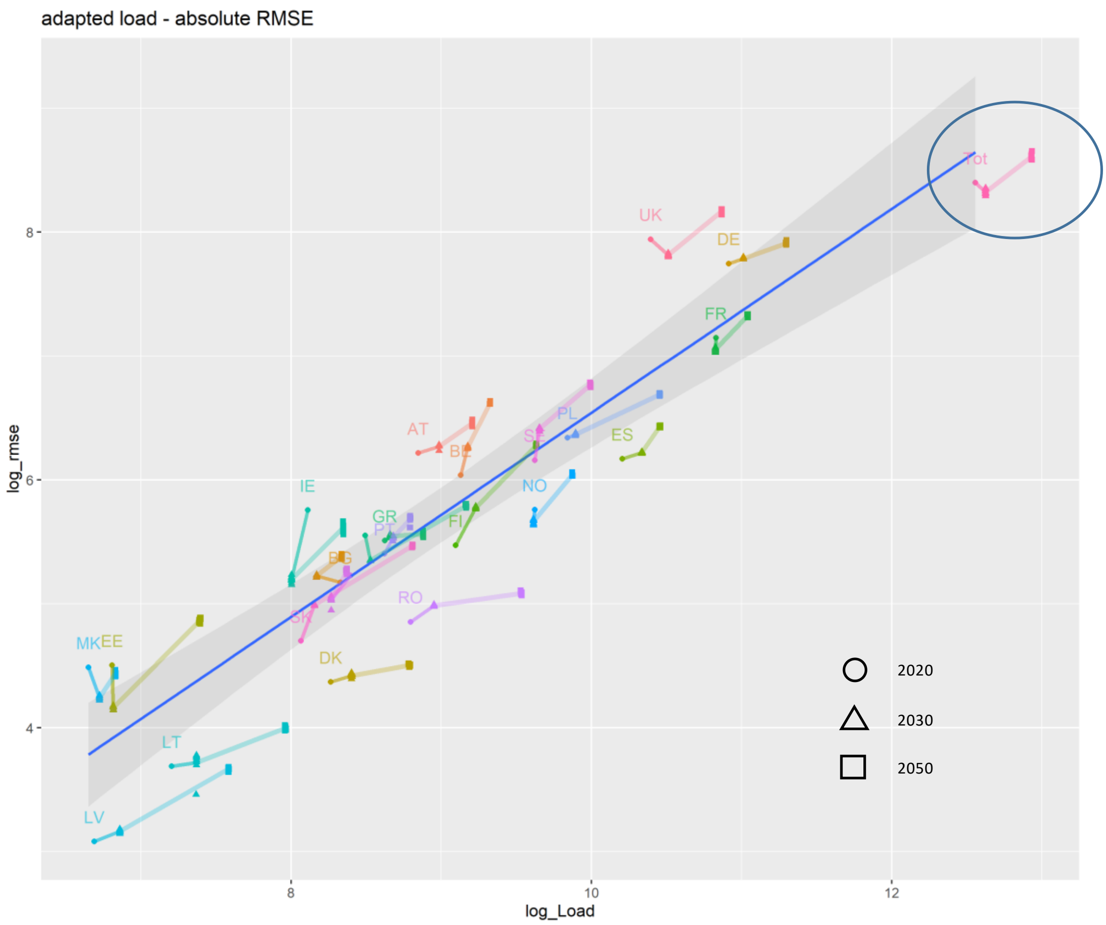


Figure 27: proposed evolution of RMSE for load between 2020 and 2050, for 33 European countries

[29] Root mean square of error, an indicator usually used to measure the accuracy of a forecast.

[30] As far as PV is concerned, the Netherlands are a clear outlier. It was assumed that this behaviour was linked to the fact that PV was an emerging technology in this country, and that the forecast process would mature and harmonize with the neighbouring countries.

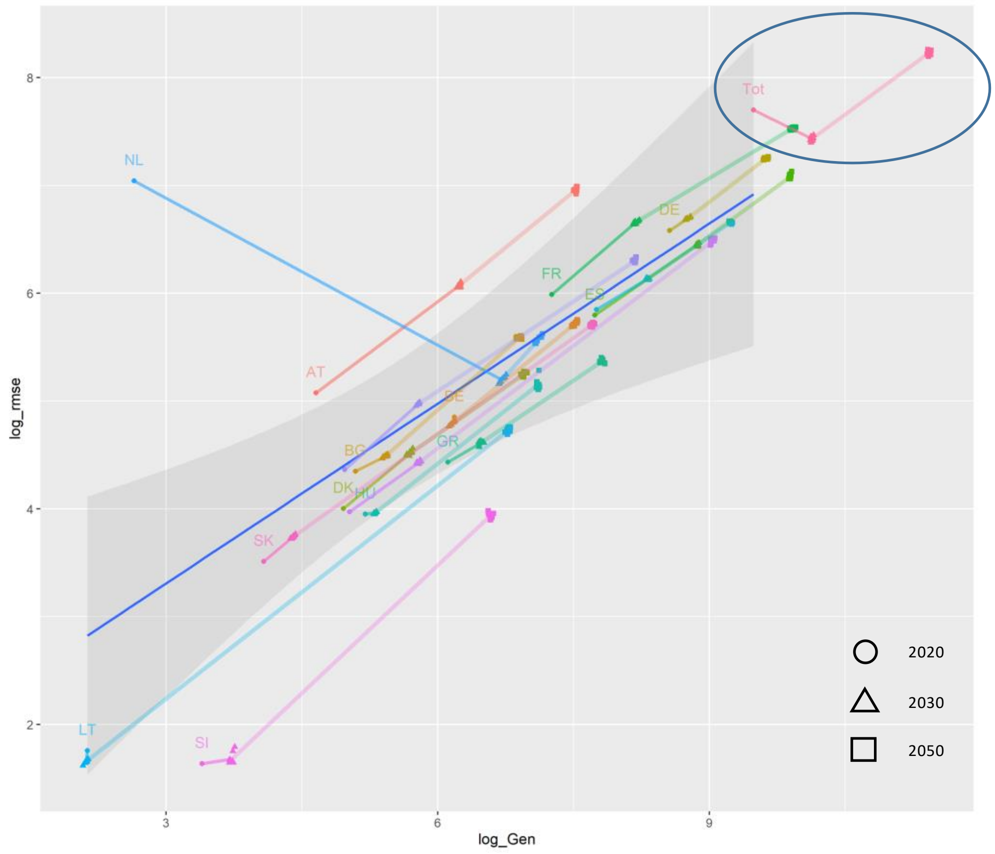


Figure 28: proposed evolution of RMSE for solar generation between 2020 and 2050, for 33 European countries

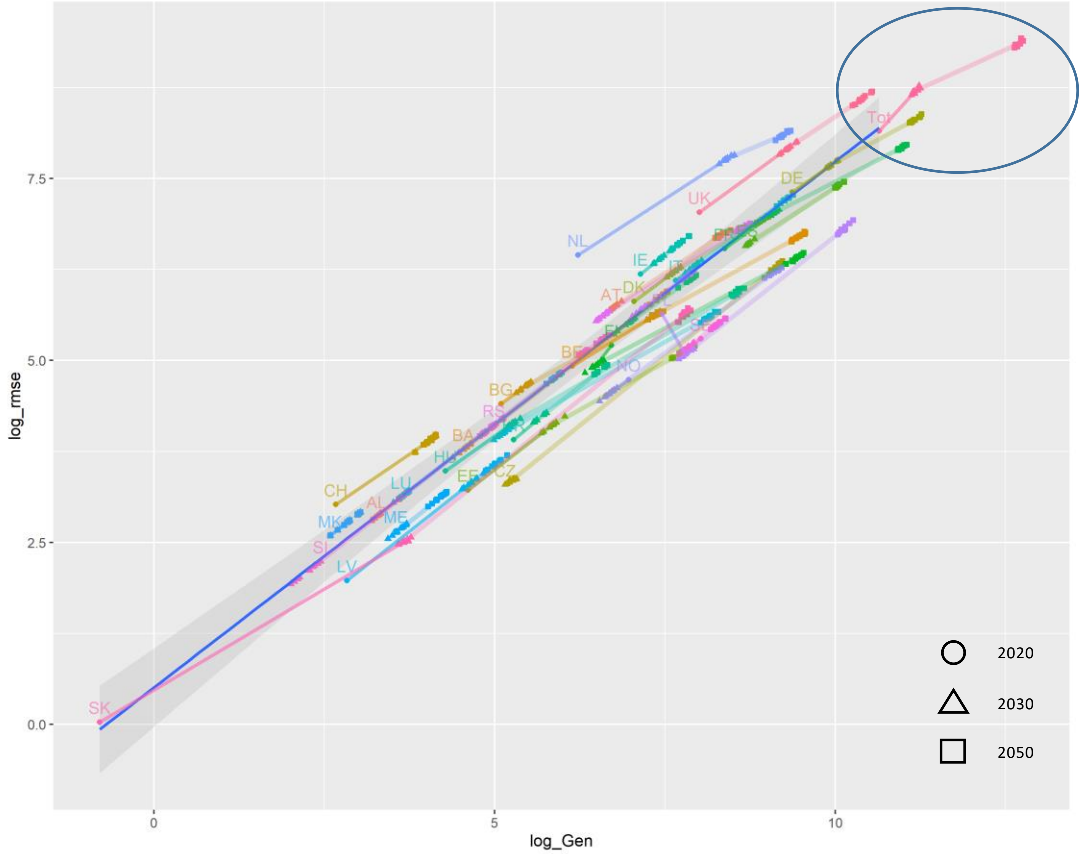


Figure 29: proposed evolution of RMSE for wind generation between 2020 and 2050, for 33 European countries

In the following, data previously used in reference simulations are now considered as measured data (i.e. error free) and referenced as “pseudo-realised data”, whereas the newly produced forecast data are considered as their day-ahead estimations, and “pseudo-forecast data”.

Note also that due to the computational complexity of producing suitable forecast data, only 10 Monte-Carlo-years of pseudo-forecast data have been computed and used OSMOSE WP1.

4.5.3 Qualitative and quantitative analysis of ENTSOE-transparency data

4.5.3.1 Cross-country correlations for load forecast error

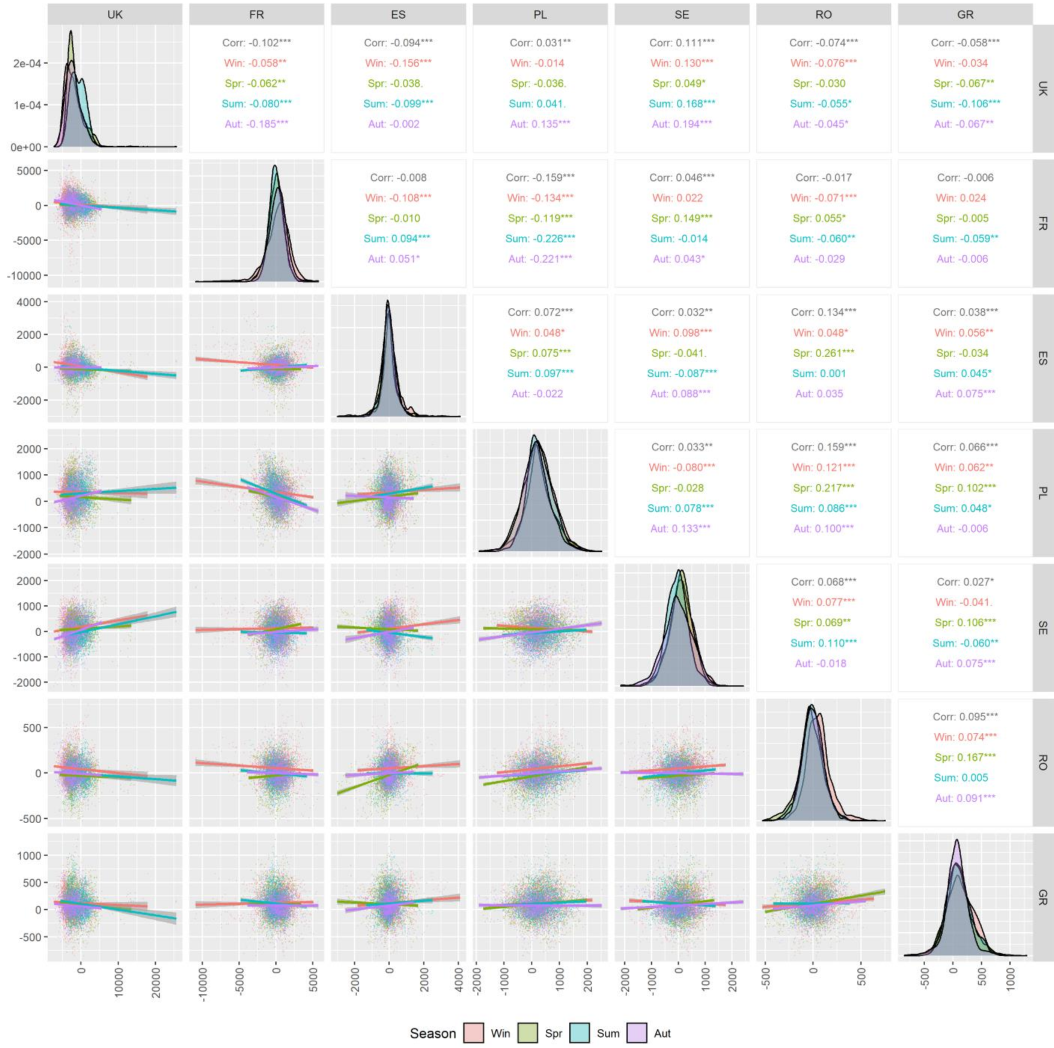


Figure 30: correlation (by season) of load forecast error in ENTSOE data for 2020 for some countries

4.5.3.2 Cross-country correlations for PV forecast error

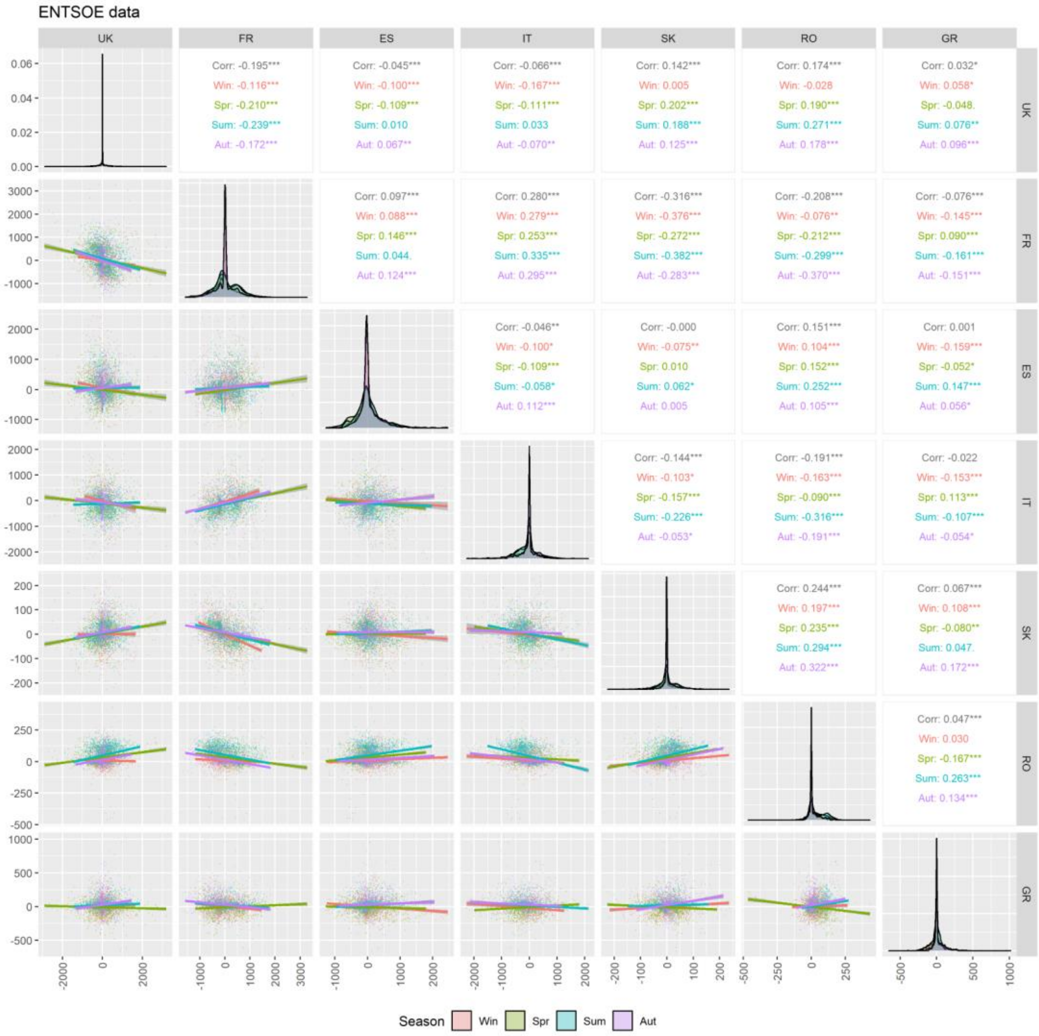


Figure 31: correlation (by season) of solar generation forecast error in ENTSOE data for 2020 for some countries

4.5.3.3 Cross-country correlations for wind forecast error

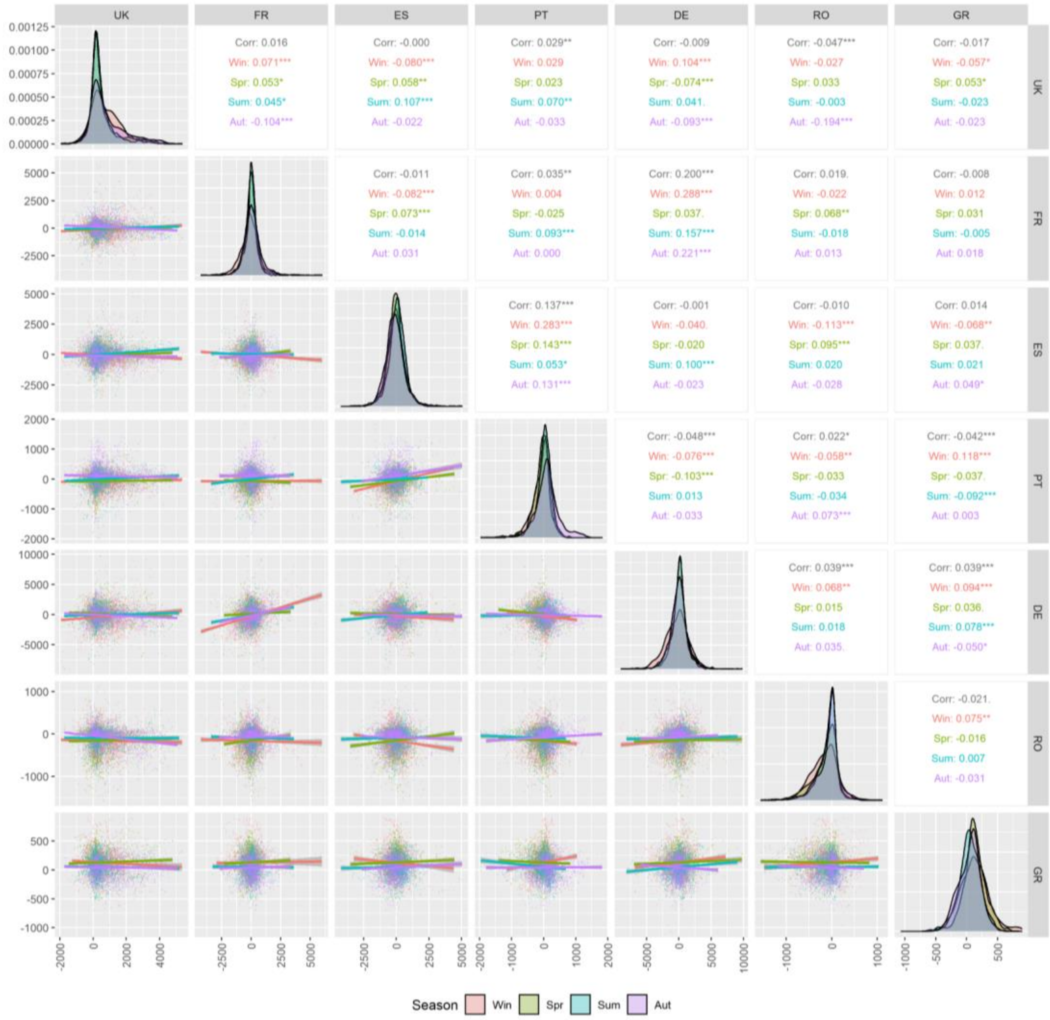


Figure 32: correlation (by season) of onshore wind generation forecast error in ENTSOE data for 2020 for some countries

4.5.3.4 Cross-variable correlation

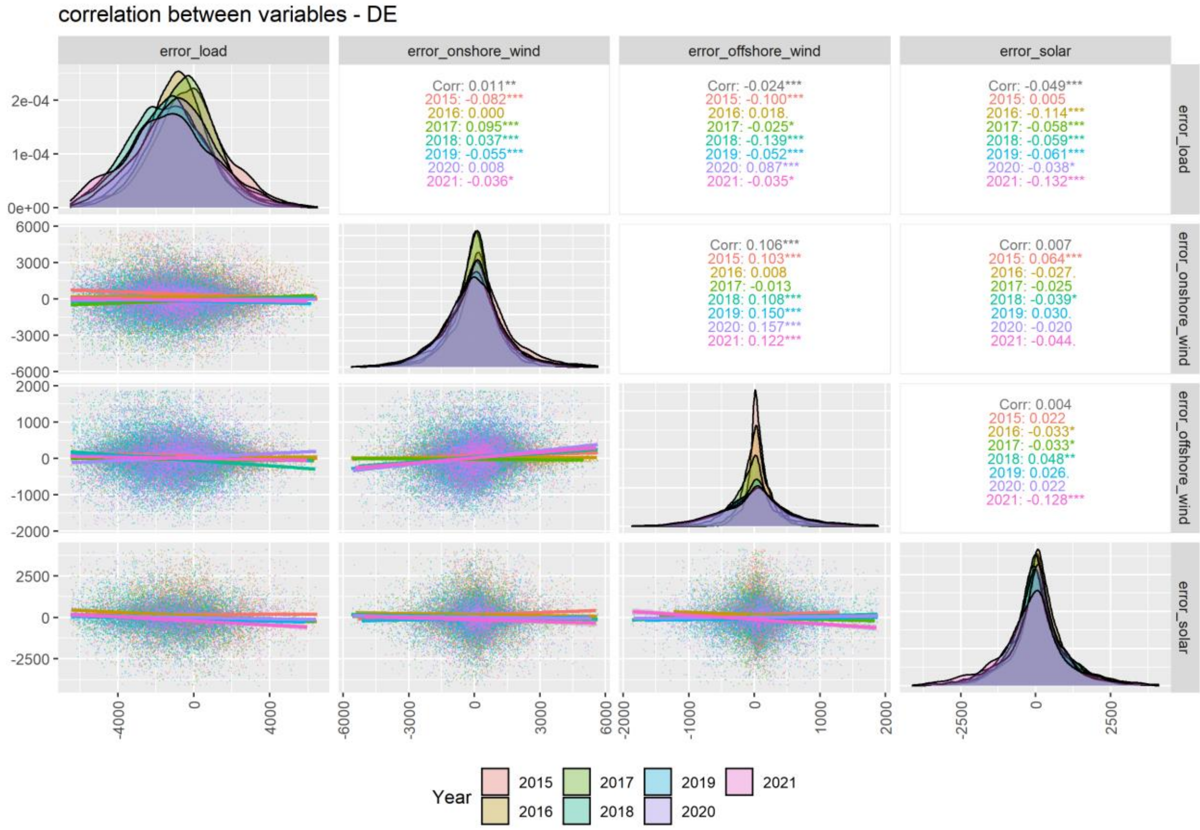


Figure 33: correlation between weather-dependent variables for Germany in 2020

4.5.4 Calibration on 2020 ENTSOE-transparency data

4.5.4.1 Load time-series - winter

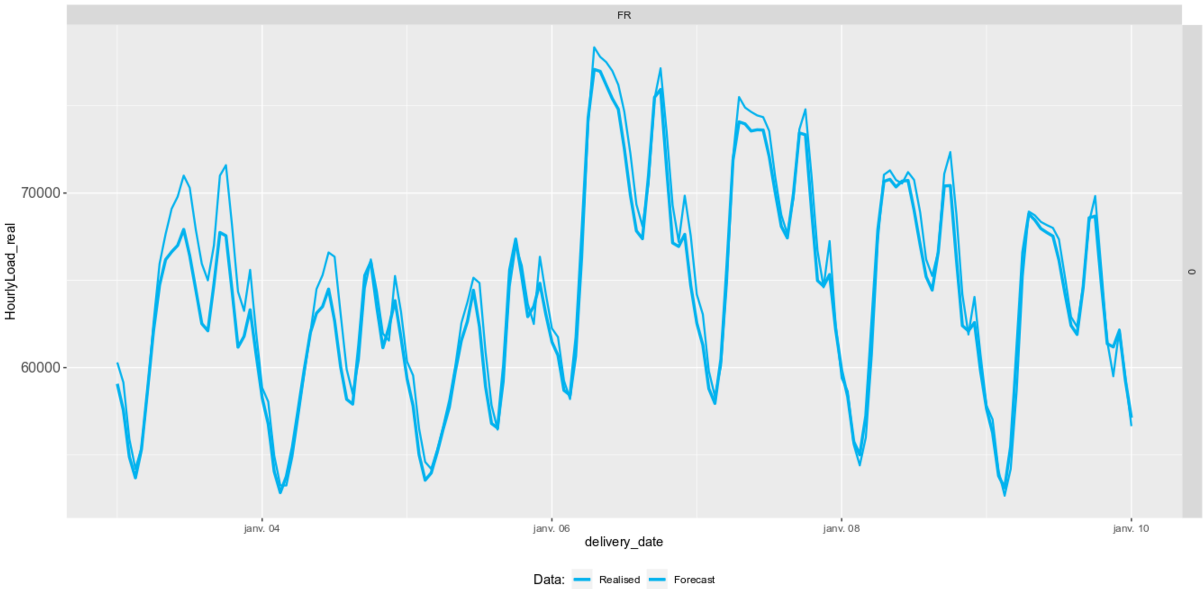


Figure 34: ENTSOE transparency day ahead load forecast time series – France in year 2020 realised data (bold) vs day-ahead forecast (solid)

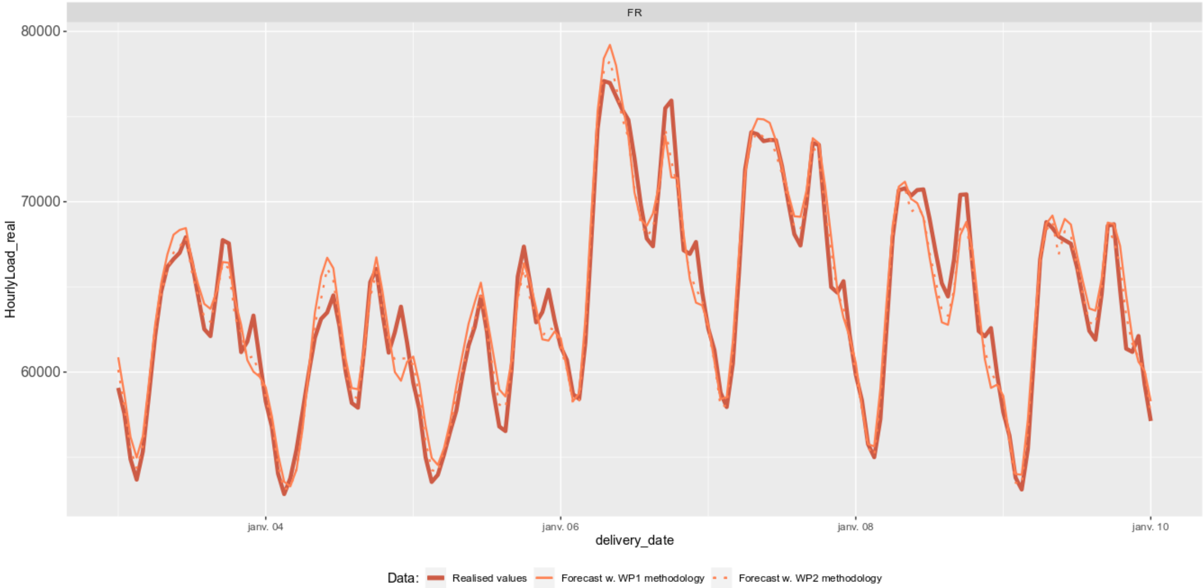


Figure 35: simulation of day ahead load forecast time series – France in year 2020 realised data (bold) vs day-ahead forecast in WP2 (dotted) vs adapted day-ahead forecast in WP1 (solid)

4.5.4.2 PV generation time series - winter

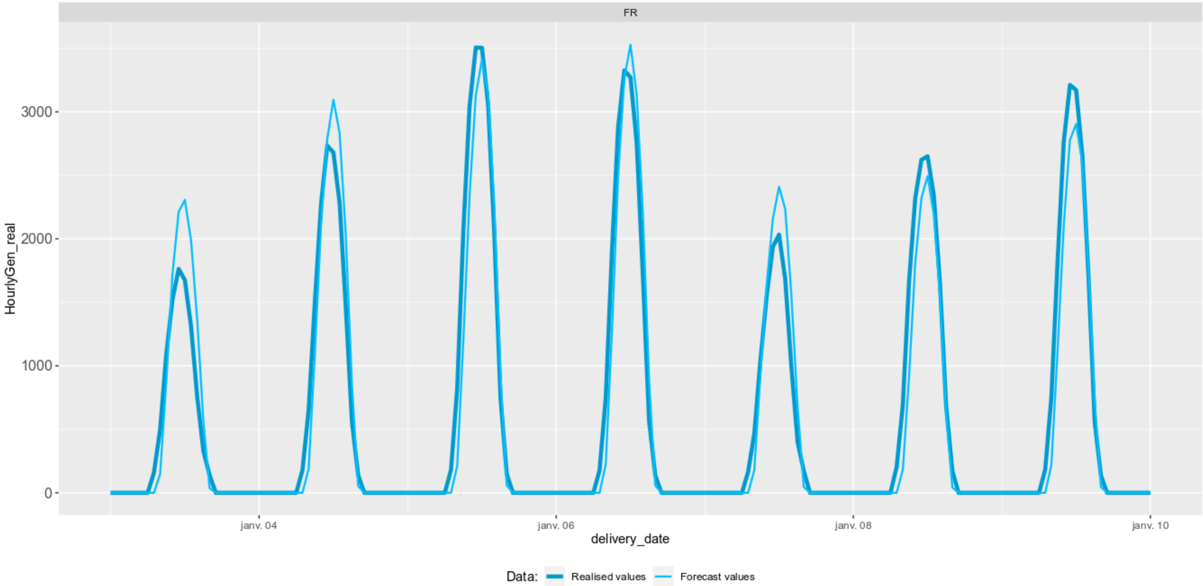


Figure 36: ENTSOE transparency day ahead solar generation forecast time series – France in year 2020 realised data (bold) vs day-ahead forecast (solid)

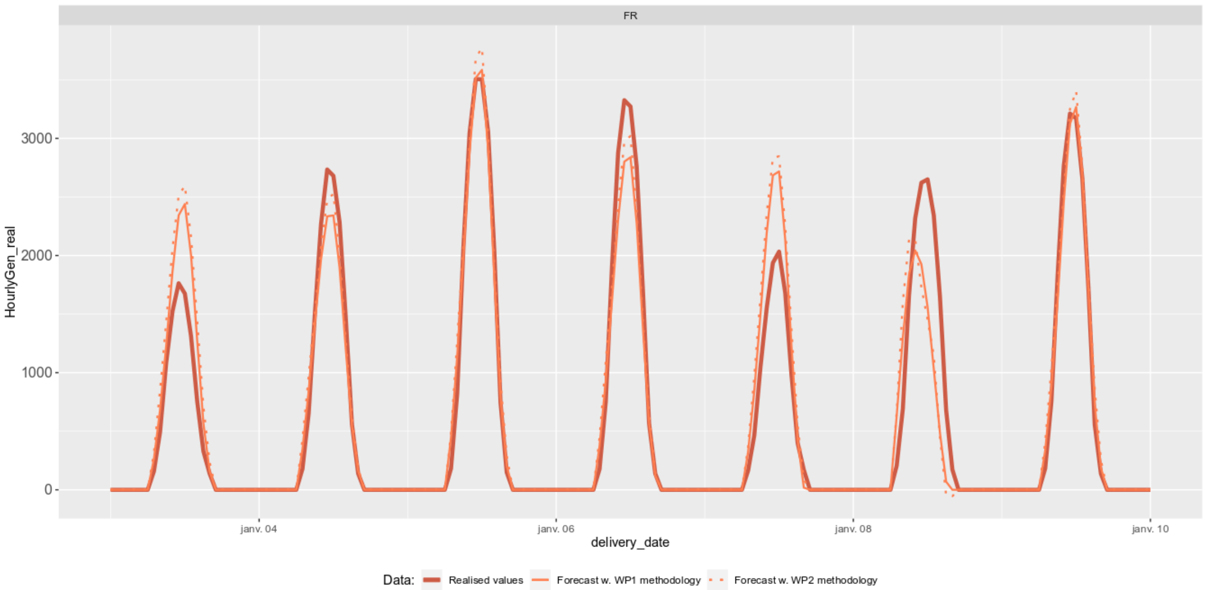


Figure 37: simulation of day ahead solar generation forecast time series – France in year 2020 realised data (bold) vs day-ahead forecast in WP2 (dotted) vs adapted day-ahead forecast in WP1 (solid)

4.5.4.3 Wind generation time-series - Winter

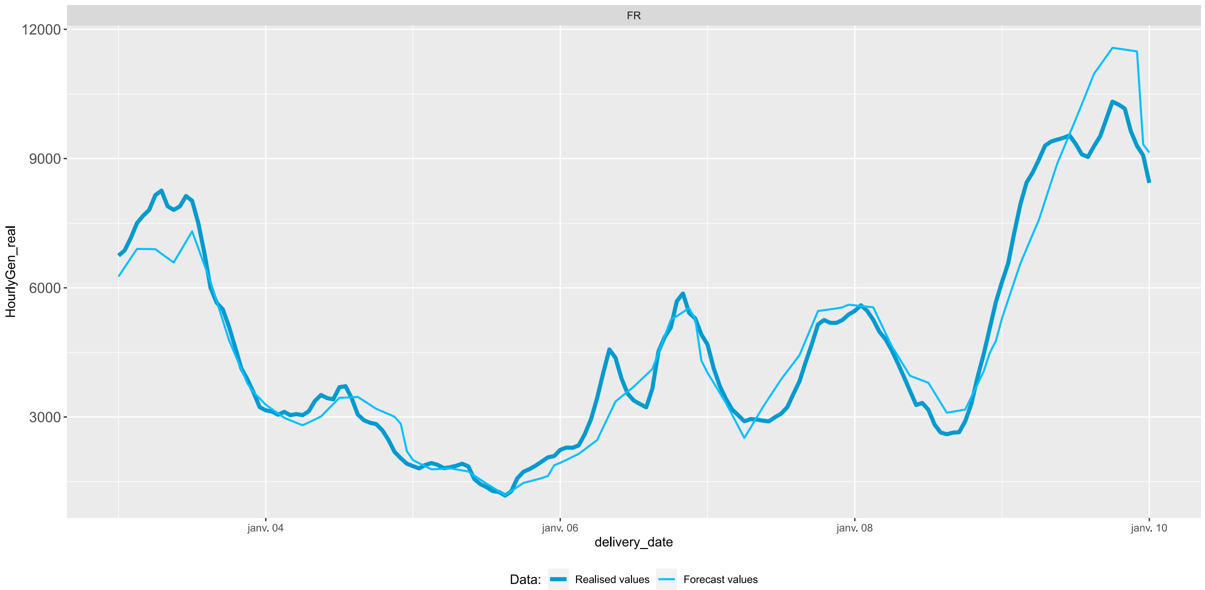


Figure 38: ENTSOE transparency day ahead wind generation forecast time series – France in year 2020 realised data (bold) vs day-ahead forecast (solid)

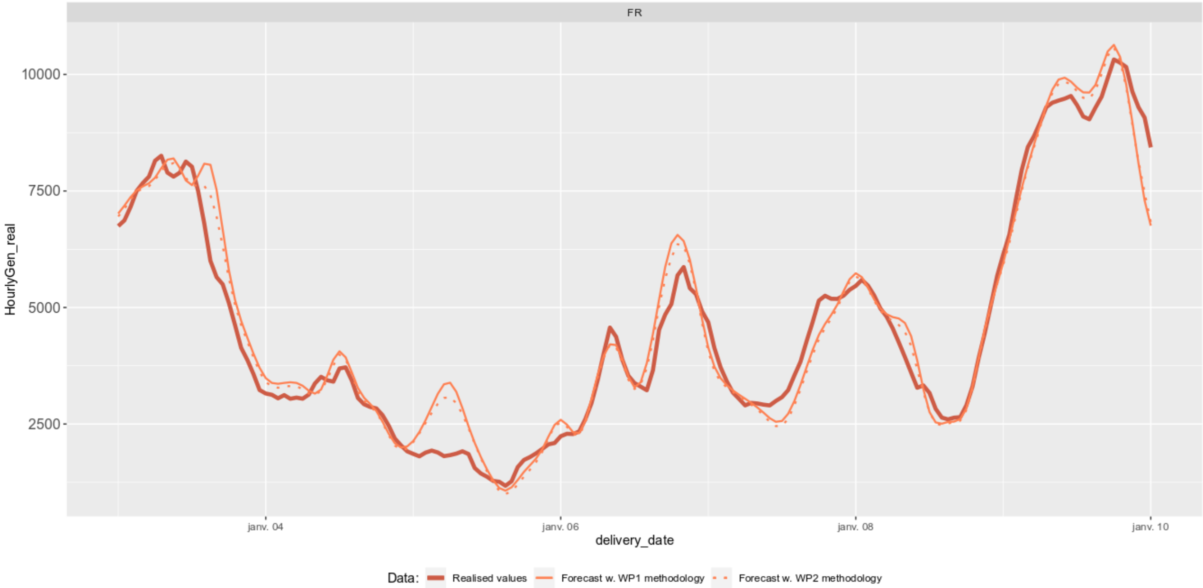


Figure 39: simulation of day ahead wind generation forecast time series – France in year 2020 realised data (bold) vs day-ahead forecast in WP2 (dotted) vs adapted day-ahead forecast in WP1 (solid)

4.5.4.4 Temporal autocorrelations for load forecast error

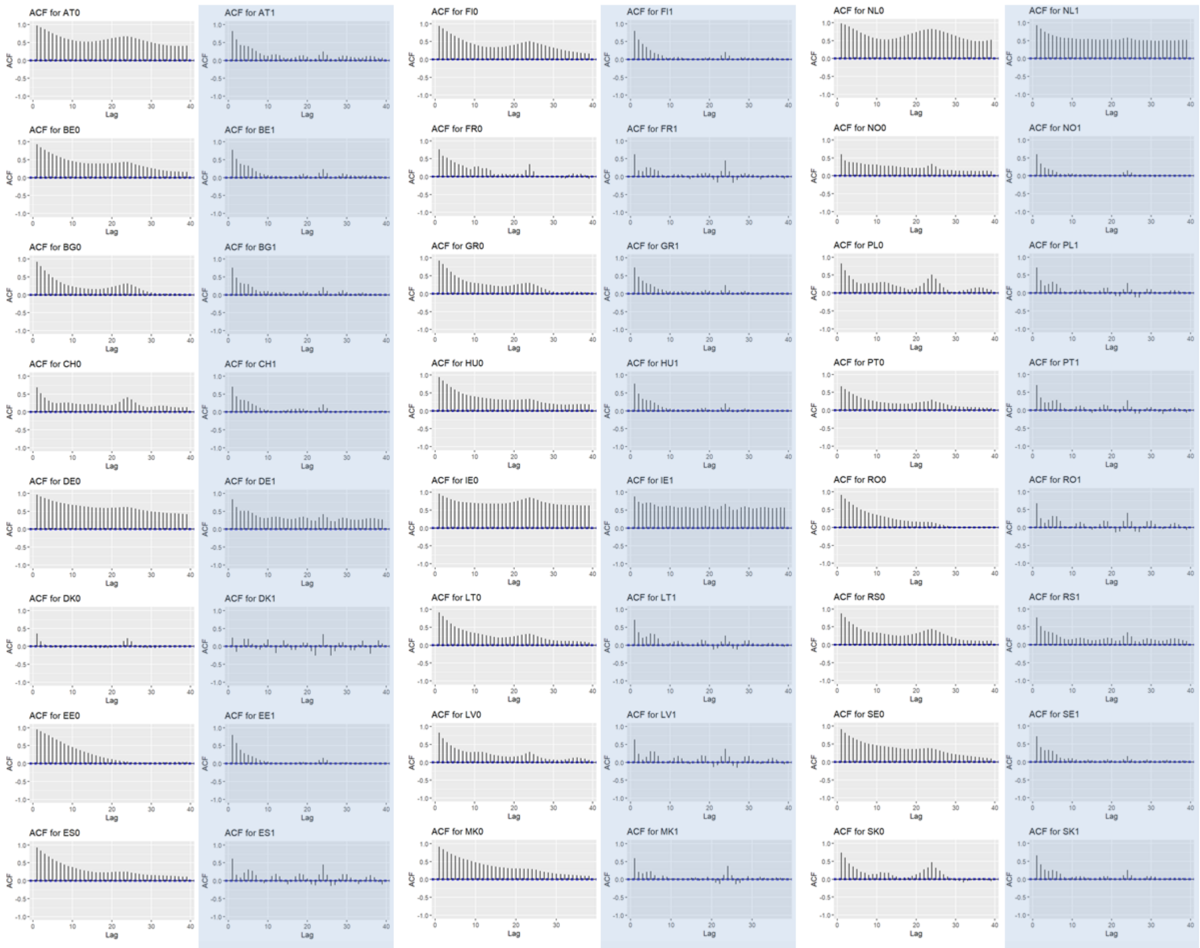


Figure 40: ENTSOE load forecast error – European countries for year 2020 ENTSOE data (white) vs simulated data (blue)

4.5.4.5 Temporal autocorrelations for PV generation forecast error

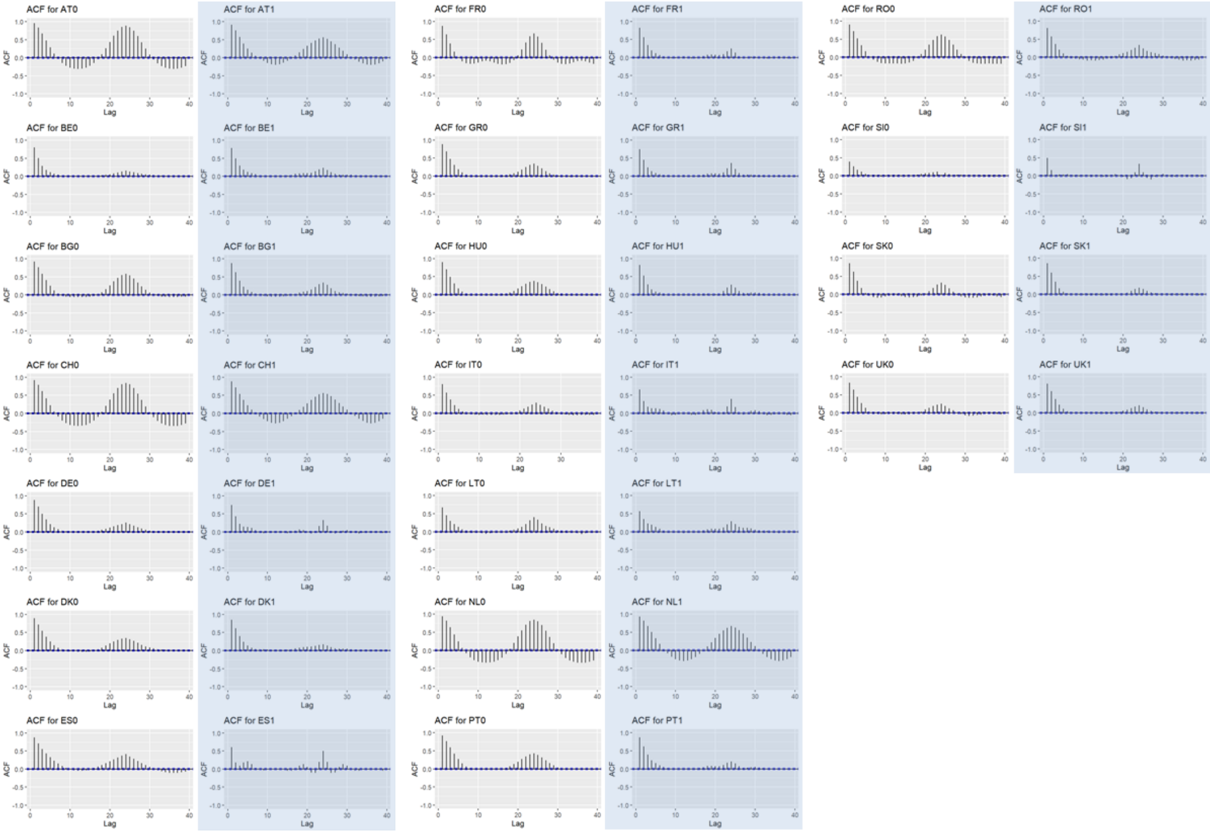


Figure 41: ENTSOE PV generation forecast error – European countries for year 2020 ENTSOE data (white) vs simulated data (blue)

4.5.4.6 Temporal autocorrelations for wind generation forecast error

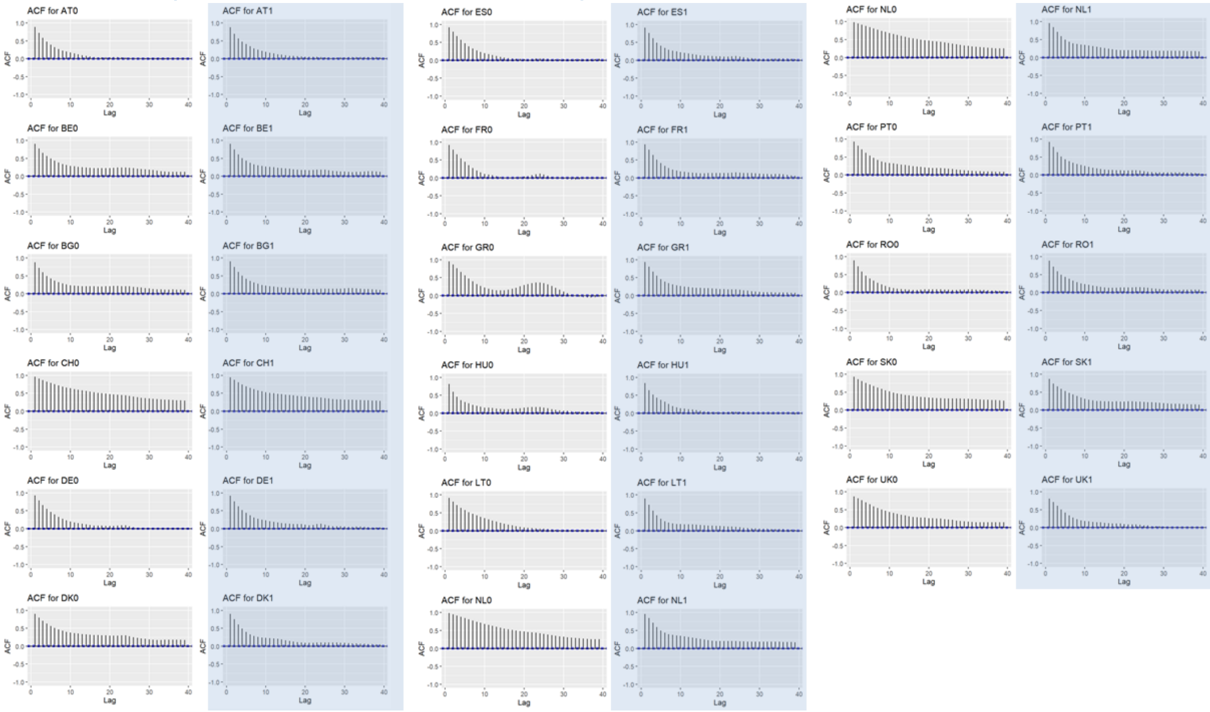


Figure 42: ENTSOE PV generation forecast error – European countries for year 2020
ENTSOE data (white) vs simulated data (blue)

4.5.4.7 Load duration curve for load forecast

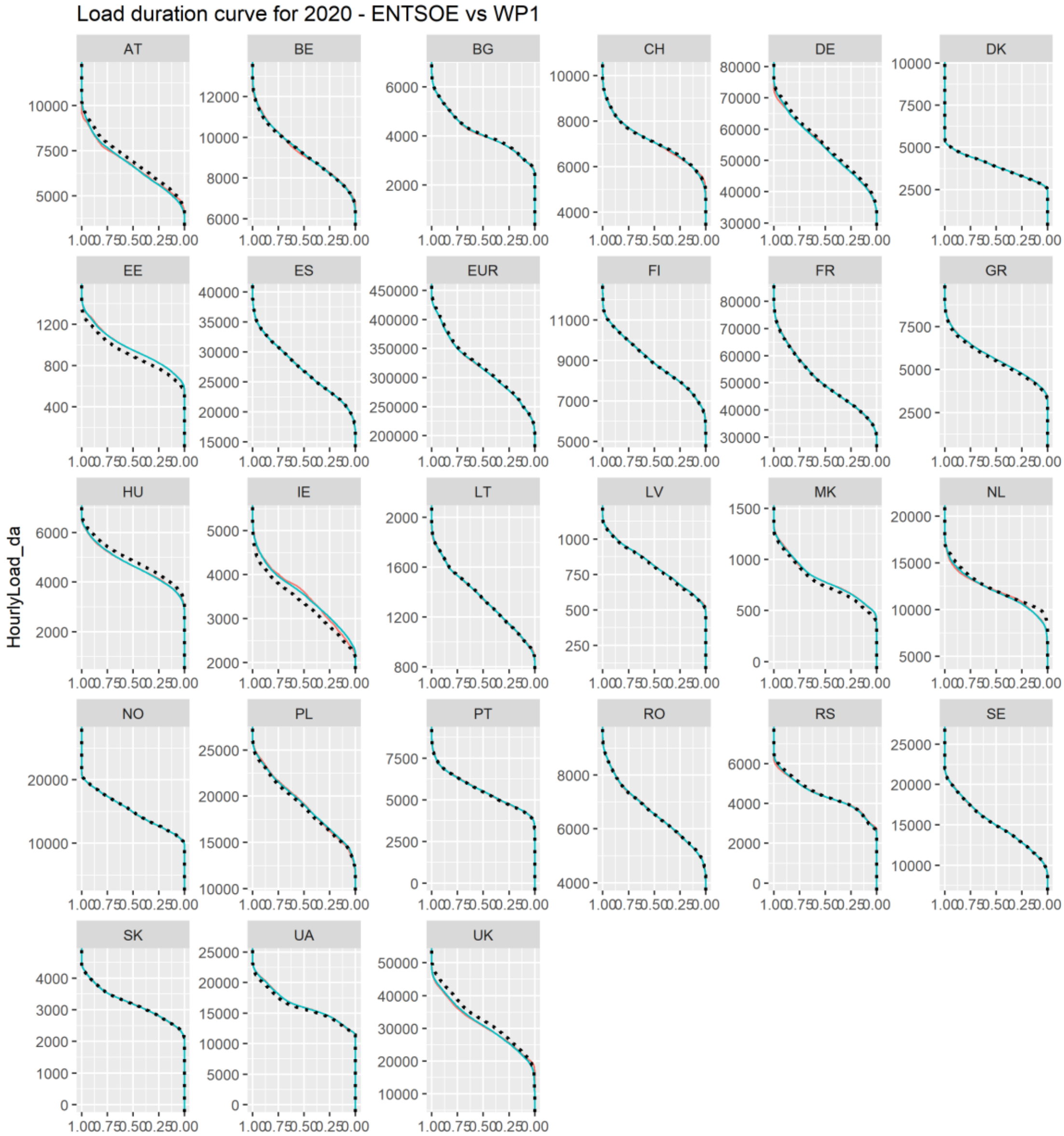


Figure 43: Load duration curve for load – European countries for year 2020 realised data (dot) vs ENSTOE forecast (red) vs WP1 simulated forecast (blue)

4.5.4.8 Load duration curve for wind generation forecast

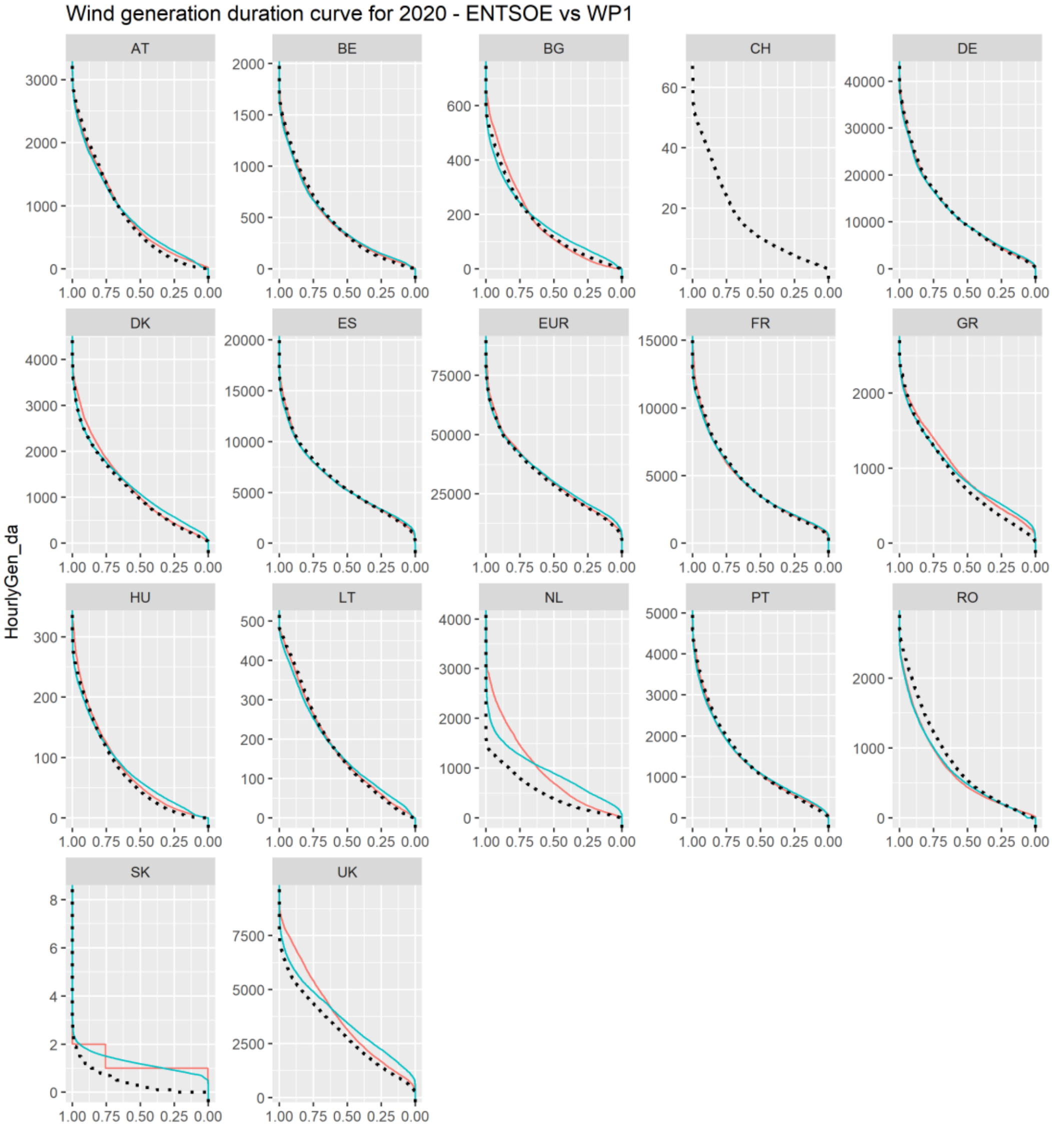


Figure 44: Load duration curve for wind generation – European countries for year 2020 realised data (dot) vs ENSTOE forecast (red) vs WP1 simulated forecast (blue)

4.5.4.9 Load duration curve for PV generation forecast

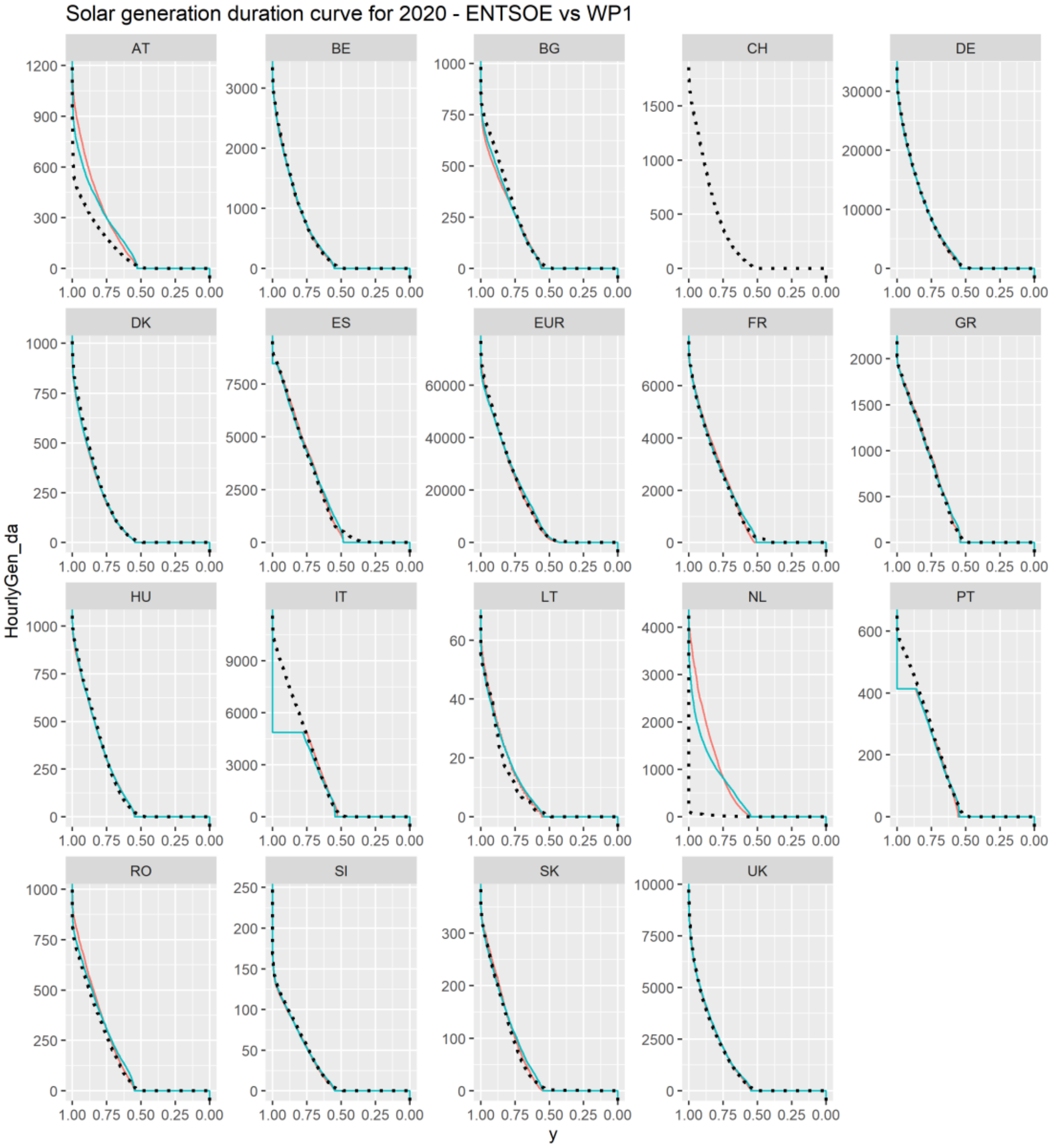


Figure 45: Load duration curve for solar generation – European countries for year 2020 realised data (dot) vs ENSTOE forecast (red) vs WP1 simulated forecast (blue)

4.5.4.10 Load forecast errors

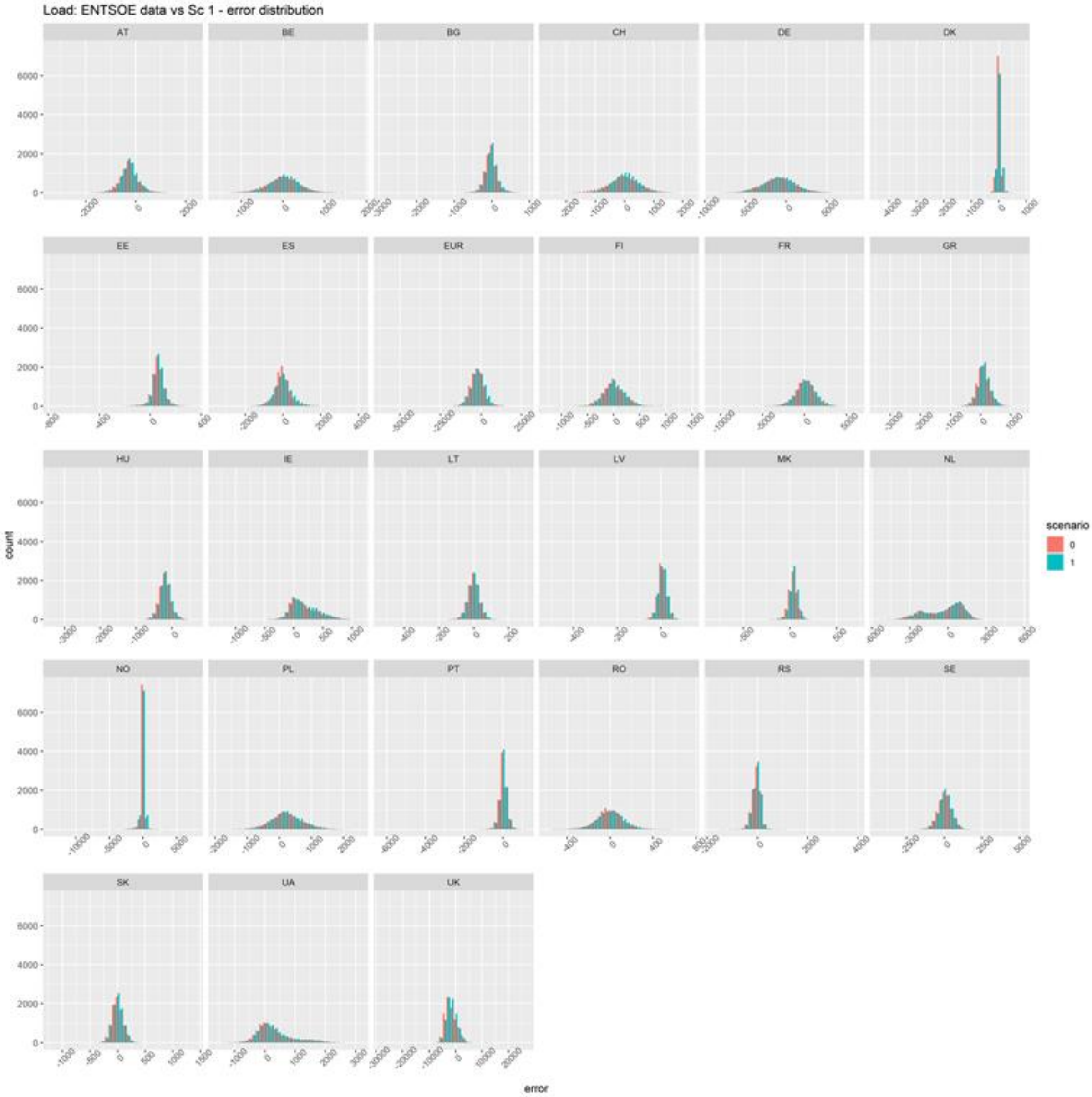


Figure 46: Forecast errors distribution for load – European countries for year 2020 ENSTOE forecast (red) vs WP1 simulated forecast (blue)

4.5.4.11 PV generation forecast errors

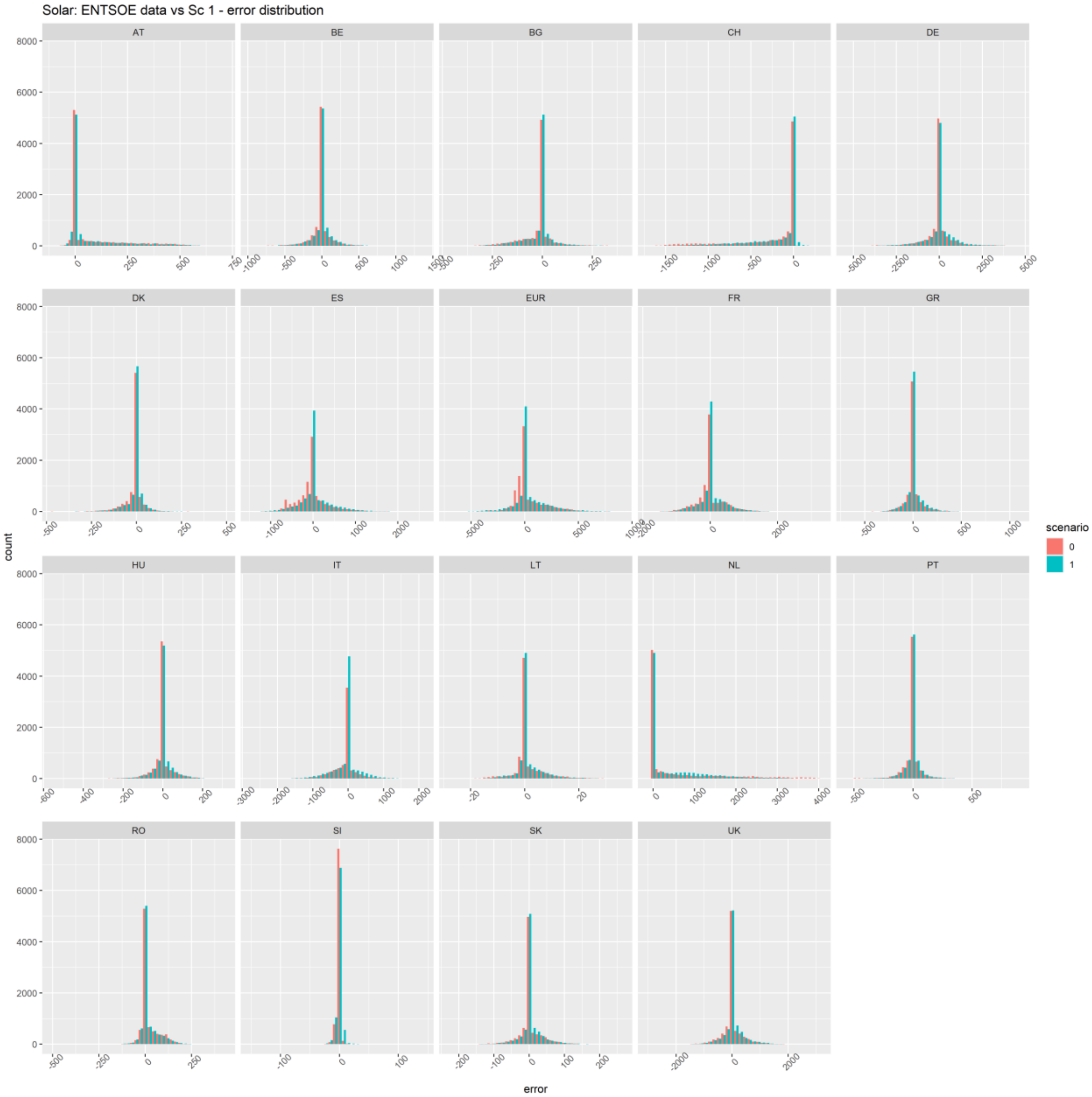


Figure 47: Forecast errors distribution for PV generation – European countries for year 2020 ENSTOE forecast (red) vs WP1 simulated forecast (blue)

4.5.4.12 Wind generation forecast errors

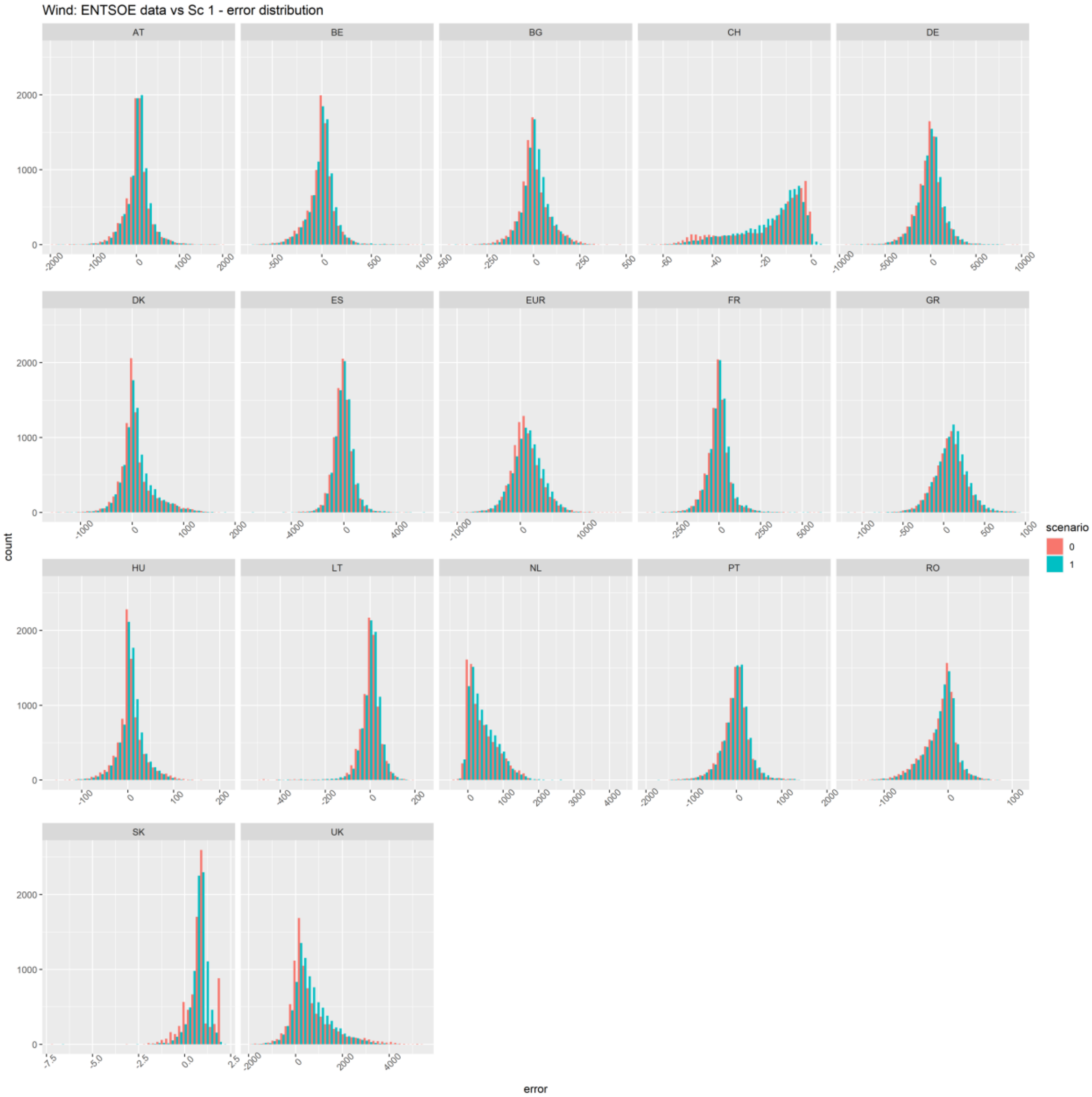


Figure 48: Forecast errors distribution for wind generation – European countries for year 2020 ENSTOE forecast (red) vs WP1 simulated forecast (blue)

4.5.5 Application to 2030

4.5.5.1 Load time-series – winter and summer weeks

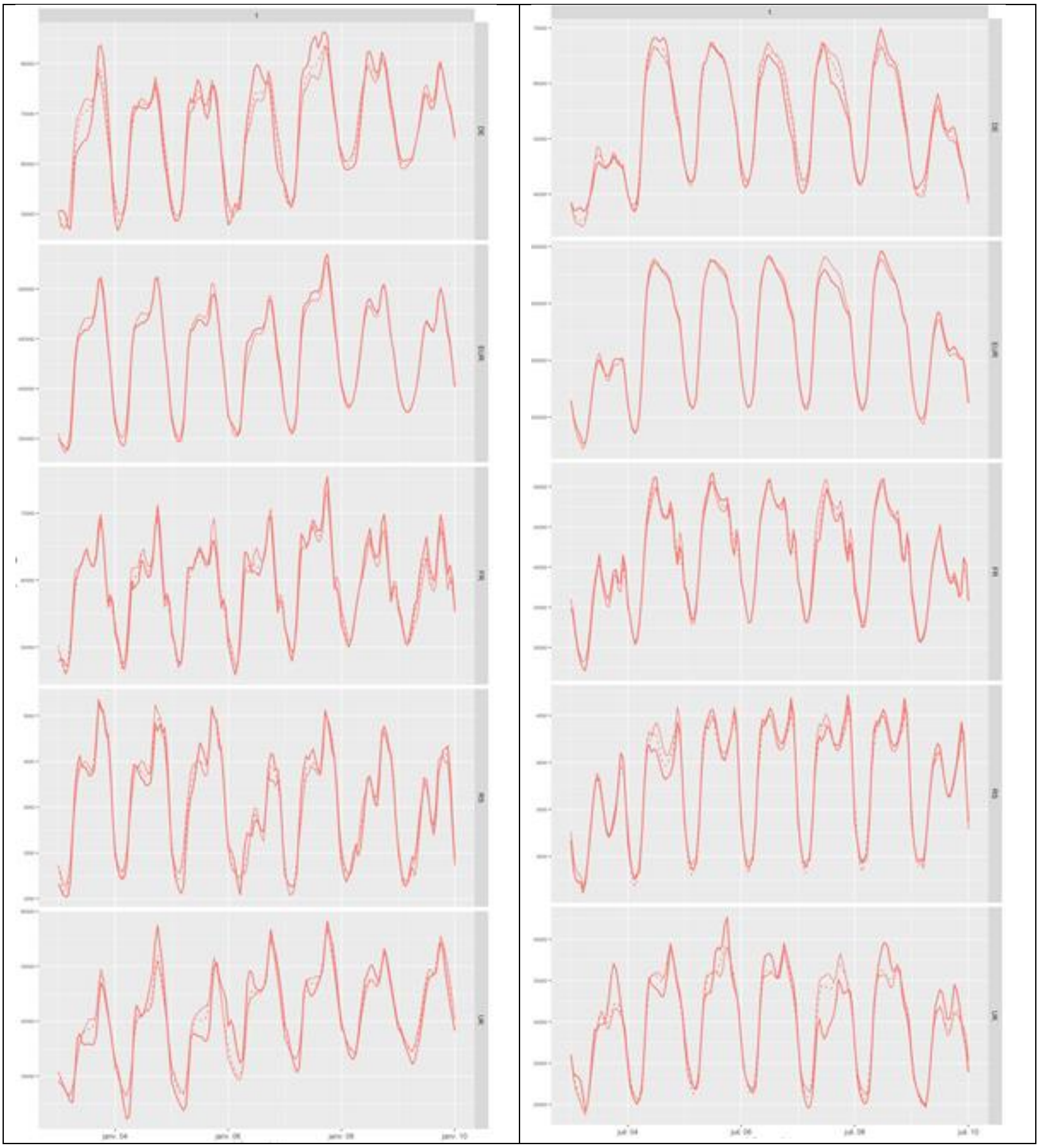


Figure 49: load pseudo-day-ahead-forecast and pseudo-realised for some European countries for 2030-pseudo-realised TS (bold) vs pseudo day-ahead-forecast (solid) vs WP2 pseudo day-ahead-forecast (dash)

4.5.5.2 PV generation time series – winter and summer weeks

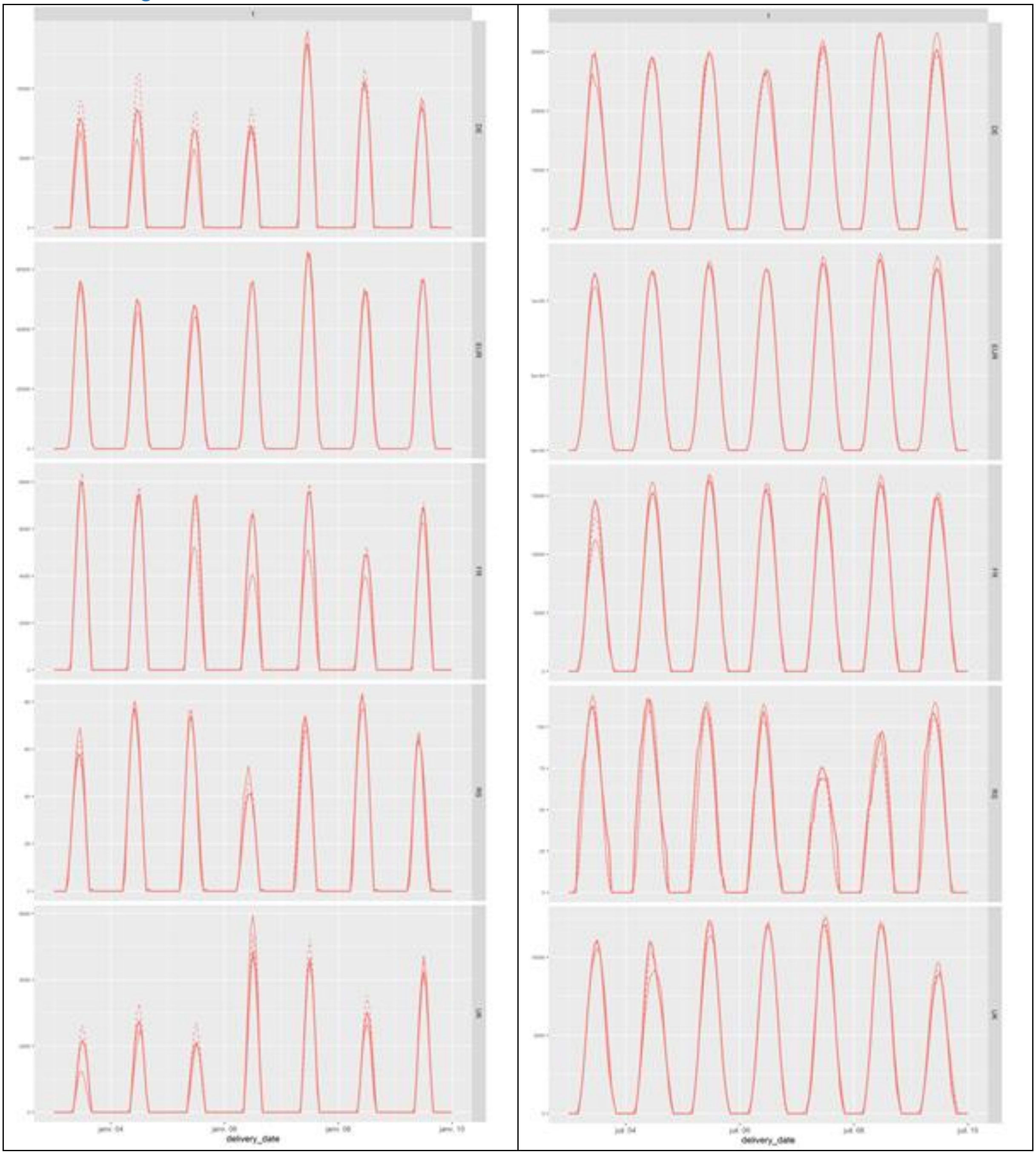


Figure 50: PV generation pseudo-day-ahead-forecast and pseudo-realised for some European countries for 2030- pseudo-realised TS (bold) vs pseudo day-ahead-forecast (solid) vs WP2 pseudo day-ahead-forecast (dash)

4.5.5.3 Wind generation time-series – winter and summer weeks

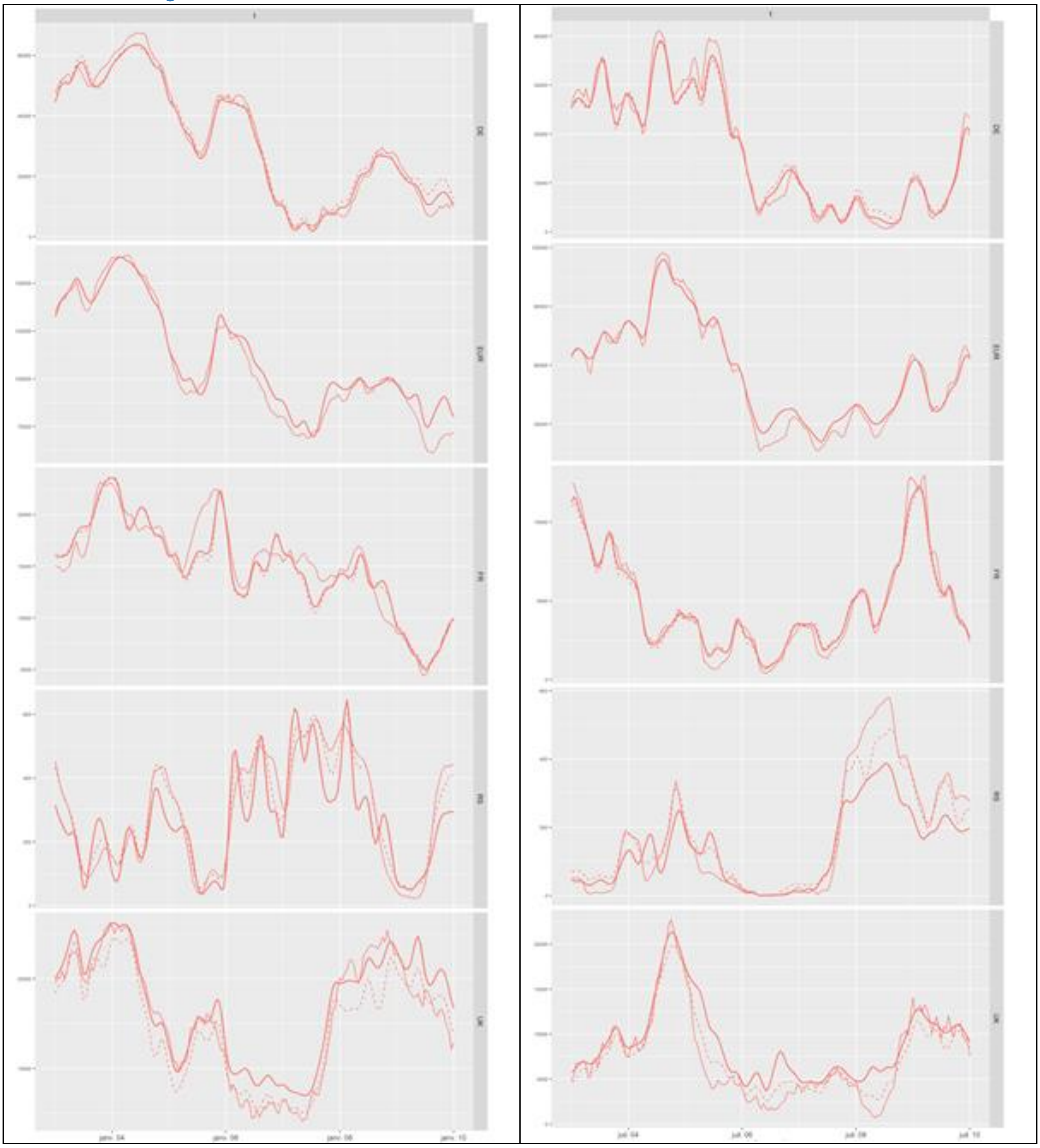


Figure 51: wind generation pseudo-day-ahead-forecast and pseudo-realised for some European countries for 2030-
pseudo-realised TS (bold) vs pseudo day-ahead-forecast (solid) vs WP2 pseudo day-ahead-forecast (dash)

4.5.6 Application to 2050

4.5.6.1 Load time-series – winter and summer weeks

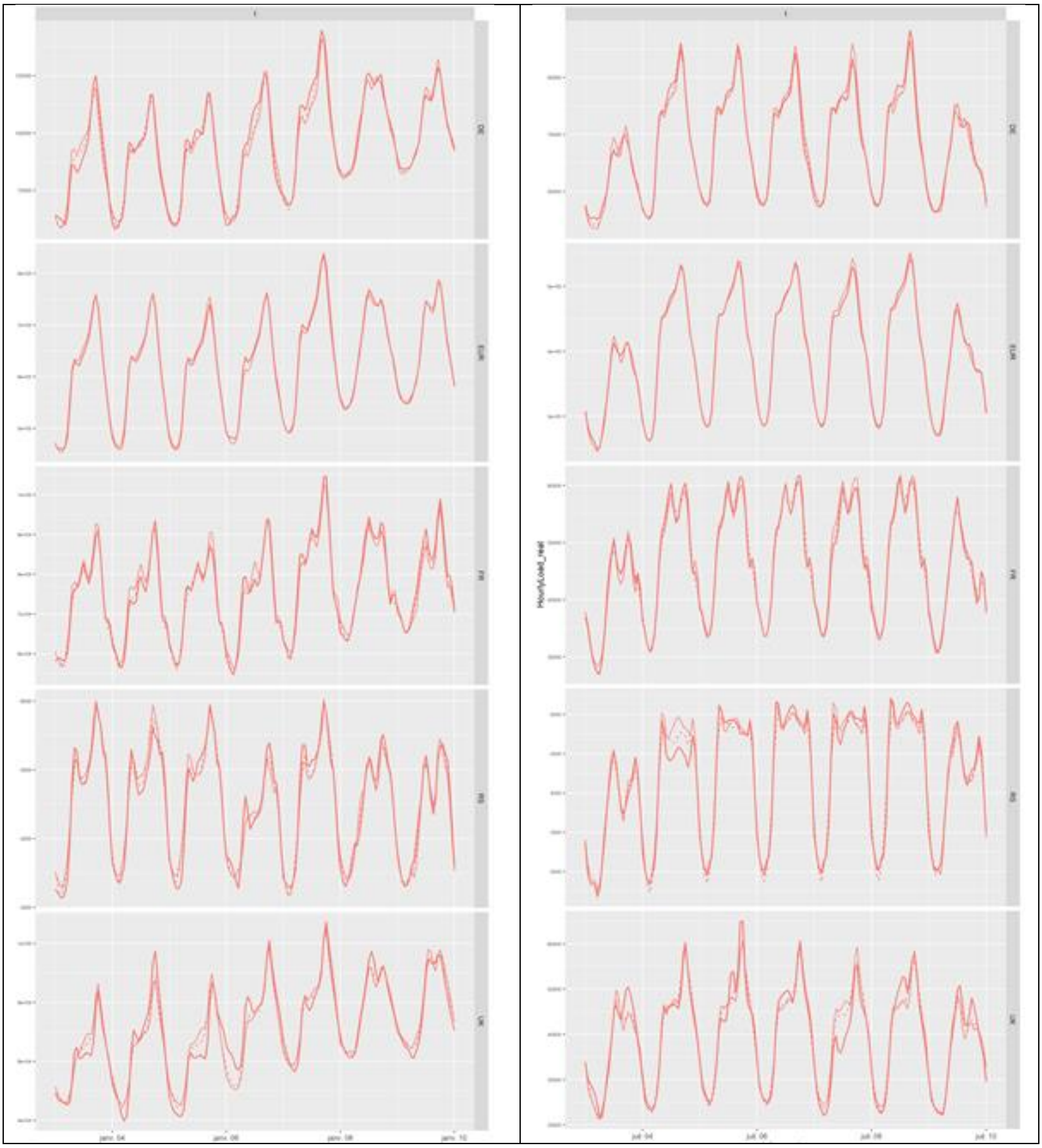


Figure 52: load pseudo-day-ahead-forecast and pseudo-realised for some European countries for 2050- pseudo-realised TS (bold) vs pseudo day-ahead-forecast (solid) vs WP2 pseudo day-ahead-forecast (dash)

4.5.6.2 PV generation time series – winter and summer weeks

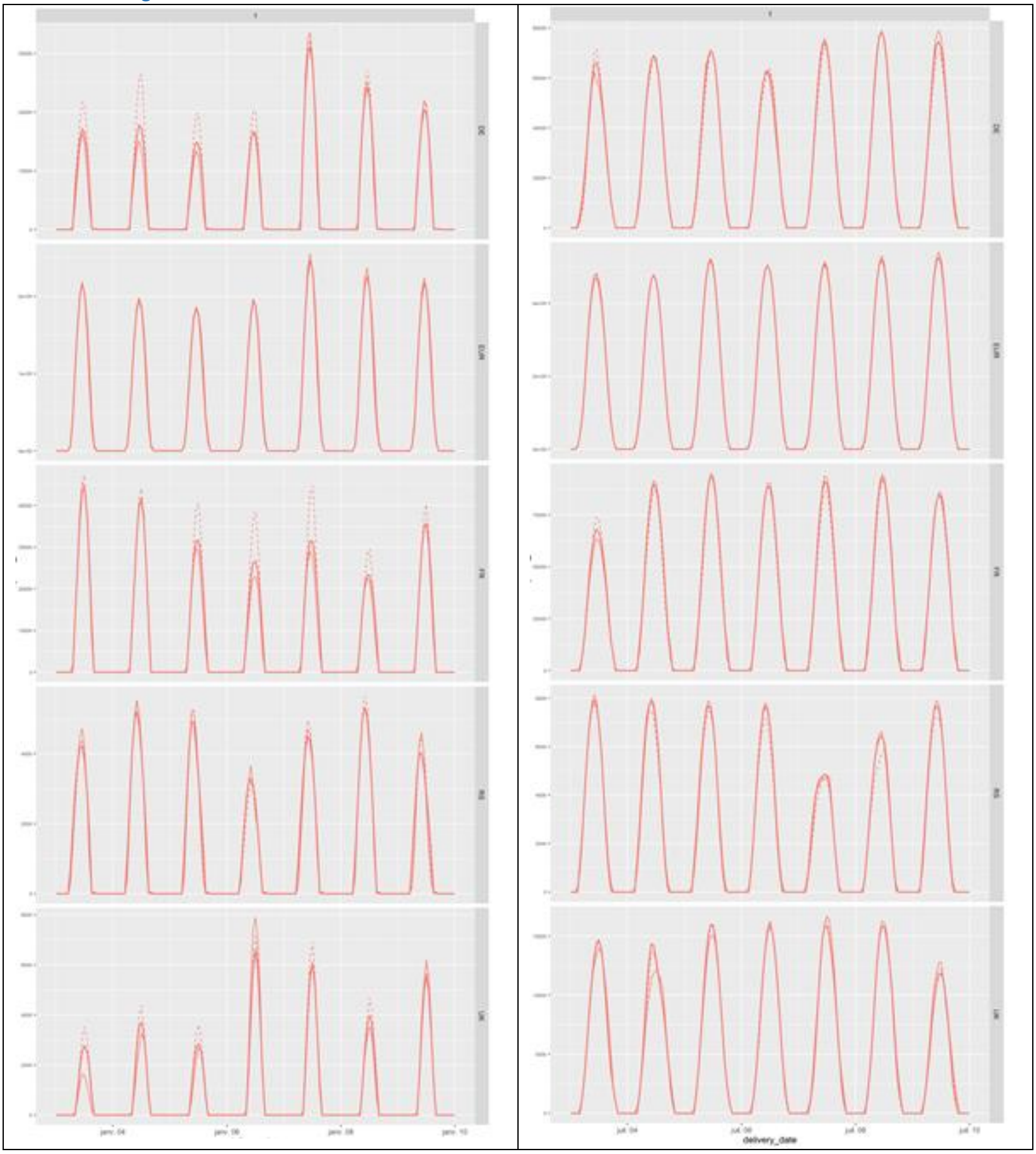


Figure 53: PV generation pseudo-day-ahead-forecast and pseudo-realised for some European countries for 2050- pseudo-realised TS (bold) vs pseudo day-ahead-forecast (solid) vs WP2 pseudo day-ahead-forecast (dash)

4.5.6.3 Wind generation time-series – winter and summer weeks

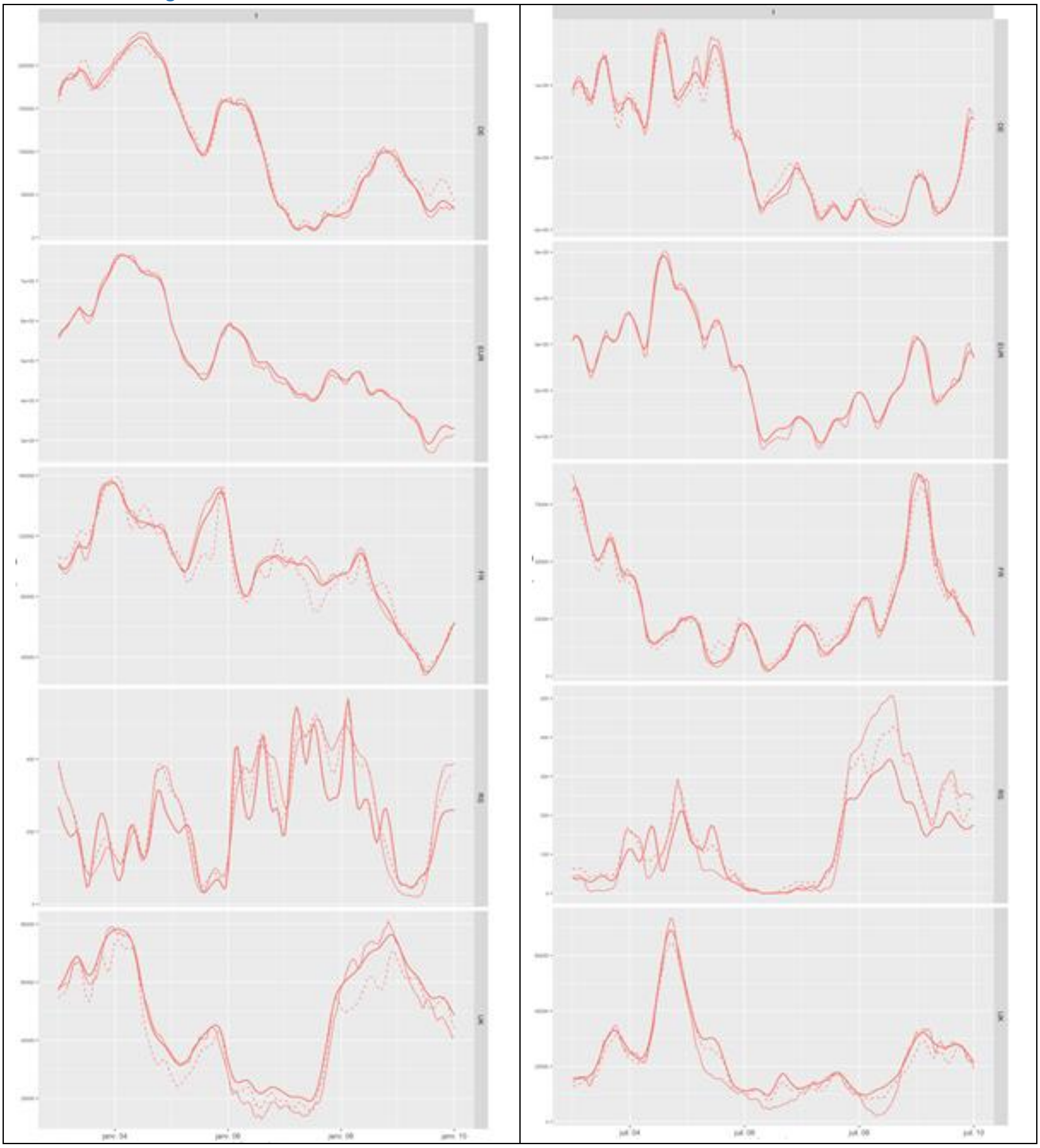


Figure 54: wind generation pseudo-day-ahead-forecast and pseudo-realised for some European countries for 2050-
pseudo-realised TS (bold) vs pseudo day-ahead-forecast (solid) vs WP2 pseudo day-ahead-forecast (dash)

4.6 File formats

All time series are provided as text files organised as tabular (csv) formats.

4.6.1 Time structure for load

In WP1 and compliantly with a target year of 2050[31], all weather year are aligned with 2050[32]:

[31] The calendar logic of H2020 Plan4RES has been retained in OSMOSE WP1.

[32] For convenience with respect to CS3 origin, the weather years are referred to as "1982" to "2016"

- the first day of all load time series is a Saturday
- the year is a non-leap year.

When generating the load time series, the Plan4RES team decided to use the C3S dataset:

- starting from the first January of the C3S dataset
- "filling" the calendar in chronological order[33]

As a consequence:

- In the WP1 "2010" load time series (2010 is a "normal" non-leap year),
  - 2050/02/05 is based on 2010/02/05 weather conditions,
  - 2050/03/05 is based on 2010/03/05 weather conditions,
  - And so on…
- In the WP1 "2016" load time series (2016 is leap year),
  - 2050/02/05 is based on 2016/02/05 weather conditions,
  - 2050/03/05 is based on 2016/03/**04** weather conditions,
  - And so on…

4.6.2 Time structure for VRES

In WP1 and compliantly with a target year of 2050[34], all weather year are aligned with 2050[35]:

- the first day of all load time series is a Saturday
- the year is a non-leap year.

In PECD, in order to address leap year issue, the original February 29 was shifted to March 01. We need to re-establish time consistency with load data. The assumption is that the consistency is ensured by the Plan4RES time reference.

As a consequence, for leap year and for RES:

- March 02 PECD => March 01 WP1
- December 30 PECD => December 29 WP1
- December 31 PECD => December 30 WP1
- December 31 WP1 => December 30 WP1 (replication)

4.6.3 Load – non thermosensitive factor

Non thermosensitive load factors are provided in:

- One file containing every country (33)
  - For each country, one 8760 hour time series for the considered horizon[36].

Name	Content
country	country name (2-letter ISO code)
time_id	time Id (from 1 to 8 760)

[33] Ex: in the WP1 "2010" load time series, 2050/02/05 is based on 2010/02/05 weather conditions.

[34] The calendar logic of H2020 Plan4RES has been retained in OSMOSE WP1.

[35] For convenience with respect to CS3 origin, the weather years are referred to as "1982" to "2016"

[36] The target year is assumed to be 2050, though no climate change effect is present is this dataset. As 2050 is not a leap year, one OSMSOSE year corresponds to 365 days, i.e. 8760 hours.

Name	Content
non_thermosensitive	hourly factor of the non thermosensitive part of the country load (between 0.0 and 1.0)[37]

4.6.4 Load – thermosensitive part

Thermosensitive load factors are provided in:

- 35 files, each of which corresponds to a Monte Carlo year
  - Each file containing every country (33) for the given Monte Carlo year
  - For each country, one 8760 hour time series for the given Monte Carlo year and the considered horizon[38].

Name	Content
country	country name (2-letter ISO code)
timestamp	time stamp of the historical weather data (YYYY-MM-DD hh:mm:ss)
time_id	time Id (from 1 to 8 760)
heating_coeff	hourly factor of the thermosensitive part of the country load (between 0.0 and 1.0)[39]

4.6.5 Load – electric vehicles

Electric vehicles load factors are provided in:

- 35 files, each of which corresponds to a Monte Carlo year
  - Each file containing every country (33) for the given Monte Carlo year
  - For each country, one 8760 hour time series for the given Monte Carlo year and the considered horizon[40].

Name	Content
country	country name (2-letter ISO code)
timestamp	time stamp of the historical weather data (YYYY-MM-DD hh:mm:ss)
time_id	time Id (from 1 to 8 760)
ev_charging	hourly factor of the ev-charging load of the country (between 0.0 and 1.0)[41]

[37] Load factors for a given country sum up to 1.

[38] The timeseries time index is the time stamp of the historical weather dataset used (between 1983 and 2016, i.e. 35 years). However, the target year is assumed to be 2050, though no climate change effect is present is this dataset. As 2050 is not a leap year, all yearly time series are shrunk to one OSMSOSE year of 365 days, i.e. 8760 hours.

[39] Load factors for a given country sum up to 1.

[40] The timeseries time index is the time stamp of the historical weather dataset used (between 1983 and 2016, i.e. 35 years). However, the target year is assumed to be 2050, though no climate change effect is present is this dataset. As 2050 is not a leap year, all yearly time series are shrunk to one OSMSOSE year of 365 days, i.e. 8760 hours.

[41] Load factors for a given country sum up to 1.

4.6.6 Generation – onshore wind

Onshore wind capacity factors are provided in:

- 35 files, each of which corresponds to a Monte Carlo year
    - Each file containing every country (33) for the given Monte Carlo year
    - For each country, one 8760 hour time series for the given Monte Carlo year and the considered horizon[42].

Name	Content
country	country name (2-letter ISO code)
timestamp	time stamp of the historical weather data (YYYY-MM-DD hh:mm:ss)
time_id	time Id (from 1 to8 760)
onshore_wind	hourly factor of the onshore wind generation of the country (between 0.0 and 1.0)[43]

4.6.7 Generation – offshore wind

Offshore wind capacity factors are provided in:

- 35 files, each of which corresponds to a Monte Carlo year
    - Each file containing every country (33) for the given Monte Carlo year
    - For each country, one 8760 hour time series for the given Monte Carlo year and the considered horizon[44].

Name	Content
country	country name (2-letter ISO code)
timestamp	time stamp of the historical weather data (YYYY-MM-DD hh:mm:ss)
time_id	time Id (from 1 to 8 760)
offshore_wind	hourly factor of the offshore wind generation of the country (between 0.0 and 1.0)[45]

4.6.8 Generation –photovoltaic

PV capacity factors are provided in:

- 35 files, each of which corresponds to a Monte Carlo year
    - Each file containing every country (33) for the given Monte Carlo year

[42] The timeseries time index is the time stamp of the historical weather dataset used (between 1983 and 2016, i.e. 35 years). However, the target year is assumed to be 2050, though no climate change effect is present is this dataset. As 2050 is not a leap year, all yearly time series are shrunk to one OSMSOSE year of 365 days, i.e. 8760 hours.

[43] Load factors for a given country sum up to 1.

[44] The timeseries time index is the time stamp of the historical weather dataset used (between 1983 and 2016, i.e. 35 years). However, the target year is assumed to be 2050, though no climate change effect is present is this dataset. As 2050 is not a leap year, all yearly time series are shrunk to one OSMSOSE year of 365 days, i.e. 8760 hours.

[45] Load factors for a given country sum up to 1.

- For each country, one 8760 hour time series for the given Monte Carlo year and the considered horizon[46].

Name	Content
country	country name (2-letter ISO code)
timestamp	time stamp of the historical weather data (YYYY-MM-DD hh:mm:ss)
time_id	time Id (from 1 to 8 760)
pv	hourly factor of the PV generation of the country (between 0.0 and 1.0)[47]

4.6.9 Generation –photovoltaic (cluster version)

PV capacity factors are provided in:

- 35 files, each of which corresponds to a Monte Carlo year
    - Each file containing every cluster (99) for the given Monte Carlo year
    - For each cluster, one 8760 hour time series for the given Monte Carlo year and the considered horizon[48].

Name	Content
timestamp	time stamp of the historical weather data (YYYY-MM-DD hh:mm:ss)
time_id	time Id (from 1 to 8 760)
country	country name (2-letter ISO code)
cluster	cluster code (e-highway convention)
pv	hourly factor of the PV generation of the cluster (between 0.0 and 1.0)[49]

4.6.10 Generation –run-of-river daily energy

Run-of-river energy data are provided in:

- 35 files, each of which corresponds to a Monte Carlo year
    - Each file containing every country (33) for the given Monte Carlo year
    - For each country, one 365 day time series for the given Monte Carlo year and the considered horizon[50].

[46] The timeseries time index is the time stamp of the historical weather dataset used (between 1983 and 2016, i.e. 35 years). However, the target year is assumed to be 2050, though no climate change effect is present is this dataset. As 2050 is not a leap year, all yearly time series are shrunk to one OSMSOSE year of 365 days, i.e. 8760 hours.

[47] Load factors for a given country sum up to 1.

[48] The timeseries time index is the time stamp of the historical weather dataset used (between 1983 and 2016, i.e. 35 years). However, the target year is assumed to be 2050, though no climate change effect is present is this dataset. As 2050 is not a leap year, all yearly time series are shrunk to one OSMSOSE year of 365 days, i.e. 8760 hours.

[49] Load factors for a given country sum up to 1.

[50] The timeseries time index is the time stamp of the historical weather dataset used (between 1983 and 2016, i.e. 35 years). However, the target year is assumed to be 2050, though no climate change effect

Name	Content
country	country name (2-letter ISO code)
day	day of the year (form 1 to 365)
year	Monte Carlo year (from 1982 to 2016)
value	daily energy

4.6.11 Generation –storage weekly energy

Reservoir energy data are provided in:

- 35 files, each of which corresponds to a Monte Carlo year
    - Each file containing every country (33) for the given Monte Carlo year
    - For each country, one 365 day time series for the given Monte Carlo year and the considered horizon[51].

Name	Content
country	country name (2-letter ISO code)
week	week of the year (1 to 53)
year	Monte Carlo year (from 1982 to 2016)
value	weekly energy

4.6.12 Generation –hydro units capacity (country version)

Hydro units maximum capacities are provided in:

- 35 files, each of which corresponds to a Monte Carlo year
    - For each country, long term characteristics of hydro units (see detail in the table below) for the each horizon

Name	Content
country	country name (2-letter ISO code)
year	horizon (2030, 2040 or 2050)
type	information type: • “Reservoir_capacity (MW)” for hydro reservoir maximum capacity • “Reservoir_energy_annual (GWh)” for hydro reservoir annual energy • “Reservoir_volume (GWh)” for reservoir storage capacity • “RoR_capacity (MW)” for run-off-river maximum capacity • “RoR_energy_annual (GWh)” for run-of-river annual energy

is present is this dataset. As 2050 is not a leap year, all yearly time series are shrunk to one OSMSOSE year of 365 days, i.e. 8760 hours.

[51] The timeseries time index is the time stamp of the historical weather dataset used (between 1983 and 2016, i.e. 35 years). However, the target year is assumed to be 2050, though no climate change effect is present is this dataset. As 2050 is not a leap year, all yearly time series are shrunk to one OSMSOSE year of 365 days, i.e. 8760 hours.

Name	Content
	• "PSP_capacity (MW)" for pump storage plant maximum capacity • "PSP_volume (GWh)" for pump storage plant storage capacity
value	numerical value corresponding to "type"

4.6.13 Generation –hydro units characteristics (cluster version)

Hydro units maximum capacities are provided in:

- One file containing every cluster (99)
    - For each cluster, long term characteristics of hydro units (see detail in the table below) for the each horizon.

Name	Content
country	country name (2-letter ISO code)
cluster	cluster code (e-highway convention)
year	horizon (2030, 2040 or 2050)
type	information type: • "Reservoir_capacity (MW)" for hydro reservoir maximum capacity • "Reservoir_energy_annual (GWh)" for hydro reservoir annual energy • "Reservoir_volume (GWh)" for reservoir storage capacity • "RoR_capacity (MW)" for run-off-river maximum capacity • "RoR_energy_annual (GWh)" for run-of-river annual energy • "PSP_capacity (MW)" for pump storage plant maximum capacity • "PSP_volume (GWh)" for pump storage plant storage capacity
value	numerical value corresponding to "type"

4.6.14 Generation –thermal units characteristics

Thermal units characteristics are provided in:

- One file containing all available technology
    - For each technology, long term characteristics of thermal units (see detail in the table below) for the each horizon.

NB: this file alos ensures the mapping between the technology description used in GENeSYS/OSeMOSYS data (TU Berlin, see [GENeSYS-MOD]) and Antares data

Name	Content
year	horizon (2030, 2050)
type_tub	type describing this technology in TU Berlin data
type_antares	type describing this technology in Antares data
name_antares	name given to the thermal unit

one_group_only	this unit corresponds to one (yes) or several (no) physical thermal units
nominal_capacity	nominal capacity (in MW)
min_up_time	minimum up time (in hours)
min_down_time	minimum down time (in hours)
min_stable_power	minimum stable power (in MW)
market_bid	proportional cost
CO2	CO_2 emissions in g_{CO2}/MWh
percentage_available	standard participation factor (between 0.0 and 1.0)

5 Appendix C: Environmental impact indicators - proof-of-concept studies

5.1 Context and objectives

Designing an optimal mix of flexibility involves determining some kind of technical-economic merit order for flexibility. Given the variety of technologies that can be used to provide flexibility, this ranking cannot reasonably be done without adopting a holistic view. This approach emphasizes our need to describe and model all types of technologies that can provide flexibility with sufficient detail to accurately reflect their interactions with the rest of the mix (their dynamic constraints, fixed and proportional costs, etc…).

However, the use of a technical-economic optimum (total costs minimization, and more generally social welfare maximisation) as a proxy for "common good" clearly points to a top down vision of energy policies. The underlying assumption is that the goal of economics is to rationally allocate resources, in a general equilibrium paradigm. To do this, externalities (in particular environmental and social ones) must be explicitly and accurately integrated, and individual utility functions are assumed to be well-known and translatable into an aggregated utility curve.

These assumptions were already highly questionable in the context of monopolies, but the shift to a decentralized world tends to exacerbate the criticisms: a local decision-making paradigm is far from a rational central planner one; the environmental crisis illustrates how difficult it is to address sustainability. For instance, maximising social welfare tends to favour commercial exchanges at the expense of sufficiency. Therefore the traditional vision of the "common good" used by system planners may conflict with the ambitions of the energy transition.

The energy transition is essentially about the most efficient solutions to reduce global Green House Gases (GEG) emissions. Unfortunately, climate change is only one aspect of current environmental concerns. The preservation of biodiversity, the exploitation and depletion of natural resources, waste or human health are just as crucial for human survival. This multi-factorial context and the strong interactions between topics (see Figure 55) give rise to controversies, particularly with regard to the production and transmission of energy. For instance:

- Hydraulics is questioned for its impact on the local ecosystem (disruption of the natural flow of rivers, creation of artificial water reservoirs leading to environmental impacts).
- Although nuclear energy is a low carbon technology, it is controversial because of the long-term radioactive waste left as an ominous legacy to future generations, its influence on the local ecosystem (discharge temperatures of water used for cooling), and the consequences in terms of dissemination of radioactive materials in case of accident.
- Variable renewable energies are criticized for their consumption of mineral resources. Solar panels are associated with a debate on the reality of their environmental balance due to the conditions of their manufacturing, often in Asia by processes that emit a lot of CO_2. Wind turbines are suspected of disturbing nearby species and are accused of containing rare earths.
- The raw material requirements related to the development of batteries for the needs of the electrical system, but more particularly for low-carbon mobility, have been highlighted.
- Finally, the other energy carriers are not excluded from this debate: methanization plants are being contested on the grounds of groundwater pollution, questions are being asked about the consequences of increased use of biomass, wood heating can

induce fine particle pollution, and the possibility of biomethane leaks in gas pipelines or methanization plants cannot be ruled out.

Like all human activities, energy production, transport or consumption technologies have an impact on the environment. In the debate, the intertwining of these different issues makes it difficult to make energy decisions, since none of them appears to be systematically the least environmentally friendly, apart from the absence of energy consumption.

The objective of the environmental component of the OSMOSE WP1 study was to move beyond assumptions and prejudices by proposing a rigorous and systematic methodology for assessing the environmental impact of a power system mix scenario. The decision was taken to still use the criterion of cost minimisation to discriminate between options, but to complement it with other numerical indicators from the field of the Environmental Analysis (e.g., critical impact on water, depletion of rare minerals, human health…), in order to try to conciliate the different perspectives.

From a methodological point of view, OSMOSE WP1 considers it essential to present the different indicators without trying to summarize them in a single socio-economic value:

- On the one hand, the analysis cannot claim to be exhaustive at this stage. The environmental analysis is still an ongoing field of research.
- On the other hand, reducing all the complexity of the world to a single indicator would prevent the actors of the democratic debate from fully measuring the different consequences of the options presented. This statement excludes in particular the use of monetization.
- In practice, individual indicators are already very difficult to put in place. Biodiversity is a typical example. Despite the strong deterioration of biodiversity observed in the world and the considerable amount of scientific work on the subject, there is currently no consensus on an aggregate indicator that could efficiently summarize the consequences of energy transition scenarios on biodiversity.
- Finally, environmental indicators currently exhibit uncertainties of different orders of magnitude. It is difficult to define a relevant and robust synthetic criterion in this context.

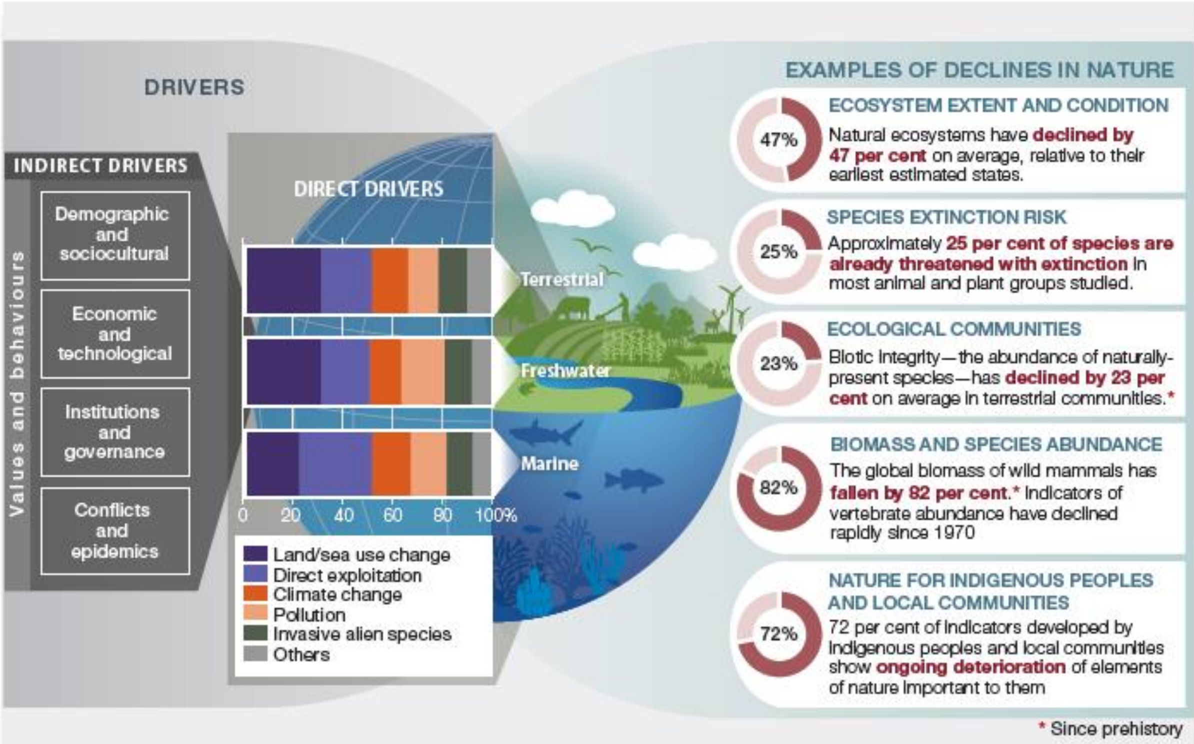


Figure 55: direct and indirect drivers of change causing global declines in nature (source [IPBES])

To truly address the issue of environmental impact, it must be recognized that the actual footprint is not limited to the power generation phase. The construction and dismantling phases of the installations and the supply of fuel also generate impacts (see Figure 56). Moreover, one must consider a perimeter beyond the power system, namely the entire energy system, including energy uses, which makes the problem even more difficult. It is also important to track down the potential hidden relocation of impacts, especially for those, like climate change, that have a global effect.

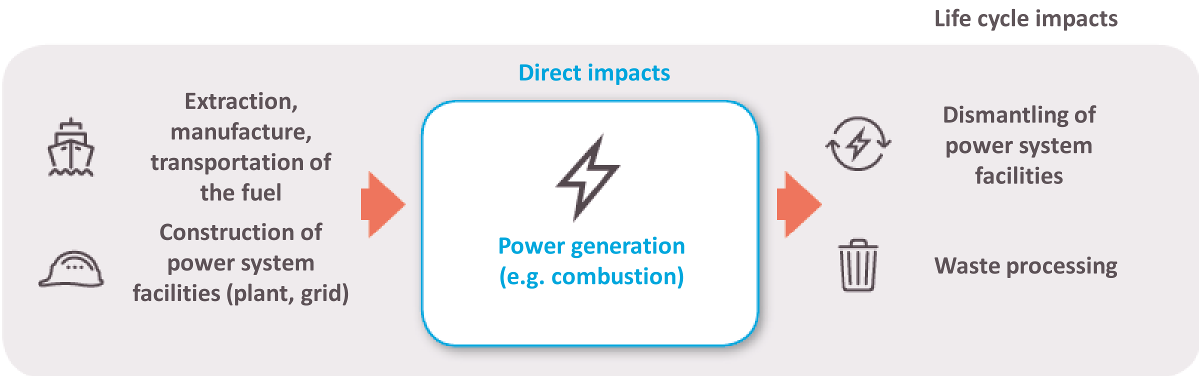


Figure 56: Flow chart of direct and life cycle impacts (source [EP 2050])

5.2 Methodology

The analysis of life cycle impacts of the electrical system requires the use of characterisation factors for each of the technologies that make up the system and for each mid-point indicators that are under scrutiny. The ecoinvent database (see [Ecoinvent]) is the most comprehensive international inventory database to date and is used for this matter. However, projecting these data to 2050 and adapting them to the OSMOSE WP1 context is a challenge.

In order to integrate the possible evolutions of the long term context in the life cycle analysis of electrical installations, the proposed methodology is based on parameterized models. Parameterized models allow the analysis to focus on the evolution of the main factors that affect the results. About 100 parameters have been introduced in the datasets, such as the life span of the facilities, the manufacturing methods, the quantity of materials, or the carbon content of the energy mix used for manufacturing:

- A sensitivity analysis is performed to identify the key parameters that significantly influence the variation of the life cycle analysis (LCA) results of the system.
- A simplified model of the system is then generated, based on only the parameters explaining the majority of the variation in environmental impacts of the system under consideration.

In practice, OSMOSE WP1 worked with the open source lca_algebraic library (see [LCA_Alg]), developed by the OIE MINES ParisTech research in the framework of the INCER-ACV project (see [INCER ACV]), and successfully tested in [EP 2050] (see details in [Douziech]).

5.3 Preliminary findings

Due to delays in the production and validation phase of the energy mix scenarios, the environmental impact assessment method could only recently be applied. This chapter will therefore be limited to presenting preliminary results, mainly with the aim of illustrating the richness and relevance of the parametric indicator analysis method through practical examples.

The results presented here focus on the French case, as some benchmarks were available due to the recent publication of the "Energy Pathways to 2050" report (see EP 2050), although the methodology generates indicators for all the countries analyzed, as well as at the European scale.

At this stage of the results analysis, it can be concluded that the energy transition carried out in the "Common Goals Achieved" (CGA) scenario changes the overall level of impact of the power system, as well as the distribution between technologies, and this for all the studied ILCD indicators (Climate change, Resources, Human health and Ecosystem quality, see sections 5.3.1 to 5.3.4).

It will be no surprise if we take into account the rise of French generation from 532 TWh in 2018 to 885 TWh in 2050 (massive electrification, see Figure 57). Moreover, the composition of the generation fleet is changing in a very profound way (see Figure 58).

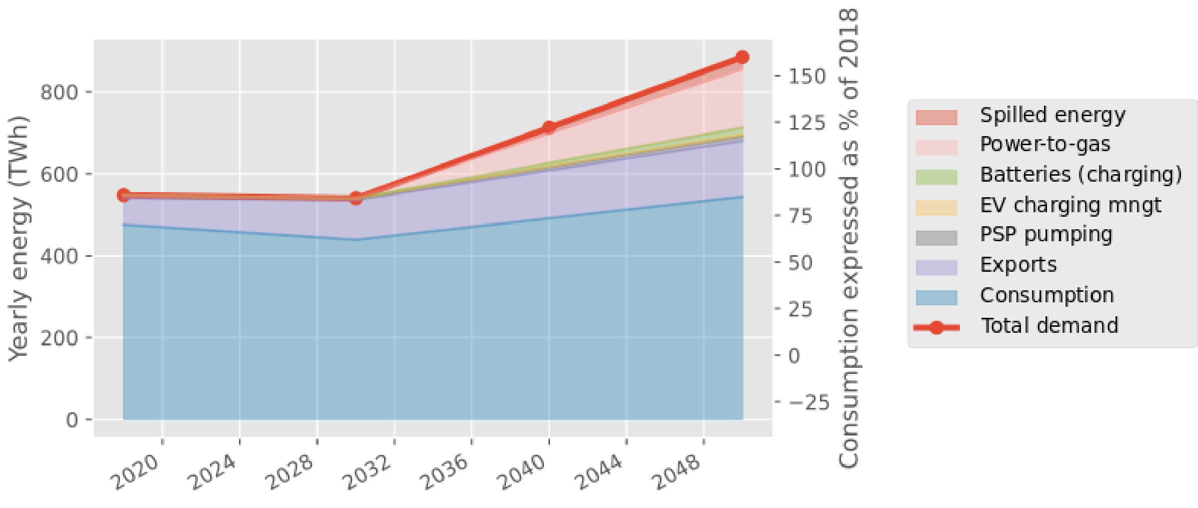


Figure 57: load uses in the Common Goals Achieved scenario - time evolution of the French mix per technology

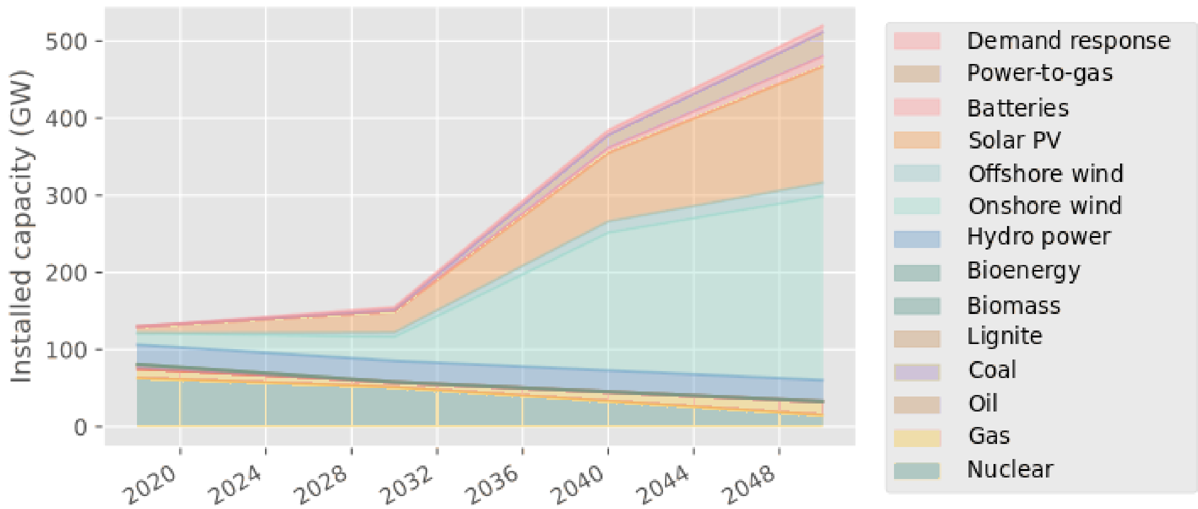


Figure 58: Installed capacity in the Common Goals Achieved scenario - time evolution of the French mix per technology

5.3.1 Indicator Climate change

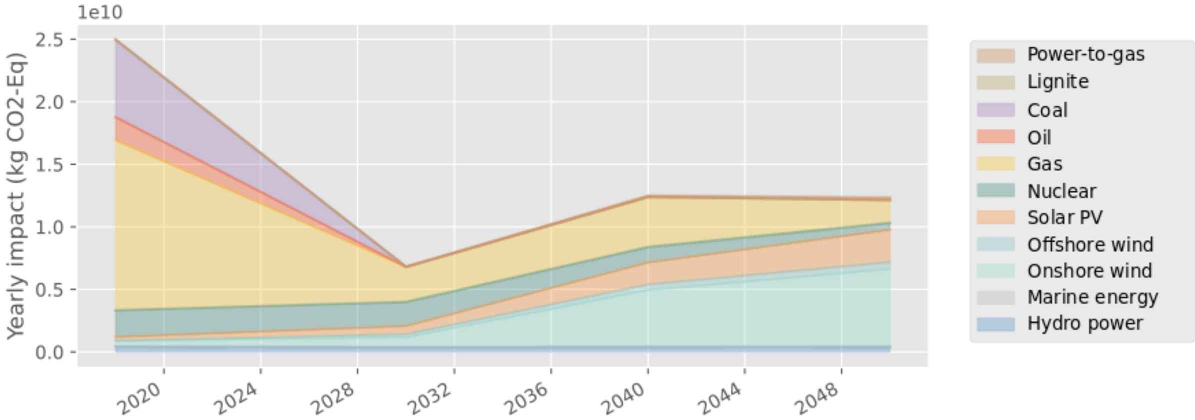


Figure 59: Climate change –total climate change per technology (ILCD 2018
time evolution of the French mix impact per technology in the Common Goals Achieved scenario

5.3.2 Indicator Human health

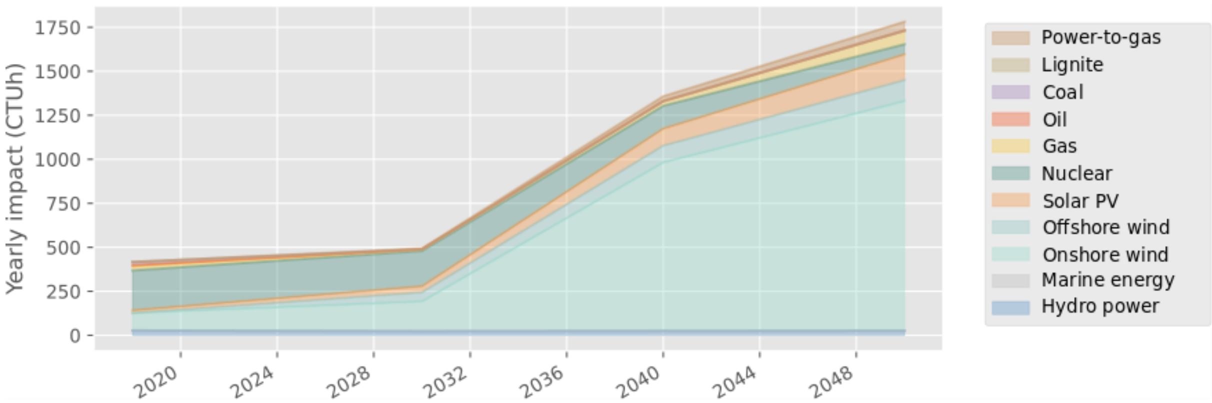


Figure 60: Human health – carcinogenic effects per technology (ILCD 2018)-
time evolution of the French mix impact per technology in the Common Goals Achieved scenario

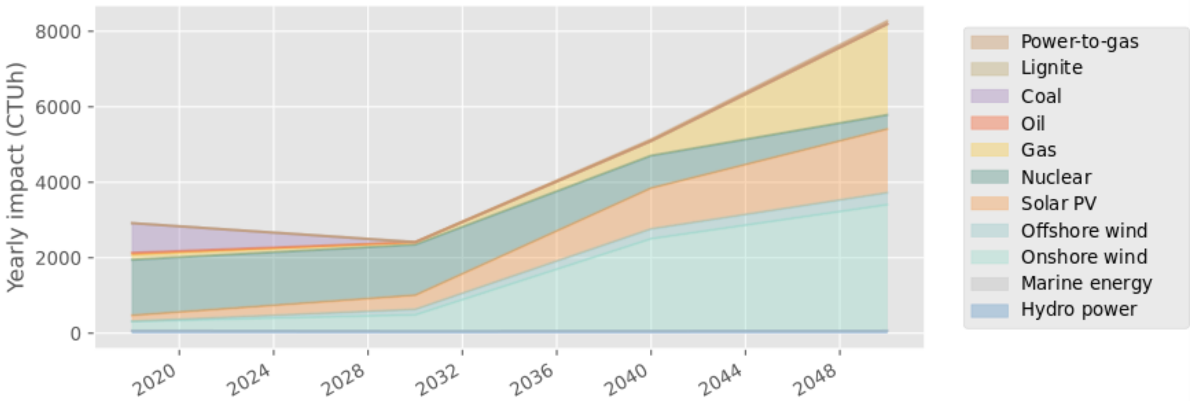


Figure 61: Human health – non-carcinogenic effects (ILCD 2018
time evolution of the French mix impact per technology in the Common Goals Achieved scenario

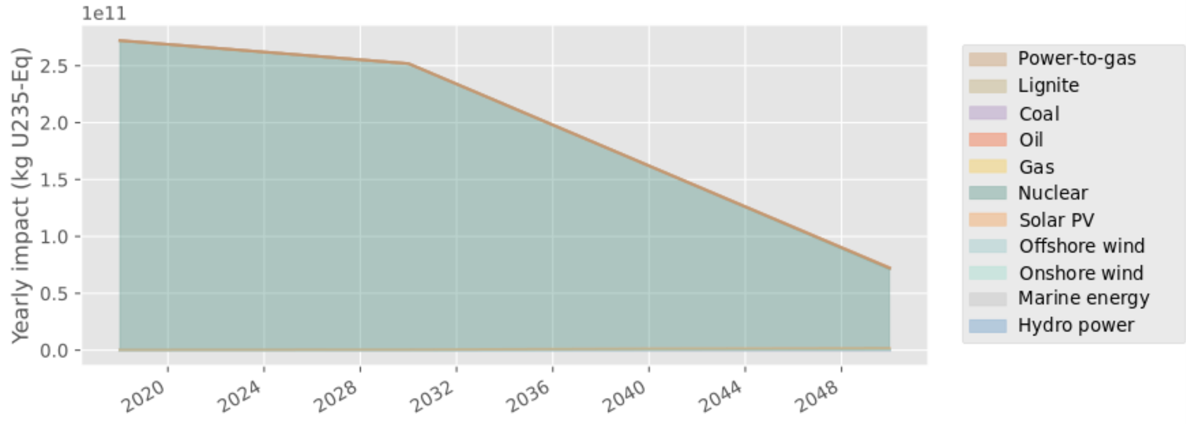


Figure 62: Human health – ionizing radiation (ILCD 2018
time evolution of the French mix impact per technology in the Common Goals Achieved scenario

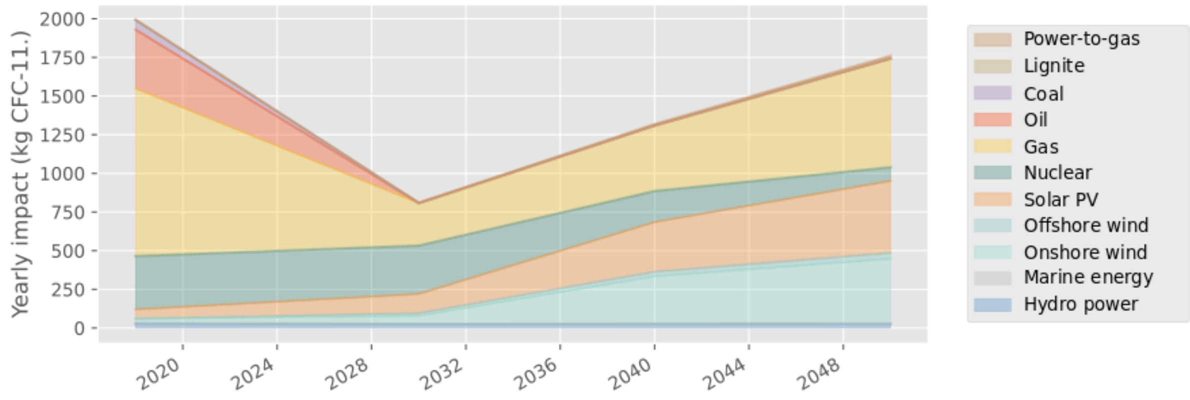


Figure 63: Human health – ozone layer depletion (ILCD 2018
time evolution of the French mix impact per technology in the Common Goals Achieved scenario

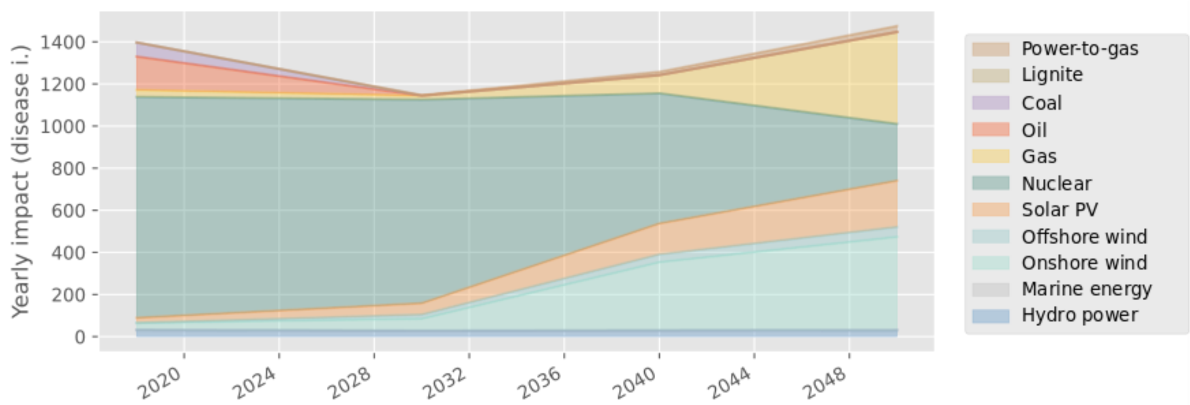


Figure 64: Human health – respiratory effects, inorganics (ILCD 2018
time evolution of the French mix impact per technology in the Common Goals Achieved scenario

5.3.3 Indicator Resources

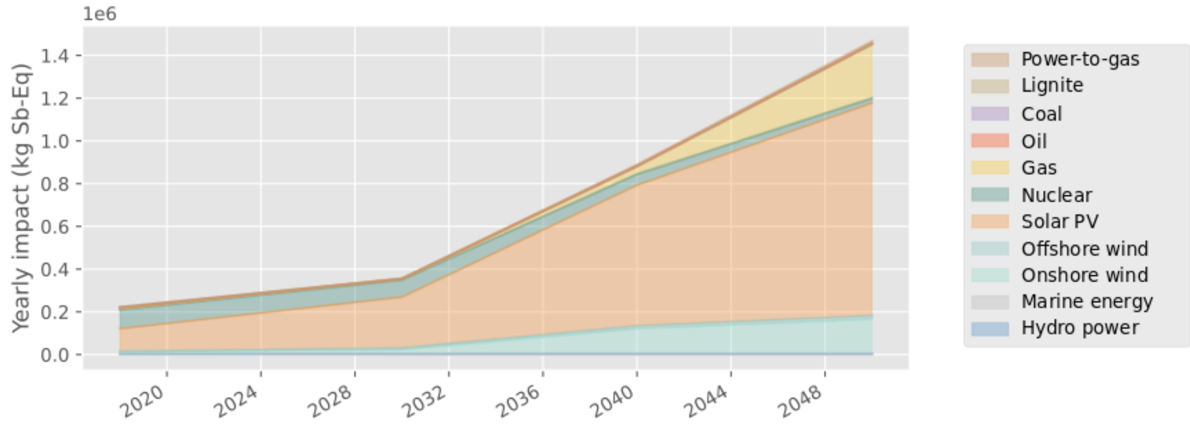


Figure 65: Resources – minerals and metals (ILCD 2018
time evolution of the French mix impact per technology in the Common Goals Achieved scenario

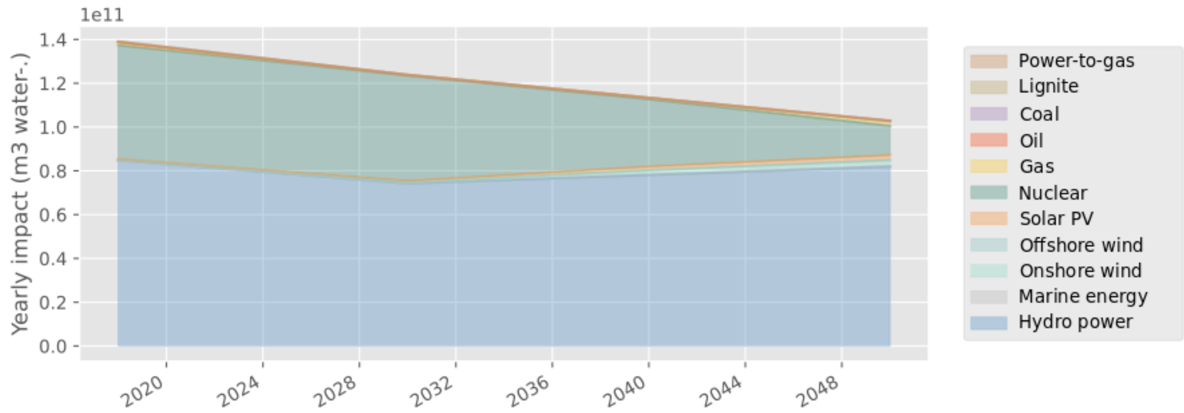


Figure 66: Resources –dissipated water (ILCD 2018
time evolution of the French mix impact per technology in the Common Goals Achieved scenario

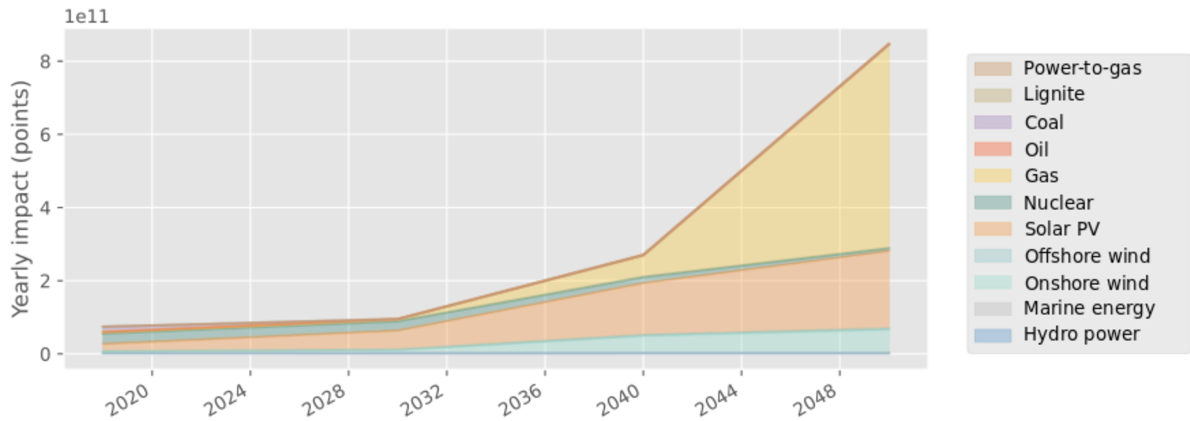


Figure 67: Resources – land use (ILCD 2018
time evolution of the French mix impact per technology in the Common Goals Achieved scenario

5.3.4 Indicator Ecosystem quality

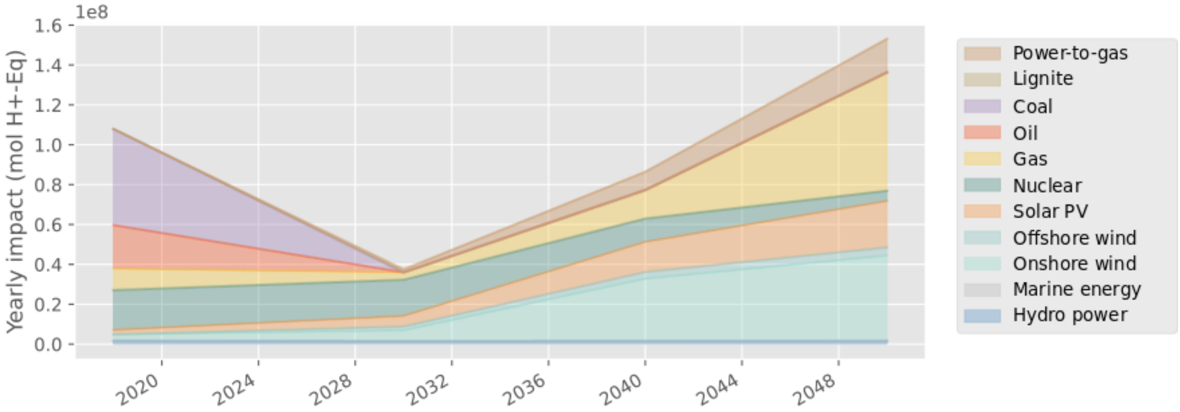


Figure 68: Ecosystem quality –fresh water and terrestrial acidification (ILCD 2018 time evolution of the French mix impact per technology in the Common Goals Achieved scenario

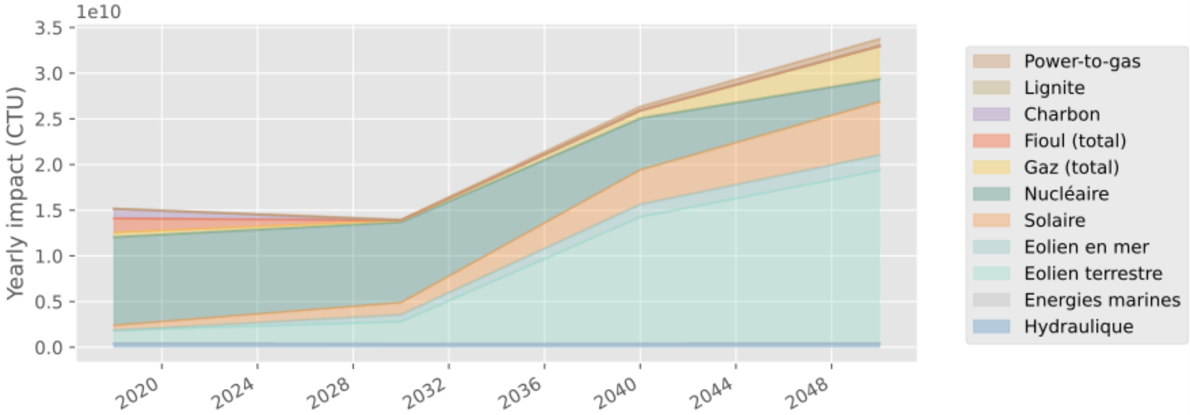


Figure 69: Ecosystem quality –freshwater ecotoxicity (ILCD 2018 time evolution of the French mix impact per technology in the Common Goals Achieved scenario

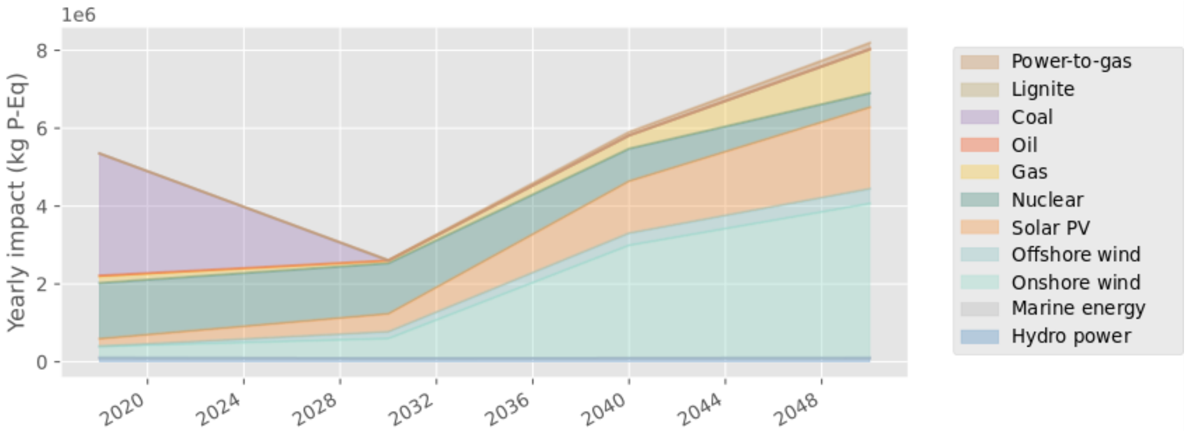


Figure 70: Ecosystem quality –freshwater eutrophication (ILCD 2018 time evolution of the French mix impact per technology in the Common Goals Achieved scenario

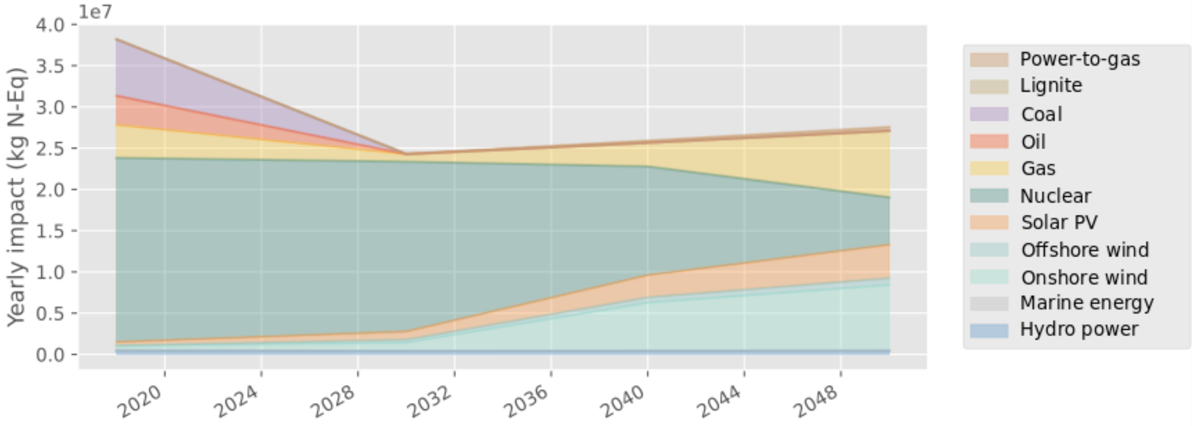


Figure 71: Ecosystem quality – marine eutrophication (ILCD 2018
time evolution of the French mix impact per technology in the Common Goals Achieved scenario

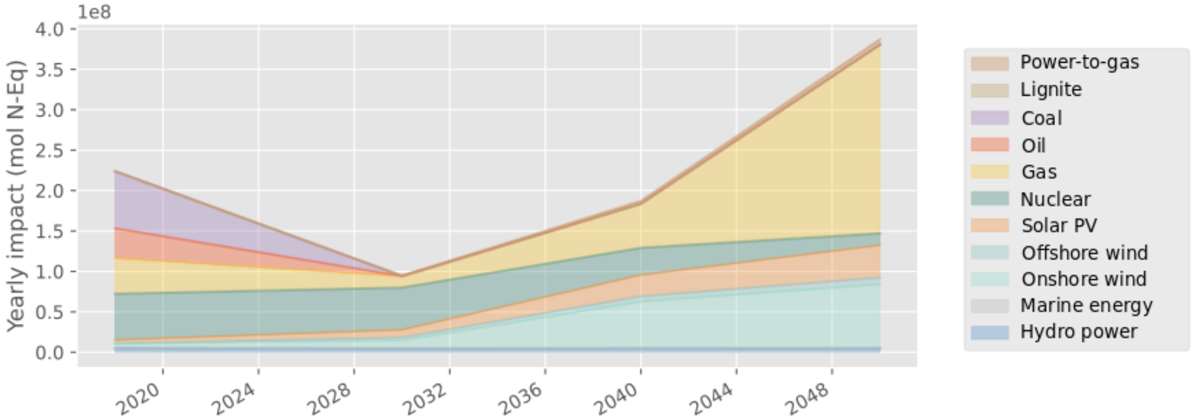


Figure 72: Ecosystem quality – terrestrial eutrophication (ILCD 2018
time evolution of the French mix impact per technology in the Common Goals Achieved scenario

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