DEMAND FORECASTING

NATIONAL ESTIMATES SCENARIO - ERAA 2022

HOURLY DEMAND TIME - SERIES

Demand Forecasting Methodology

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EXECUTIVE SUMMARY

The purpose of the report is to provide the audience transparent view on hourly demand forecasting methodology and input data key assumptions used in European Resource Adequacy Assessment (ERAA) 2022.

This report consists of 2 Parts: 1st is the hourly demand forecasting methodology description while Part 2 includes the key input data assumptions.

In the Part 1 the demand-forecasting methodology is explained. 36 demand time-series based on historical load data, climate variables (1982-2016), calendar data and technology diffusion are adjusted to meet National Estimates TSO's set targets for Average Annual Energy and Average Annual Maximum Peak of climate years 1982-2016 using methodologies described.

Part 2 consists of Pan European Market Modelling Database (PEMMDB) main input data assumptions of high level of granularity: including input historical load period, EV profiles and uptake for National Estimates Scenario per market node.

Key messages:

Part 1:

- The resulting TRAPUNTA load profiles were adjusted based on TSO's input to meet National Estimates KPI's – Target Average Annual Energy and Average Annual Peak - for Target Years 2025, 2027 and 2030 – using methodologies described in Part 1.
- ENTSO-E recently introduced a proposal for the European Resource Adequacy Assessment (ERAA) methodology. Pushed by the introduction of the ERAA methodology, ENTSO-E formalised its need for a unique tool that would undertake high-quality electricity demand forecasting and profiling for all ENTSO-E studies (i.e. short, medium and long-term).

Part 2:

- The EV profiles were categorized into 4 categories each for different UTC zones (UTC, +1, +2). Alternative EV profiles were submitted for specific TSO's.

PART 1 – HOURLY DEMAND FORECASTING METHODOLOGY

Introduction

For the creation of hourly load profiles for most of the European countries, ENTSO-E uses a temperature regression and load projection model that incorporates with uncertainty analysis under various climate conditions. The model comes in a software application developed by an external provider. It is important to mention that the Member States for ERAA 2021 could have provided also their own hourly demand time-series directly to ENTSO-E, using other methodologies than the ENTSO-E one (for details please see the Appendixes 2, 3, 4)

It allows to easily perform electric load prediction starting from data analysis of historical time series (electric load, temperature, climatic variables and other). Its overarching goal is to introduce an advanced forecasting tool which eventually will lead to a stronger harmonization of forecasting activities and comparability of their outcomes provided by ENTSO-E members.

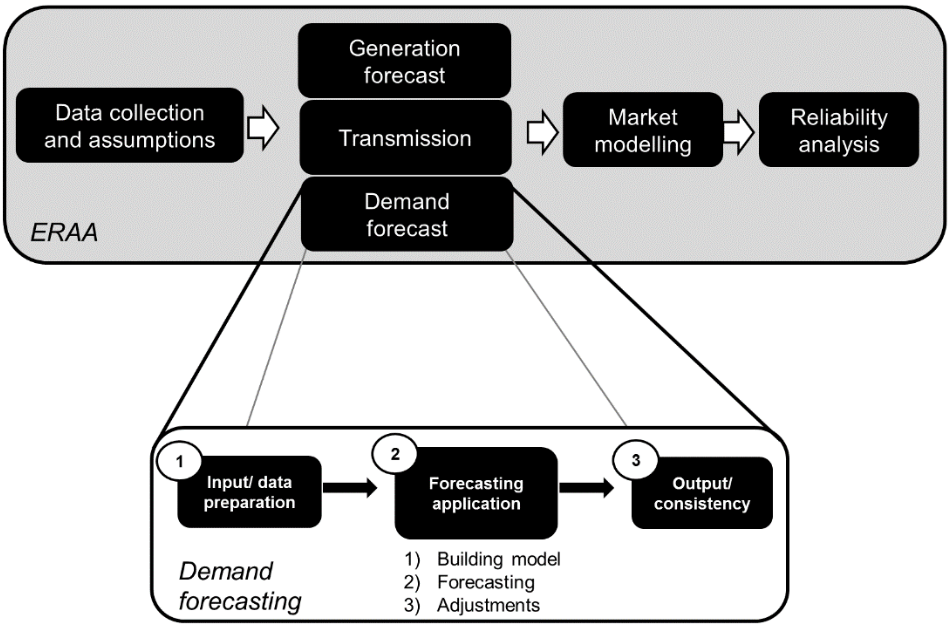


Figure 1: The embedding of demand forecasting in European resource adequacy assessment

Figure 1 shows the position of demand forecasting within the European resource adequacy assessment (ERAA). As can be seen, it provides together with generation capacity forecasts and transmission capacity information fundamental input to market modelling. A more detailed description of input data, methodology and consistency checks are described in the following document.

TRAPUNTA approach: data-driven load prediction

The TRAPUNTA tool has been conceived to address the problem of electric load prediction based on temperature and other climatic variables. More precisely, the tool is meant to provide an estimate of the daily load profile based on historical data of the load and of the climatic variables affecting the load. In addition, the tool has been prepared to perform load adjustment to consider the electrical market evolution such as the penetration of the heat pump technology, the increase of electric cars, batteries, the evolution of the base load, etc…

This introduction focuses on the problem of load prediction based on historical climatic data, for which a dedicated innovative methodology has been devised and implemented in TRAPUNTA.

A general overview

The TRAPUNTA methodology is proposed to overcome the limitations of traditional approaches by allowing the possibility of reconstructing entire daily load profiles. The idea is to isolate significant load components via a mathematical analysis of the available integral load profiles. To achieve this goal, TRAPUNTA uses a mathematical technique named Proper Orthogonal Decomposition (POD) and based on the Singular Value Decomposition (SVD) factorization of the available daily load profiles for a given market node. The SVD factorization allows to extract a set of few orthogonal basis functions that can then be used for reconstructing different load profiles for the same node. The following paragraphs introduce the mathematical foundations of the approach, and provide an example of the capabilities of TRAPUNTA, including:

- Prediction of the whole daily load profile
- Analysis of the changes in the whole daily load profile during the year
- Identification of dependencies associated to different groups of days
- Identification and representation of bank holidays in specific market nodes
- Identification of seasonal trends, such as daylight-saving time and summer vacation period.
- Decomposition of the load components and reconstruction of a generic daily load profile

As mentioned, the methodology is based on the extraction of a few independent (orthogonal) load components via an SVD decomposition of the available daily loads. These load components represent optimal basis functions for the reconstruction of a generic daily load profile.

SVD factorization allows isolating load components that:

- can be used to optimally reconstruct a generic load profile. The SVD has the property of producing basis functions that are ordered by importance, so that the first few ones allow retaining most of the information available.

- tend to be related to different physical components of the load, which implies different types of dependencies over the climatic variables or the types of days.

The TRAPUNTA methodology employs these features to optimally reconstruct daily profiles while minimizing the degrees of freedom and limiting overfitting. In particular, an SVD is performed on the daily load profiles to extract the optimal basis functions for load reconstruction. The coefficients associated to the basis functions are parameterized based on the climatic variables and information on the types of days. For each coefficient (and basis function) only the most significant dependencies are retained.

TRAPUNTA approach: electric load correction

In addition to a load prediction based on climatic variables (and groups of days), TRAPUNTA gives the user the possibility to correct these predictions based on information and estimates about other load components. In particular, the possibility is provided to include predictions about:

- electric vehicles,
- sanitary water,
- air conditioning fraction,
- air conditioning load,
- heating heat pumps fraction,
- heating heat pumps load,
- batteries impact,
- additional base loads,
- energy demand increase.

Electric vehicles

The load component due to the use of electric vehicles is added based on the following values provided by the correspondents:

- number of additional electric vehicles in the target year added to the system after 2016 and market node with respect to
- consumption of the average electric vehicle for each category, expressed in kWh/100km
- effective usage of the average EV user of each category, divided in weekdays and weekend, expressed in km/day
- daily distribution of the effective usage – “EV load profile”

The load adjustment is computed as:

$$L_{0-24} = 10^{-5} \times \mathrm{N} \times \mathrm{C} \times \mathrm{EU} \times \mathrm{norm}(D_0 - D_{24}) \quad (1)$$

where L is the load adjustment in MW, N is the number of additional vehicles, C is the consumption, EU is the effective usage, D is the given distribution, and norm() is an operation that rescales the distribution to unitary area - using constant interpolation, which means that the load is considered constant inside each 1-hour interval).

Sanitary Water

A load profile variation due to the change in sanitary water load is added based on the following parameters:

- daily thermal load increment for both air-to-water and geothermal technologies, expressed in MWh/day,
- daily distribution of the daily thermal load
- air-to-water COP
- geothermal COP, expressed as a single value, since it depends on the effective underground water or soil temperature rather than external air temperature

$$ALday, hour = \frac{DTI * norm(Phour)}{COP(Tday, hour, Hday, hour)} * \frac{AF}{100} \quad (2)$$

where AL is the load adjustment in MW, DTI is the Daily Thermal load Increment, P is the given profile, COP(T,H) is the COP, expressed as a function of both temperature and humidity, DTI is the additional daily thermal load necessary to heat up sanitary water.

Air conditioning fraction

A load profile variation due to the use of air conditioning is obtained by specifying the following parameters:

- the additional fraction of thermal load,
- the COP curve as function of the relative humidity and temperature

The comfort temperature is defined as the temperature for which there's a minimum of the electrical load, as a function of the temperature, for each hour in the model.

First, the comfort temperature is computed as follows:

$$T_{comfort}: L_{model}\left(T_{comfort}, param.\right) < L_{model}\left(T_{comfort}, param.\right) \tag{3}$$

$$\forall T \neq Tcomf$$

where L_{model} is the load computed by the regression model, param. are all the input used to compute the regression and T a generic population weighted temperature. The additional load is computed as:

$$AL_{day,hour} = \frac{L_{day,hour}(T_{real}) - L_{day,hour}(T_{comf})}{COP(T_{day,hour}, H_{day,hour})} * \frac{AF}{100} \tag{4}$$

Air conditioning load

An additional load that does not depend on the regression. This additional load is obtained as linearly dependent on the temperature when the temperature is greater than the comfort one.

A load profile variation is obtained specifying the following parameters:

- thermal sensitivity
- comfort temperature
- the COP curve as function of the relative humidity and temperature (a scalar for geothermal air conditioning)

The additional load by air conditioning it then computed as:

$$AL_{day,hour} = \max\left(\frac{(T_{day,\ hour} - T_{comfort}) * Sens}{COP(T_{day,hour}, H_{day,hour})}, 0\right) \tag{5}$$

Heat Pumps fraction

A load profile variation due to the use of heating heat pumps is obtained specifying the following parameters:

- the additional fraction of thermal load,
- the COP curve as function of the relative humidity and temperature (a scalar for geothermal air conditioning, since it depends on the effective underground water or soil temperature rather than external air temperature)

The additional load is computed as:

$$AL_{day,hour} = \frac{L_{day,hour}(T_{comf}) - L_{day,hour}(T_{real})}{COP(T_{day,hour}, H_{day,hour})} * \frac{AF}{100} \quad (6)$$

where AF is the additional fraction specified by the user, T comf is the comfort temperature. As it is for sanitary water, there are two contributions related to heat pumps fraction: replacing and non-replacing. The first one is used to specify the new load coming from heat pumps (COP>1) that substitutes the existing load coming from resistive electric heaters (COP=1). The second specifies the load from heat pumps as an additional load (e.g., from gas water heaters replacements). The cumulative growth is calculated from the annual percentage with respect to the reference year - target year interval.

Heat Pumps load

A load profile variation is obtained specifying the following parameters:

- thermal sensitivity,
- comfort temperature,
- the COP curve as function of the relative humidity and temperature (a scalar for geothermal air conditioning)

The additional load by heat pumps is then computed as:

$$AL_{day,hour} = \max\left(\frac{(T_{comfort} - T_{day,\ hour}) * Sens}{COP\left(T_{day,hour}, H_{day,hour}\right)}, 0\right) \quad (7)$$

Hybrid heat pumps fraction

Similarly, to traditional heating pumps, the load profile variation due to the use of hybrid heating heat pumps is obtained specifying the following parameters:

- the additional fraction of thermal load
- the COP curve as function of the relative humidity and temperature (a scalar for geothermal air conditioning, since it depends on the effective underground water or soil temperature rather than external air temperature)
- A threshold temperature, below which, the pump switches to gas consumption and its electricity consumption goes to zero.

As it is for sanitary water, there are two contributions related to heat pumps fraction: replacing and non-replacing. The first one is used to specify the new load coming from heat pumps (COP>1) that substitutes the existing load coming from resistive electric heaters (COP=1). The second specifies the load from heat pumps as an additional load (e.g., from gas water heaters replacements). The cumulative growth is calculated from the annual percentage with respect to the reference year - target year interval.

Battery impact

In general, batteries in Trapunta can be used to model any storage system simple enough to be described by the few parameters available (power, capacity, efficiency, usage).

The impact of the batteries is estimated as a single concentrated battery. Its properties are:

- maximum total power
- total capacity
- cycle efficiency

The battery can operate in 4 different ways:

- Fixed load and discharge, computed as

$$RV = \min\left(\frac{MTP * FF}{\max\left(\max\left(norm\left(P_{charge}\right)\right), \max\left(norm\left(P_{discharge}\right) * E\right)\right) * TC * FF}\right) \quad (8)$$

$$AL_{day,hour} = \left(norm(Pcharge) - norm(Pdischarge) \cdot E\right) \cdot TC \cdot FF \cdot RV \quad (9)$$

where RV is a correction due to the maximum total power constraint, MTP is the maximum total power, TC is the total capacity, FF is the fraction of the battery dedicated to this type of operation E is the cycle efficiency and the P s are the charge and discharge profiles.

- Photovoltaic load and discharge. computed exactly as a fixed load and discharge, but where the load shape is obtained by rescaling the irradiance to unitary area for each day.
- Peak reduction, that computes the following problem on each day:

$C, D\colon minmax(L - C + D)$, load (L) governing equation

$C > 0,\ D > 0$, positive charge (C) and discharge (D) constraint

$C < MTP,\ D < MTP$, maximum charge and discharge (MTP) constraints

$max(cumsum(C))\ <\ TC$, maximum capacity (TC) constraint on charging

$max(cumsum(D))\ <\ TC$, maximum capacity (TC) constraint on discharging

$D * E\ =\ C$, energy conservation constraint, considering the efficiency (E)

- ❖ Ramp-up rate reduction, computed as the following minmax problem on each day:

$C, D\!:\ minmax\left(\frac{d}{dt}(L - C + D)\right)$, load (L) governing equation

$C > 0,\ D > 0$, positive charge (C) and discharge (D) constraint

$C < MTP,\ D < MTP$, maximum charge and discharge (MTP) constraints

$max(cumsum(C))\ <\ TC$, maximum capacity (TC) constraint on charging

$max(cumsum(D))\ <\ TC$, maximum capacity (TC) constraint on discharging

$D * E\ =\ C$, energy conservation constraint, considering the efficiency (E)

Additional base load

A load profile variation due to the presence of additional base loads is computed based on:

- ❖ additional daily load
- ❖ hourly profile

The hourly profile is rescaled to unitary area, and is multiplied by the additional daily load value to get the actual load profile during the day, i.e.:

$$AL_{day,hour} = norm(P_{hour}) * ADL_{day} \tag{10}$$

where P is the hourly profile and ADL is the value of the additional daily load.

Energy demand

A load profile variation due to an increase (or decrease) of electric demand is added based on the following inputs:

- ❖ temperature dependent increase
- ❖ temperature independent increase

$$AL_{day,hour} = L_{day,hour}(T_{comf}) * \frac{DF}{100} + \left(L_{day,hour}(T) - L_{day,hour}(T_{comf})\right) * \frac{IF}{100}$$

The temperature dependent fraction of the total load is estimated using the comfort load where *DF* is the temperature dependent load increase (as percentage), and *IF* the independent one.

Target demand functionality

The load profile is adjusted to meet an annual target demand - the value of the average yearly energy demand (TWh) – as determined by the correspondents. The additional load can be re-distributed in three different ways:

- Proportional, computed as:

$$AL_{day,hour} = \left(L_{day,hour} * \left(\frac{TD}{sum\left(sum\left(L_{day,hour}\right)\right)} - 1\right) \right) \tag{11}$$

where TD is the annual target demand, L day,hour is the adjusted load (sum(sum()) indicates the yearly integral).

- Baseload, computed as:

$$AL_{day,hour} = \left(\left(\frac{TD - sum(sum\left(L_{day,hour}\right))}{N_{hours}} - 1\right) \right) \tag{12}$$

where N hours is the number of hours in a year.

- Temperature-independent, computed as:

$$AL_{day,hour} = \left(TD - sum(sum\left(L_{day,hour}\right))) * \left(\frac{IND_{day,hour}}{sum\left(sum\left(IND_{day,hour}\right)\right)} * FR + \frac{DEP_{day,hour}}{sum(sum(DEP_{day,hour}))} * (1 - FR) \right) \right) \tag{13}$$

where IND is the Temperature independent load, DEP is the temperature dependent load, and FR is the user-inputter fraction of additional load to be added to the temperature independent part of the load

Linear Additive-Multiplicative Approach for Reciprocally Proportional Rescaling of Average Annual Peak

The load profile is adjusted to meet an annual average peak demand as determined by the correspondents.

(1) $$C_1 = TP/AP\,(d1_{CY,h})$$

(2) $$d2_{CY,h} = d1_{CY,h} * C_1;\ CY \in [1982,2016]; h \in [1,8760]$$

(3) $$C_{2,CY} = 1/YP(d2_{CY,h})_{CY}$$

(4) $$d3_{CY,h} = d2_{CY,h} * \ C_{2,CY}; CY \in [1982,2016]; h \in [1,8760]$$

(5) $$C_{3,CY} = \sum_{h=1}^{h=8760} d3_{CY,h}; CY \in [1982,2016]$$

(6) $$C_4 = Avg(\sum_{h=1}^{h=8760} d1_{CY,h}); CY \in [1982,2016]$$

(7) $$C_5 = Avg(\sum_{h=1}^{h=8760} d2_{CY,h}); CY \in [1982,2016]$$

(8) $$C_6 = \frac{C_4}{C_5}$$

(9) $$C_{7,CY} = \ C_{3,CY} * C_6; CY \in [1982,2016]$$

(10) $$C_{8,CY} = \ C_{7,CY} - C_{3,CY}; CY \in [1982,2016]$$

(11) $$d4_{CY,h} = 1 - d3_{CY,h}; CY \in [1982,2016]; h \in [1,8760]$$

(12) $$C_{9,CY} = \frac{1}{\sum_{h=1}^{h=8760} d4_{CY,h}}\ ;\ CY \in [1982,2016]$$

(13) $$d5_{CY,h} = d3_{CY,h} + d4_{CY,h} * C_{9,CY} * C_{8,CY}; CY \in [1982,2016]; h \in [1,8760]$$

(14) $$C_{10,CY} = \max\left(d2_{CY,h}\right); CY \in [1982,2016]; h \in [1,8760]$$

(15) $$d6_{CY,h} = d5_{CY,h} * C_{10,CY}; CY \in [1982,2016]; h \in [1,8760]$$

TP – $User\ defined\ Average\ Maximum\ Target\ Peak(MW)$
$AP(d1_{CY,h})$ – $Average\ Maximum\ Peak\ (MW)\ of\ all\ Climatic\ Years$ (1982 – 2016)
$d1_{CY,h}$ – $Demand\ hourly\ Value$ "1" (MW) – "$Trapunta\ Output$"
$d(i)_{CY,h}$ – $Intermediary\ Demand\ Value$ "i" (MW); $i \in (2,5)$
$C(i)_{CY,h}$ – $Intermediary\ Demand\ Coefficient\ Value\ (MW)$; $i \in (1,10)$
$YP(d(i)_{CY,h})_{CY}$ – $Yearly\ Peak\ of\ Demand\ Value$ (i) $(d(i)_{CY,h})$
$d6_{CY,h}$ – $Average\ Peak\ Adjusted\ hourly\ Demand$ Value (MW)

Current challenges, limitations, and further ongoing developments

In accordance with Article 23 of the Regulation (EU) 2019/943 of the European Parliament and Council of 5 June 2019 on the internal market for electricity (recast) ENTSO-E recently introduced a proposal for the European Resource Adequacy Assessment (ERAA) methodology. Pushed by the introduction of the ERAA methodology, ENTSO-E formalised its need for a unique tool that would undertake high-quality electricity demand forecasting and profiling for all ENTSO-E studies (i.e. short, medium and long-term). In relation to this need, the Task Force recognized a potential gap of the actual version of TRAPUNTA with respect to the expressed quality requirements of short-term and medium-term adequacy studies.

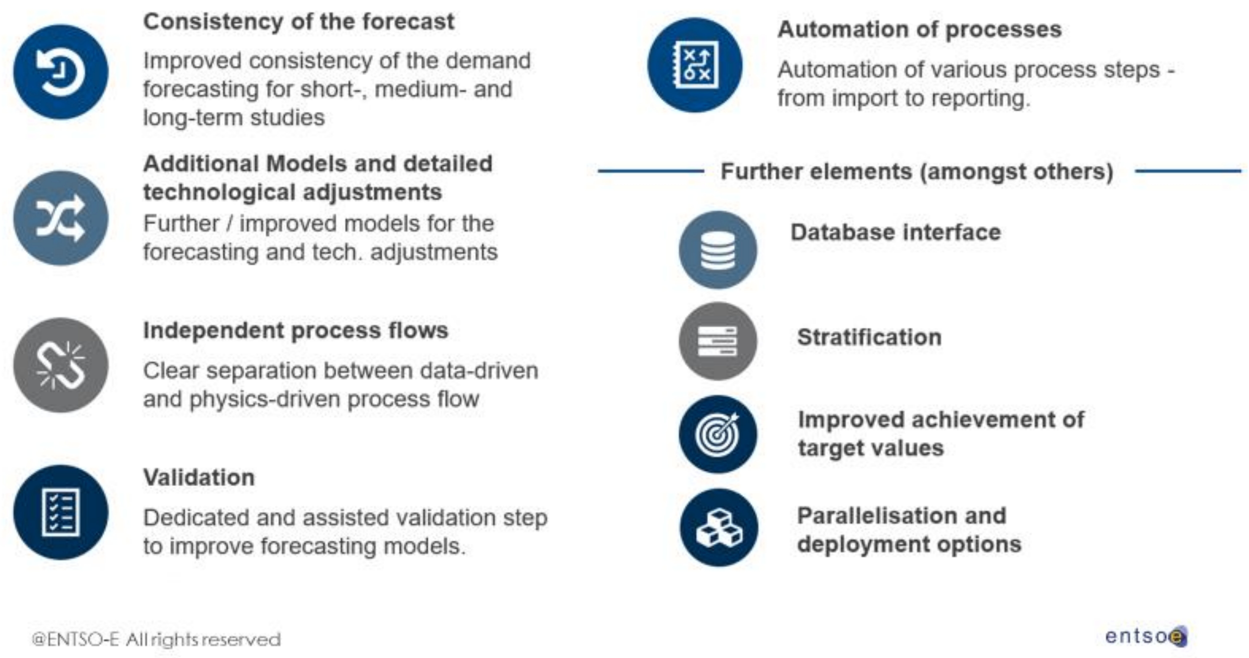


Figure 2 - Key improvements

The key project objective for the remainder of the Task Force Demand Forecasting Methodology activities involves the creation of a common methodology and the development of an upgraded version of the TRAPUNTA tool able to perform hourly load forecasting for all studies carried out within ENTSO-E (i.e. for short, medium, and long-term studies), ensuring the achievement of commonly-defined quality standards related to both energy and peak forecasts. The renewed scope of the Task Force Demand Forecasting Methodology is to define a unique methodology and develop a tool able to cover all ENTSO-E studies and time-horizons. The project will build upon the current version of the TRAPUNTA tool, develop a novel modelling framework and upgrade models/integrate functionalities to ensure the achievement of determined quality standards for all bidding zones.

PART 2 – INPUT DATA

Key Assumptions:

The EV profiles that were used were categorized into 4 categories each for different UTC zone (UTC, +1,+2).

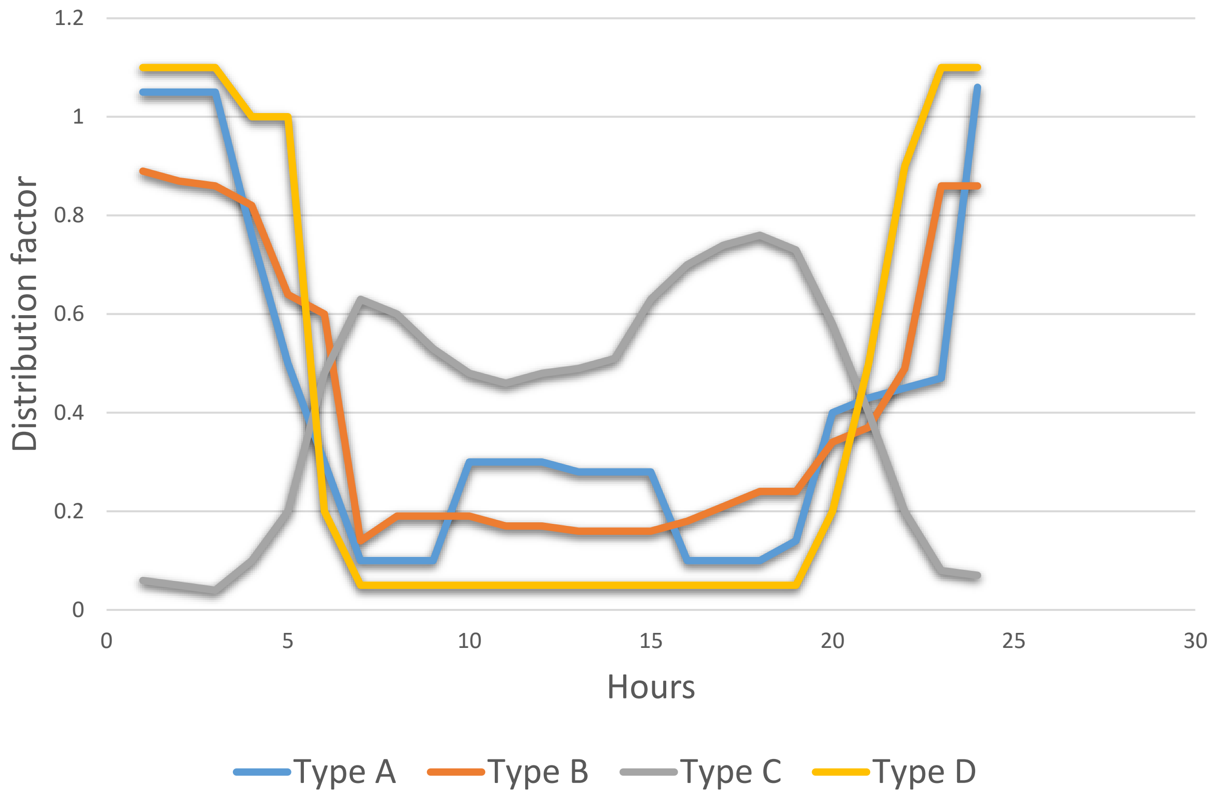


Figure 3. General EV profiles

Alternative EV profiles were submitted by following countries:

Market Node / Country	Alternative EV profile	Market Node / Country	Alternative EV profile
AL00	No	**PL00**	Yes
BA00	No	**TR00**	Yes
BG00	No	**Italy**	Yes
CH00	No	**PT00**	No
CY00	No	**AT00**	Yes
CZ00	No	**BE00**	Yes
DKE1	No	**DE00**	Yes
DKW1	No	**FR00**	Yes
EE00	No	**Greece**	No
ES00	Yes	**SK00**	Yes
FI00	No	**Sweden**	No
HR00	No	**SI00**	No
HU00	No	**RS00**	No
IE00	Yes	**UA01**	No
LT00	No	**UK00**	Yes
LV00	No	**UKNI**	Yes
MK00	No	**Norway**	No
ME00	No	**NL00**	Yes
MT00	No		

Table 1 - Alternative EV profiles

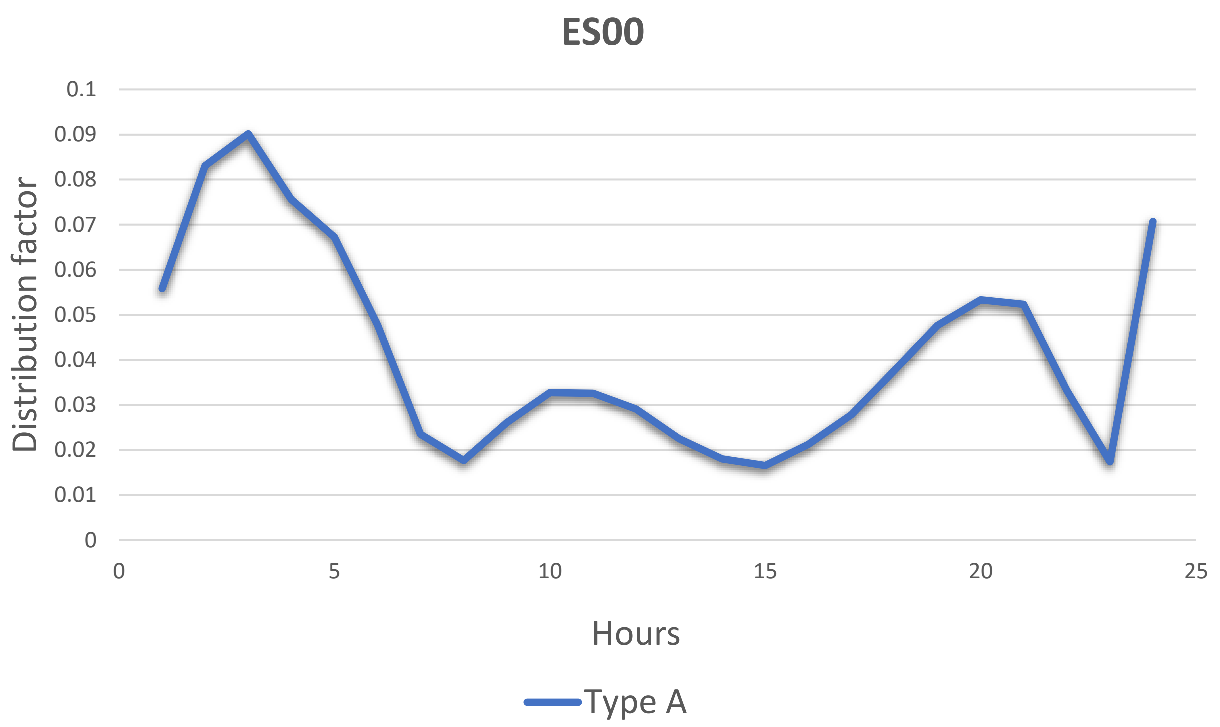


Figure 4. Spain EV profile

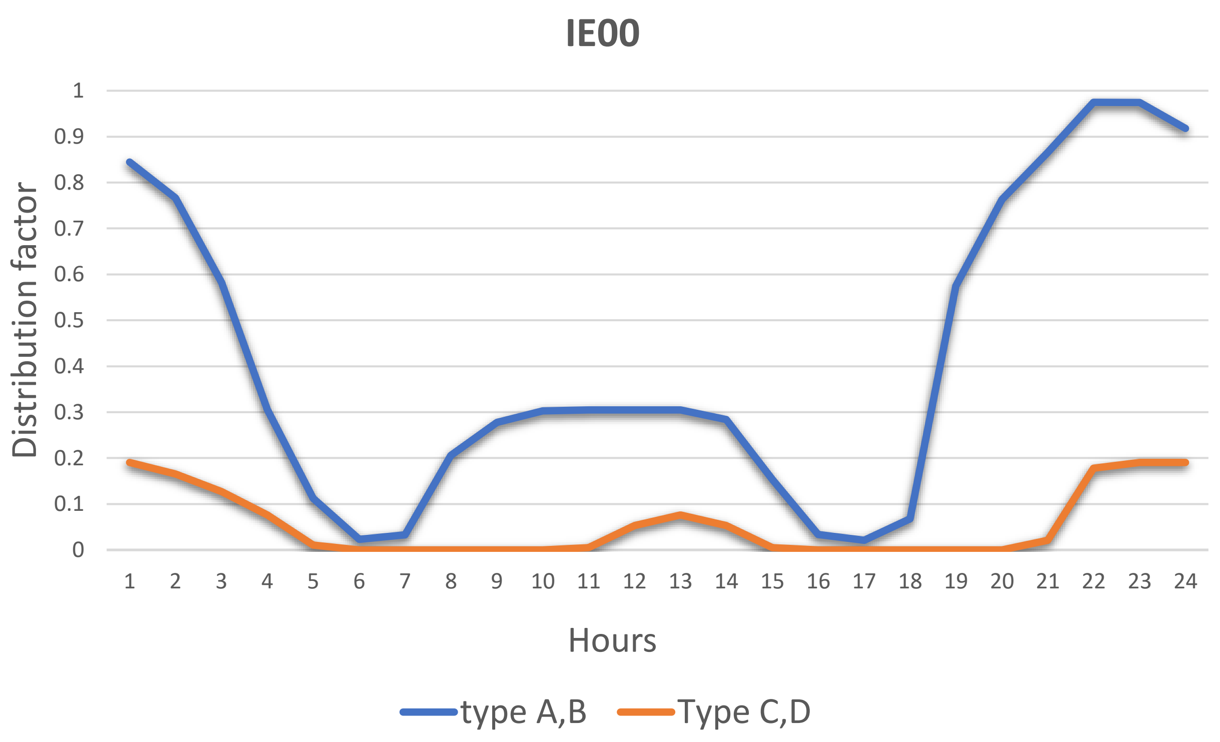


Figure 5. Ireland EV profile

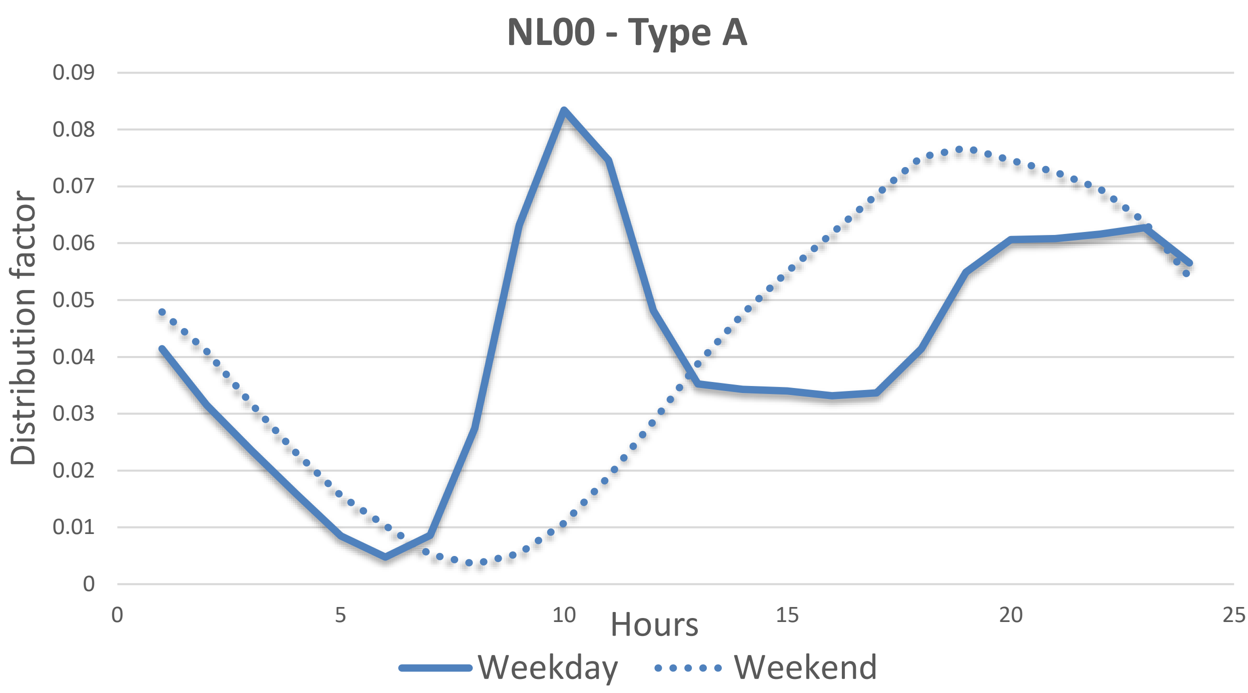


Figure 6. Netherlands EV Type A profile

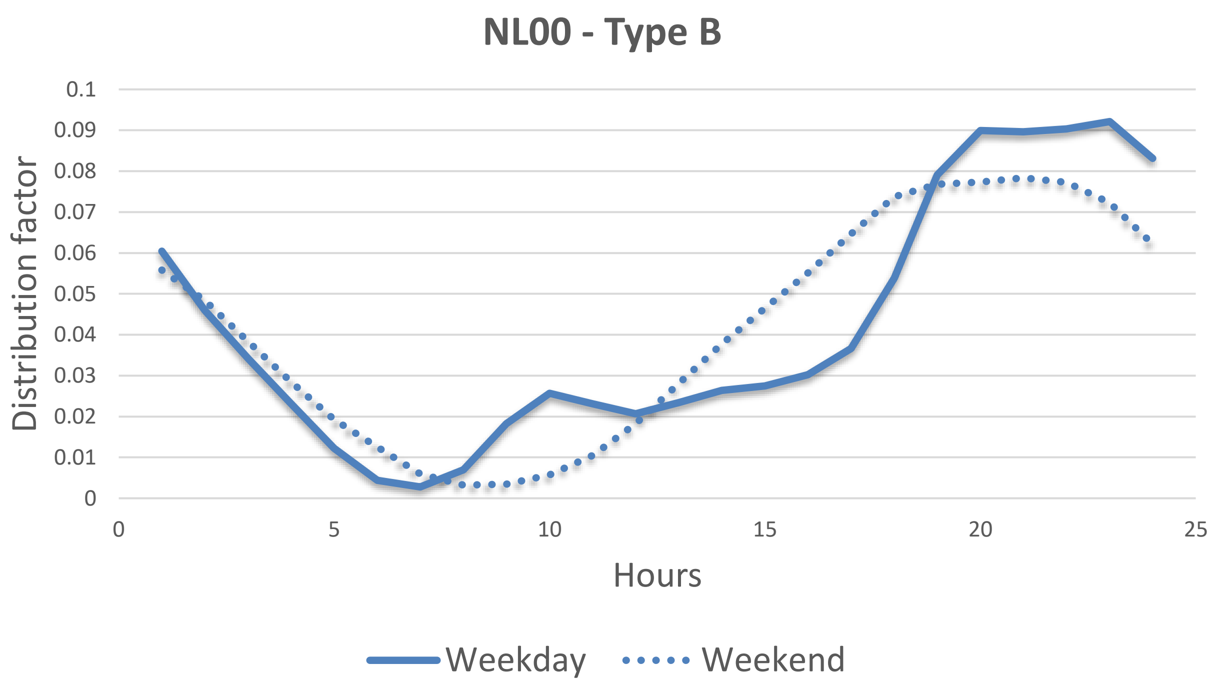


Figure 7. Netherlands EV Type B profile

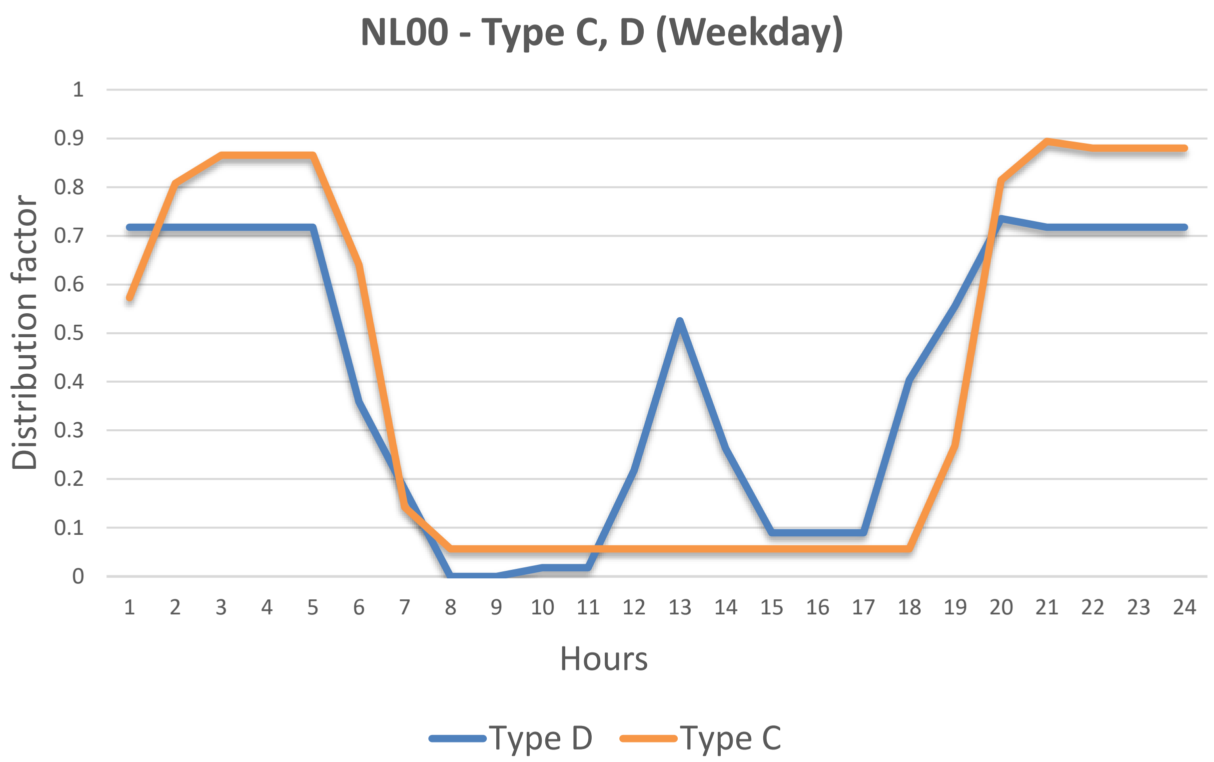


Figure 8. Netherlands EV Type C,D profile

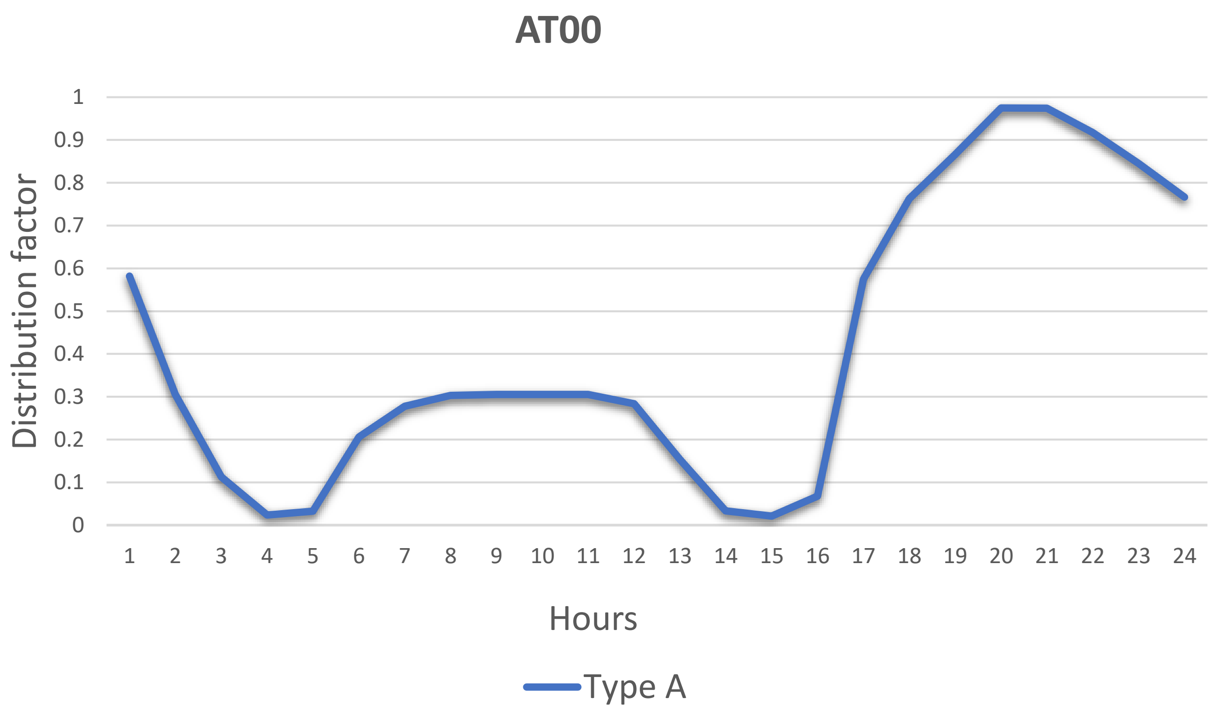


Figure 9. Austria EV Type A profile

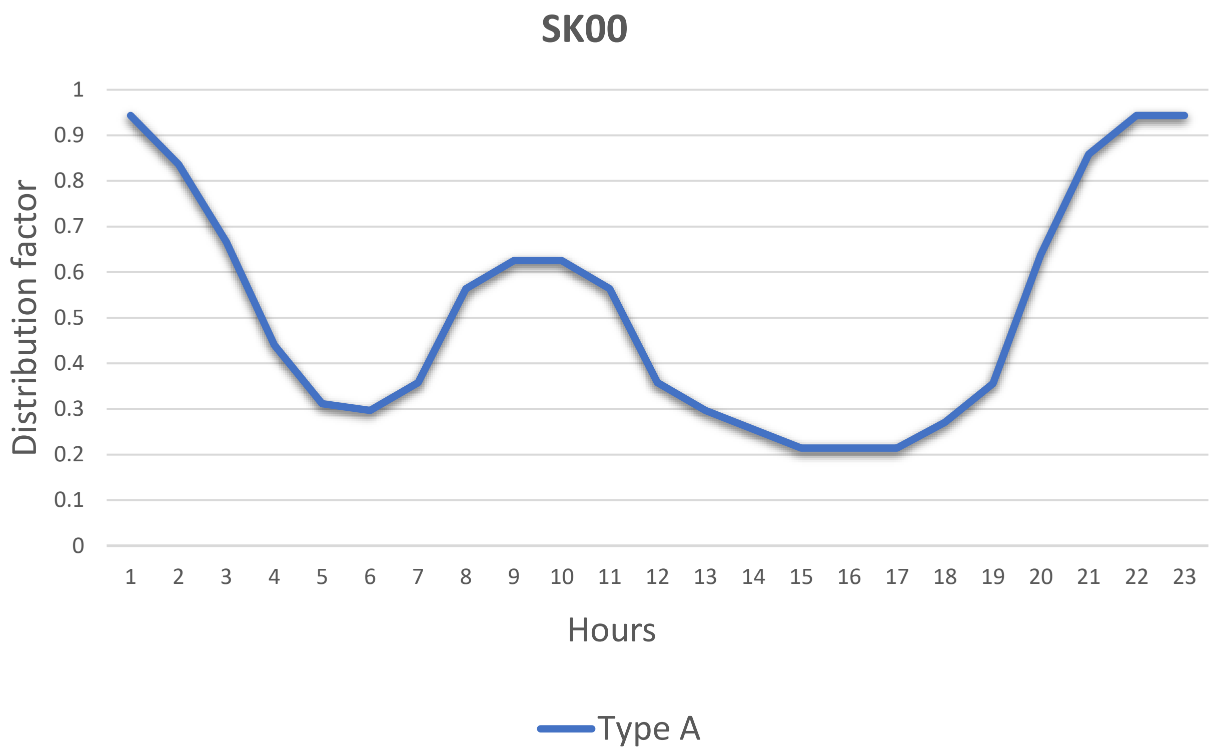


Figure 10. Slovakia EV Type A profile

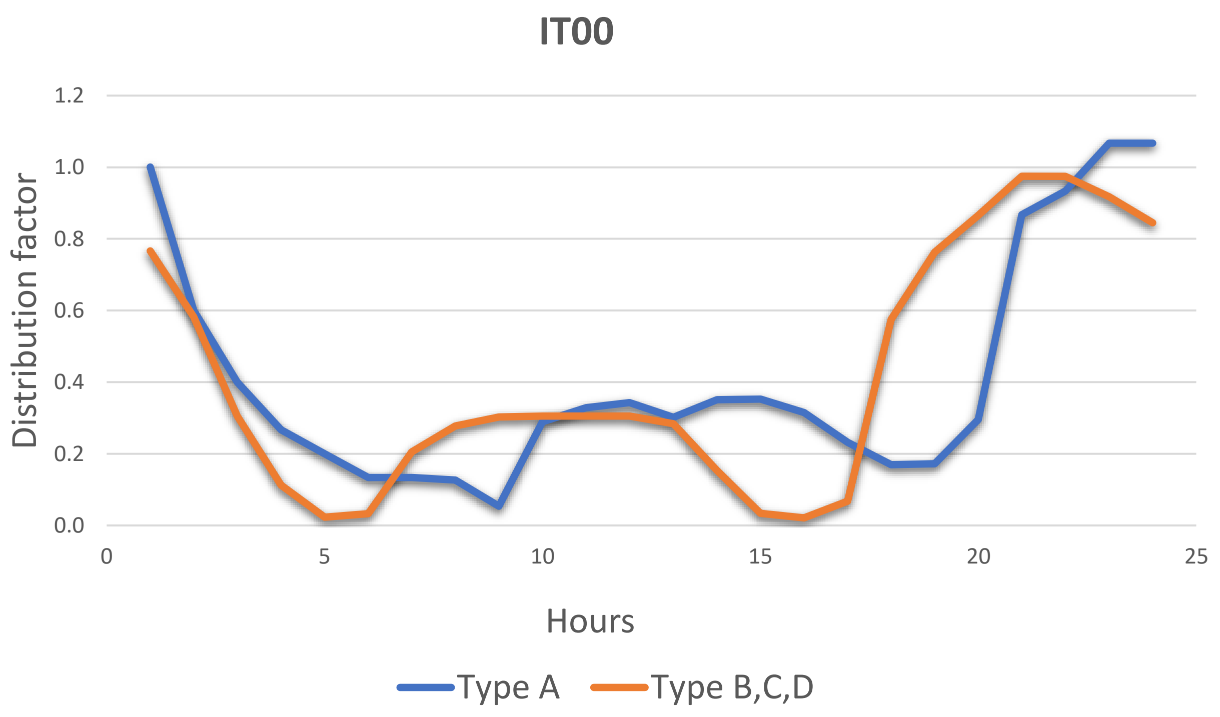


Figure 11. Italy EV profile

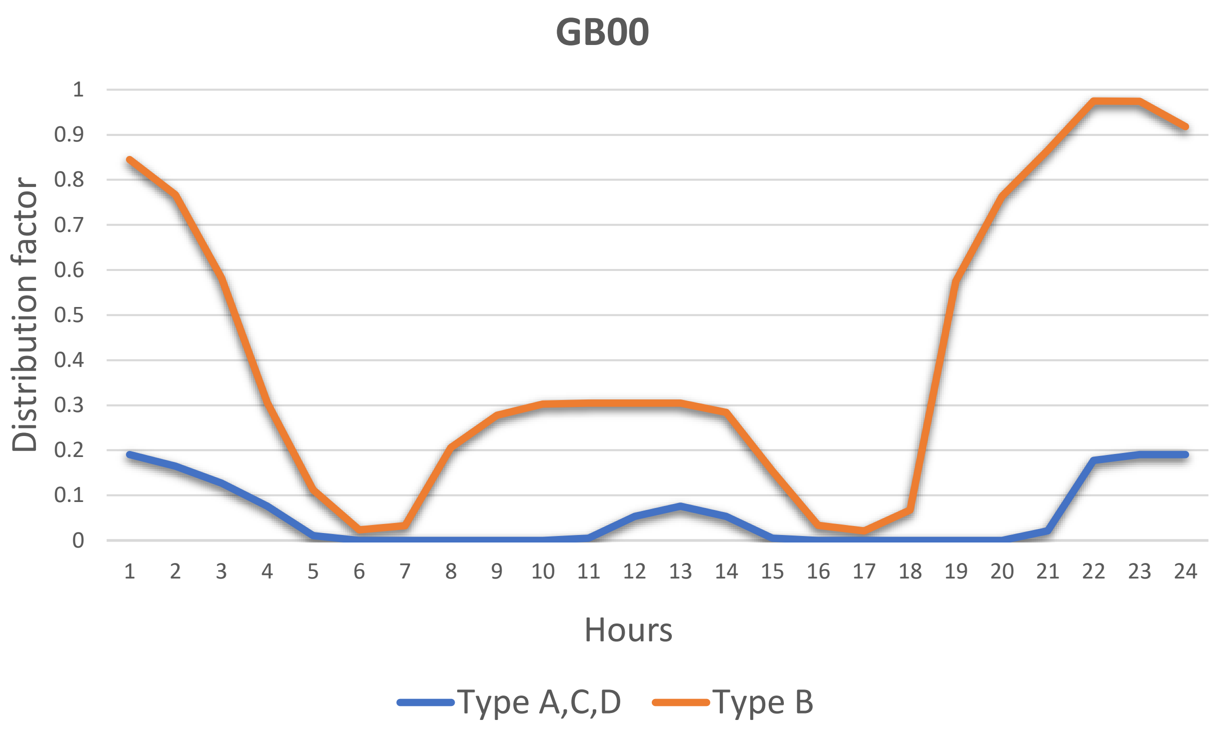


Figure 12. United Kingdom EV profile

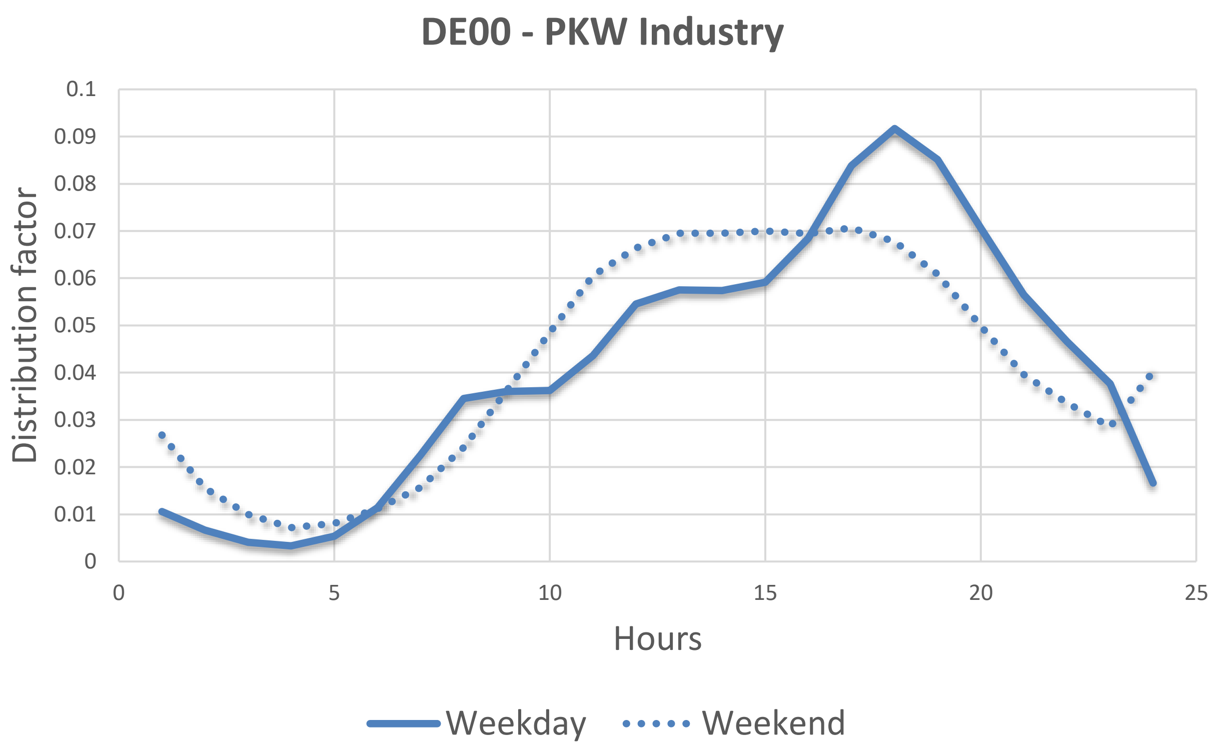


Figure 13. Germany EV industry profile

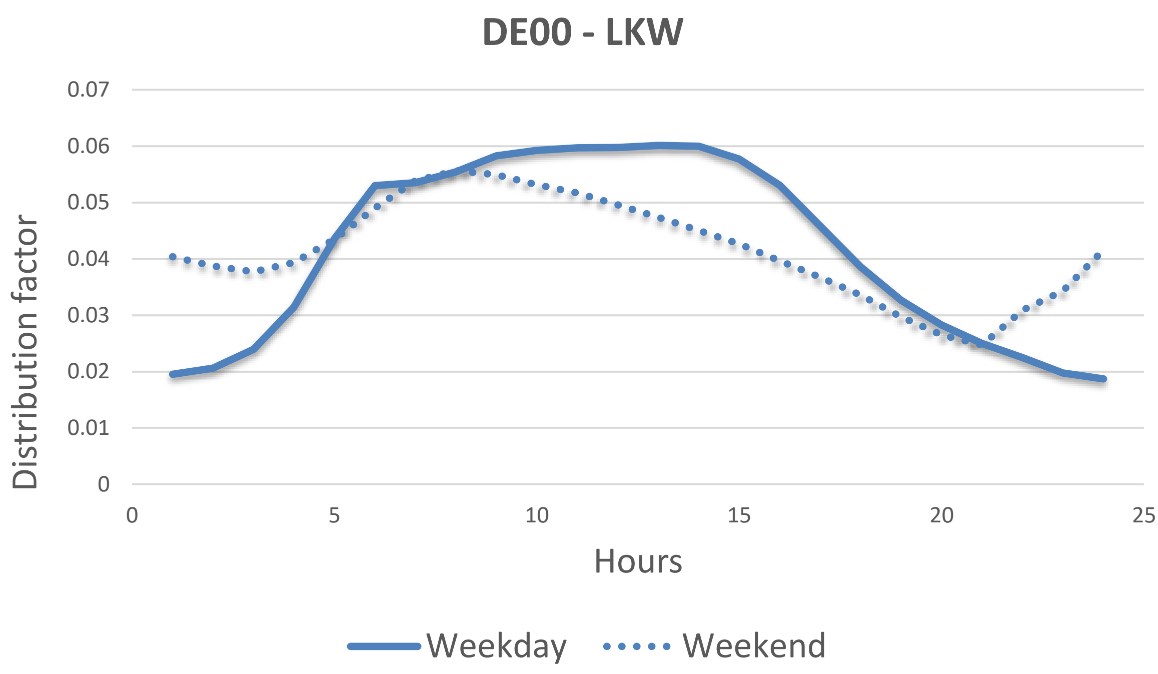


Figure 14. Germany LKW profile

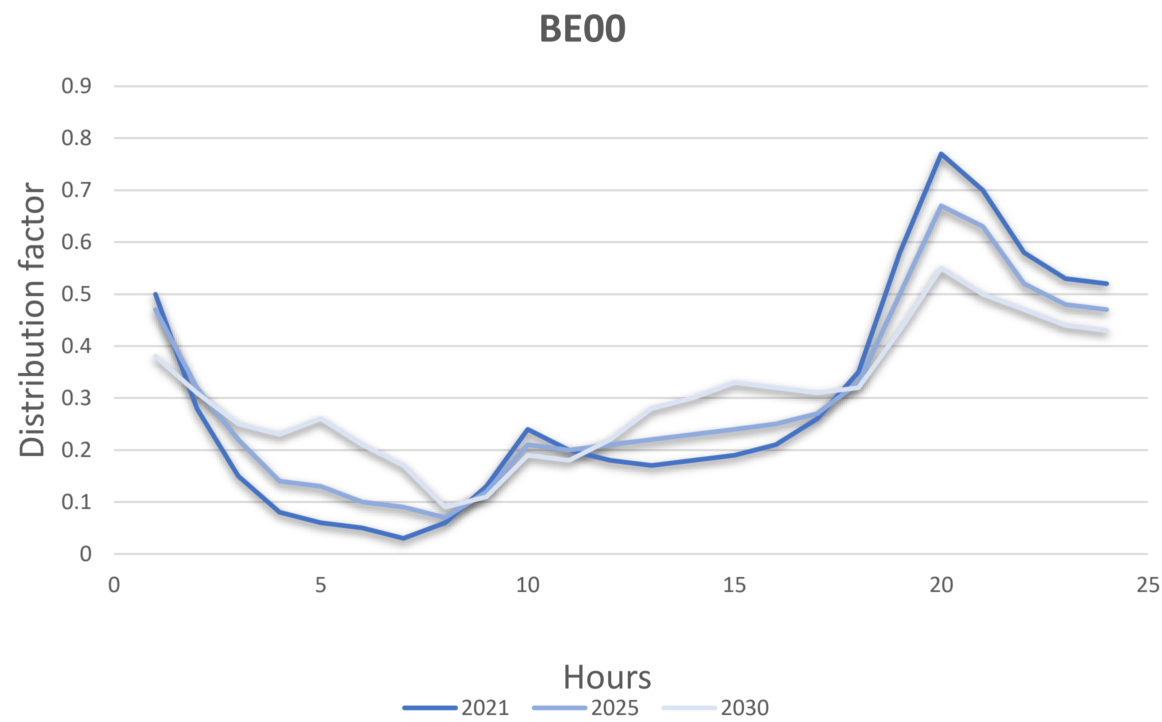


Figure 15. Belgium EV Type A profile

Focus on the historical load input data

Load on a power system is referred to as the hourly average active power absorbed by all installations connected to the transmission network or to the distribution network. The load is the value at a given moment of the electrical power supplied or absorbed at any point of a system as determined by an instantaneous measurement or by the integration of power during a given period of time. Load can refer to a consumer, an appliance, a group of consumers or appliances or a network. Load is the power consumed by the network including (+) the network losses but excluding (-) the consumption for pumped storage and excluding (-) the consumption of generating auxiliaries.

Source: ENTSO-E Statistical Yearbook 2011

Following table summarizes the input load data used for model creation for different Market Nodes

Market Node	Input historical Load (years)	Market Node	Input historical Load (years)
AL00	2016 - 2019	**TR00**	2016 – 2019
BA00	2016 - 2019	**Italy**	2016 – 2019
BG00	2016 - 2019	**PT00**	2016 – 2019
CH00	2016 – 2019	**AT00**	2016 – 2019
CY00	2016 - 2019	**BE00**	2016 - 2019
CZ00	2016 – 2019	**DE00**	2016 – 2019
DKE1	2016 – 2019	**FR00**	2016 – 2019
DKW1	2016 – 2019	**Greece**	2016 – 2019
EE00	2016 – 2019	**SK00**	2016 – 2019
ES00	2016 – 2019	**SE01**	2016 – 2019
FI00	2016 – 2019	**SE02**	2016 – 2019
HR00	2016 – 2019	**SE03**	2016 – 2019
HU00	2016 – 2019	**SE04**	2016 – 2019
IE00	2016 – 2019	**SI00**	2016 – 2019
LT00	2016 – 2019	**SK00**	2016 - 2019
LV00	2016 – 2019	**RS00**	2016 – 2019
MK00	2016 – 2019	**UA01**	2016 – 2019
ME00	2016 – 2019	**UK00**	2016 – 2019
MT00	2016 – 2019	**UKNI**	2016 – 2019
NL00	2016 – 2019	**NOM1**	2016 – 2019
PL00	2016 – 2019	**NON1**	2016 – 2019

Table 2 - Historical load input data used for model training

COP and other input curves

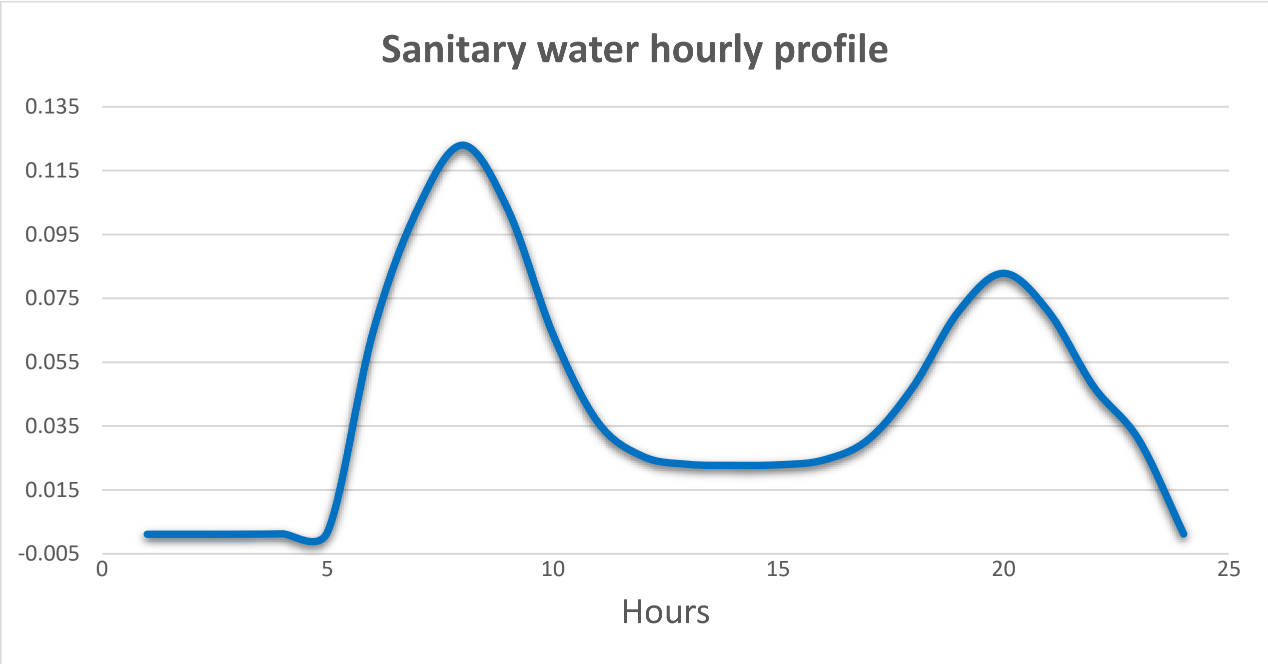


Figure 16 - Sanitary water hourly profile

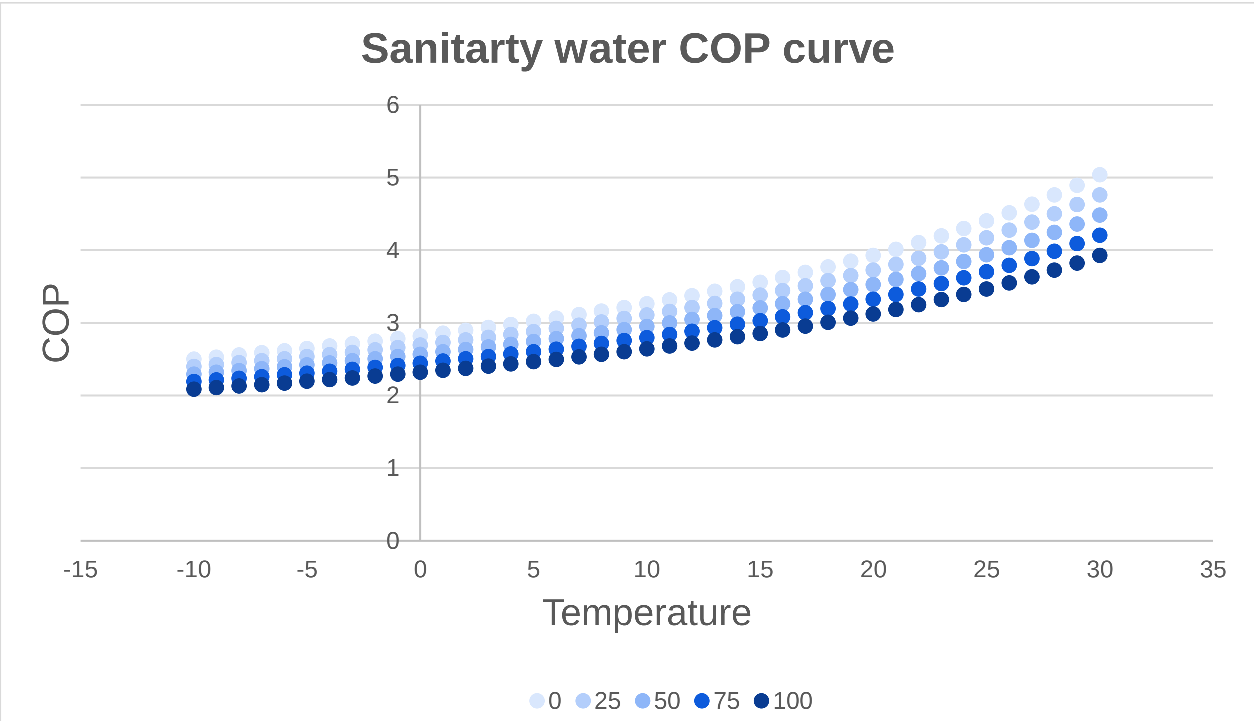


Figure 17 - Sanitary water COP curve

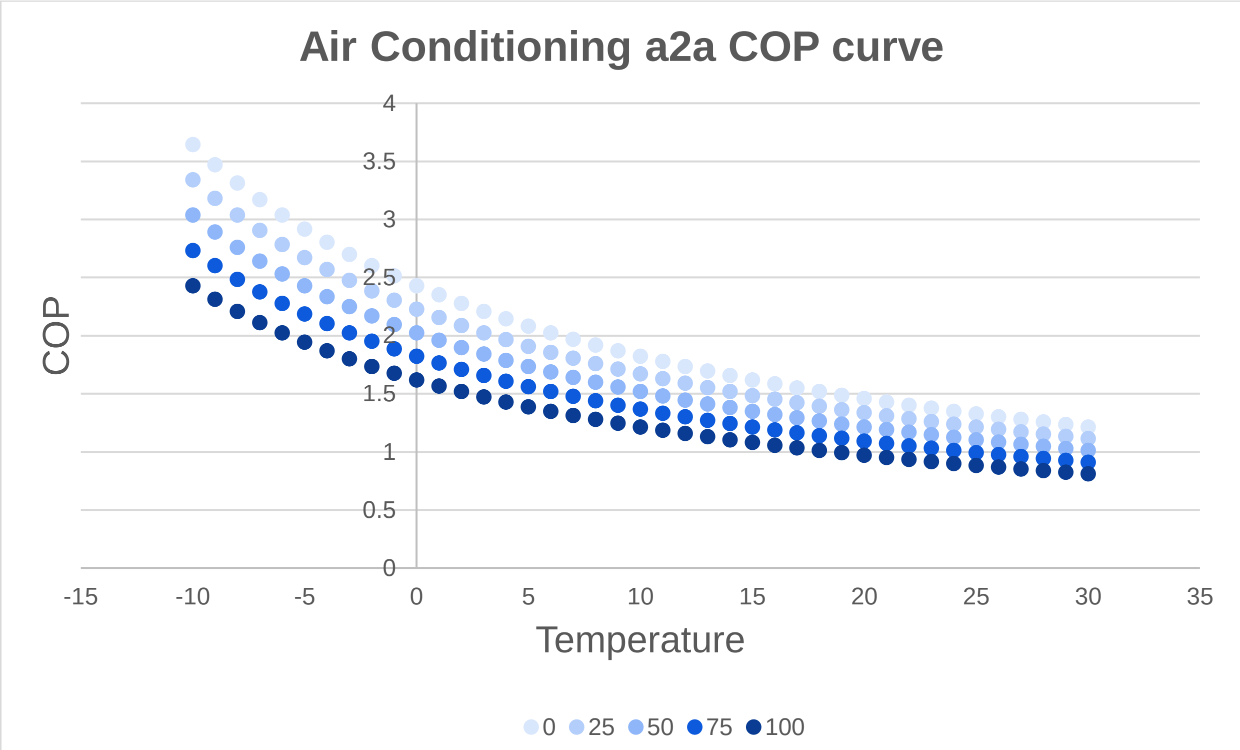


Figure 18 - Air conditioning COP curve air to air

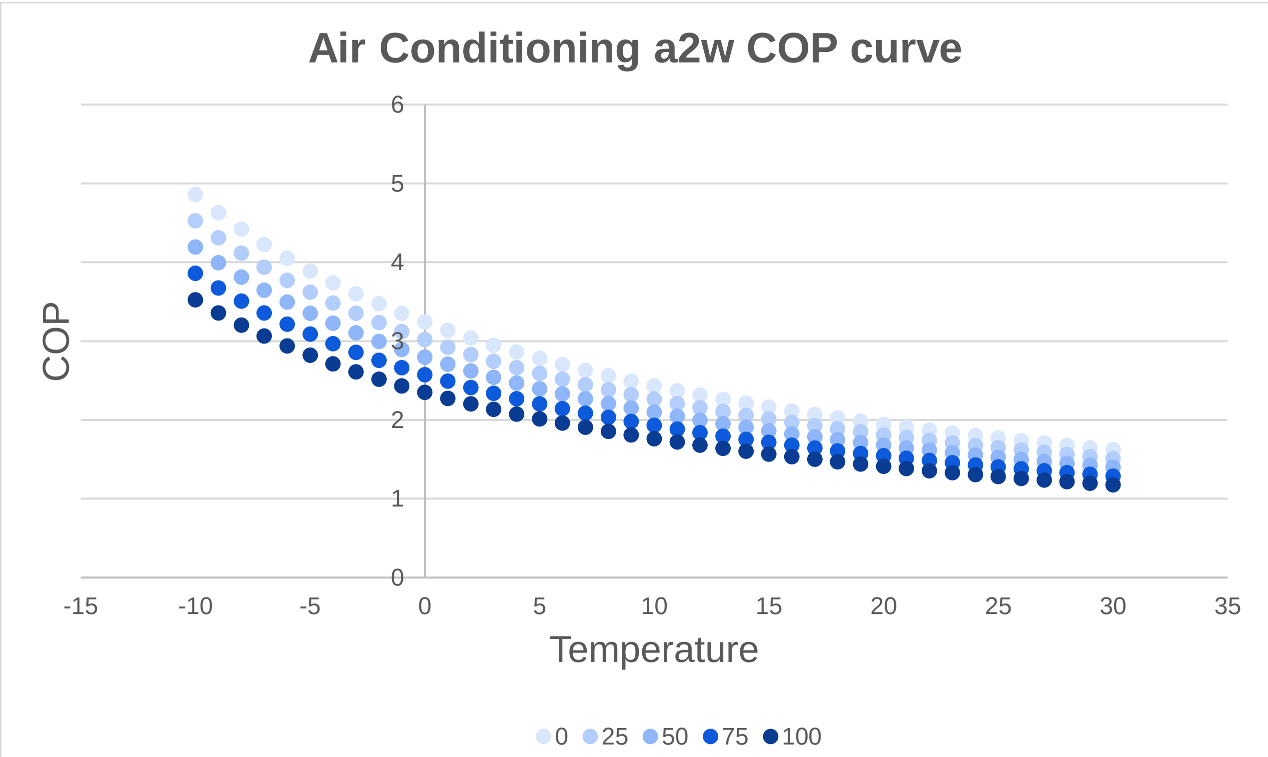


Figure 19 - Air conditioning COP curve air to water

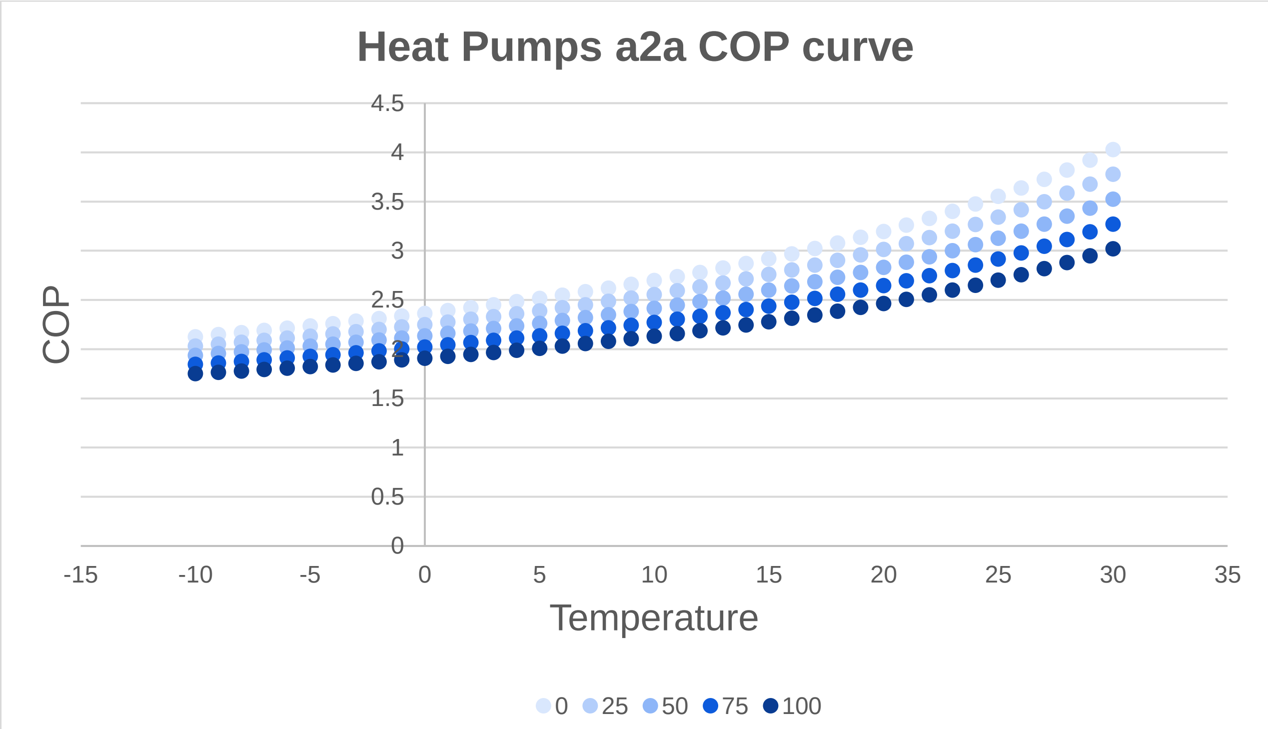


Figure 20 - Heat Pumps air to air COP

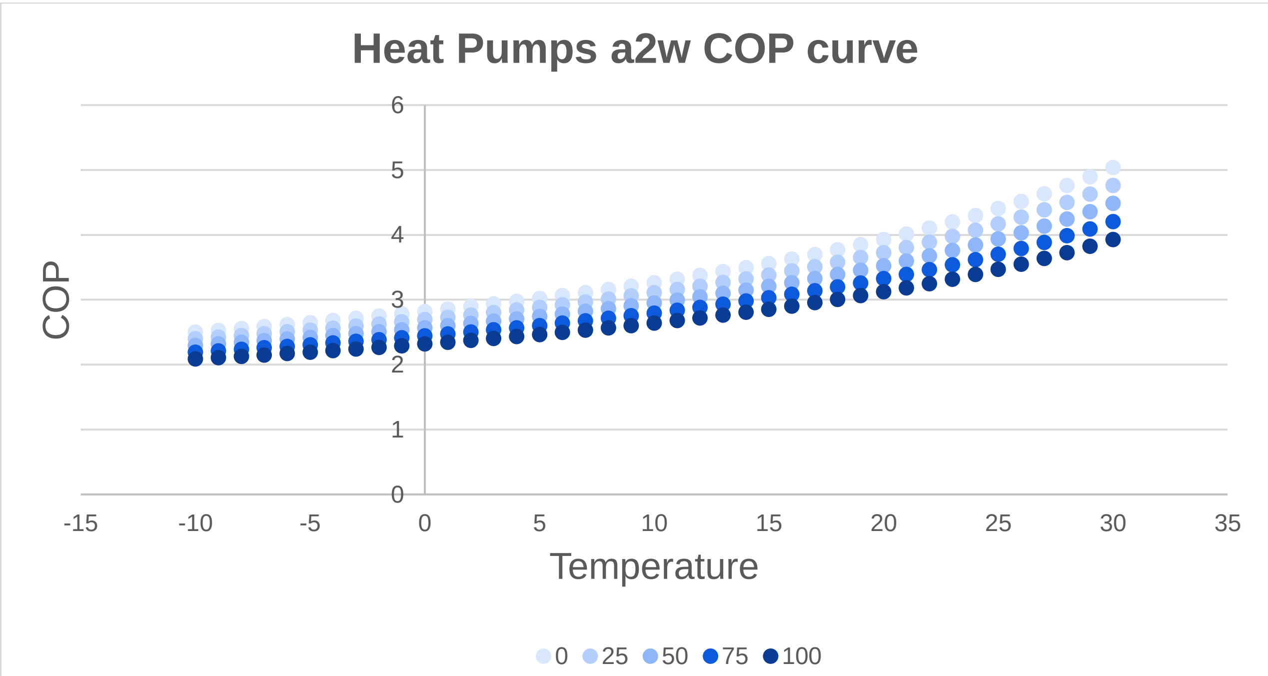


Figure 21 - Heat Pumps air to water COP

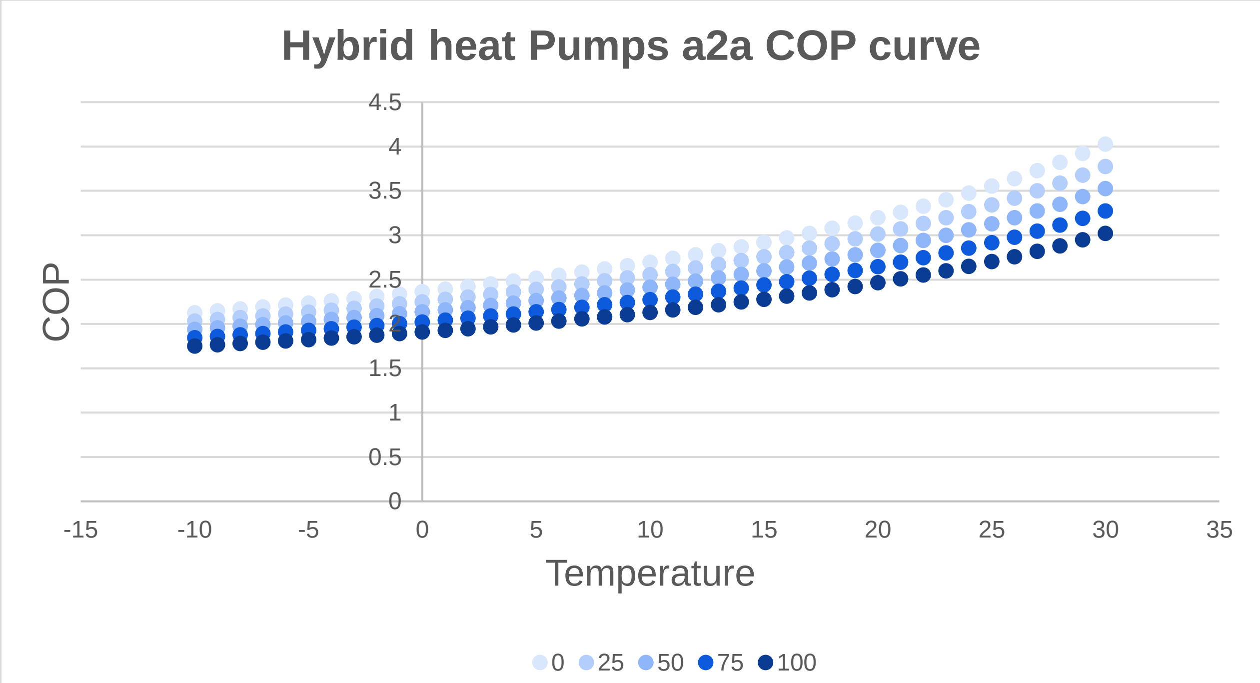


Figure 22 - Hybrid heat Pump air to air COP curve

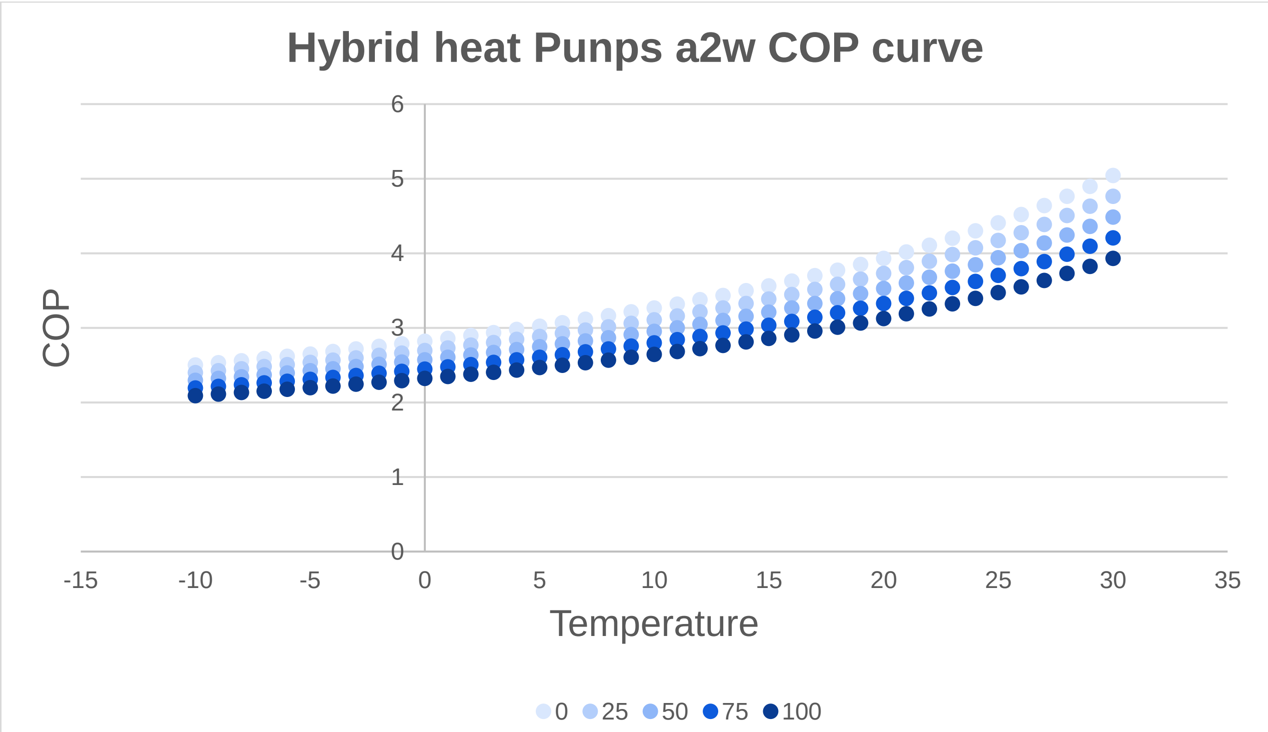


Figure 23 - Hybrid heat pump air to water COP

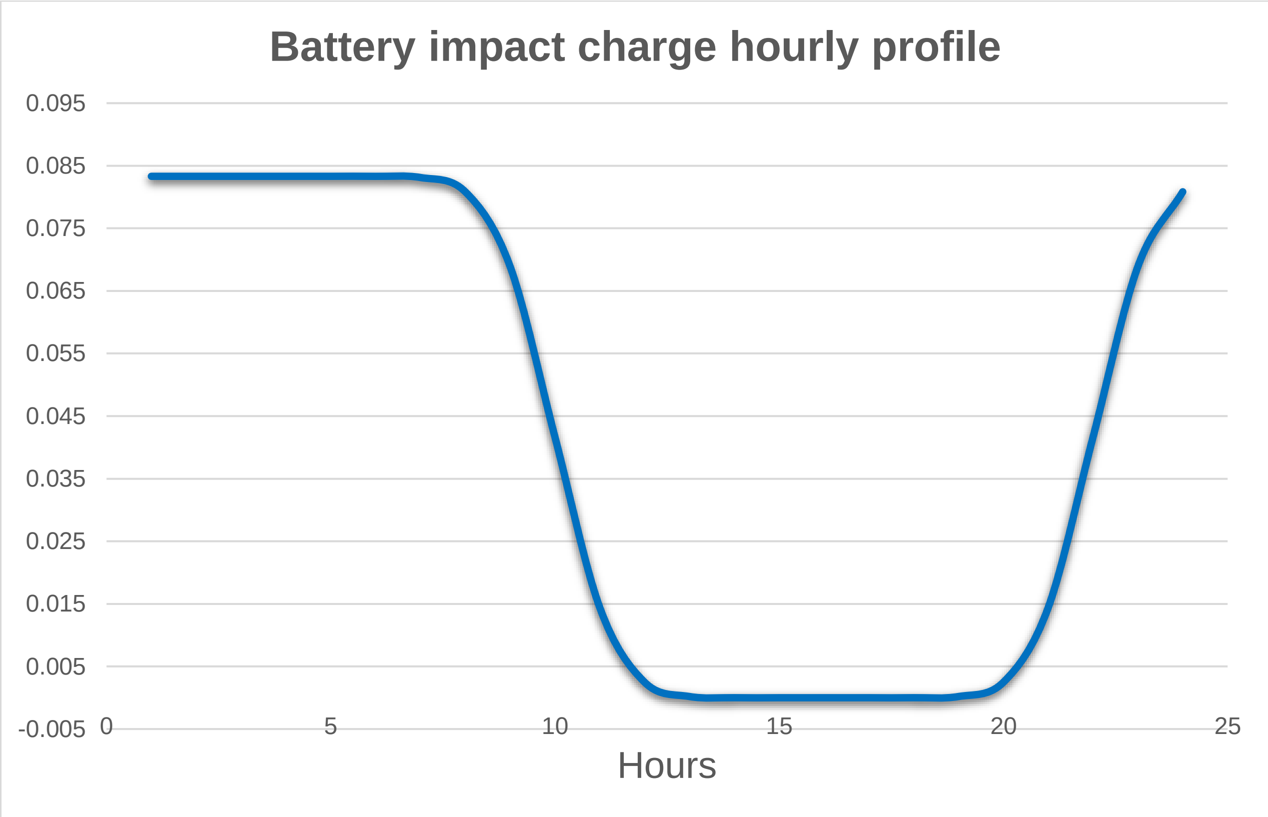


Figure 24 - Battery impact charging hourly profile

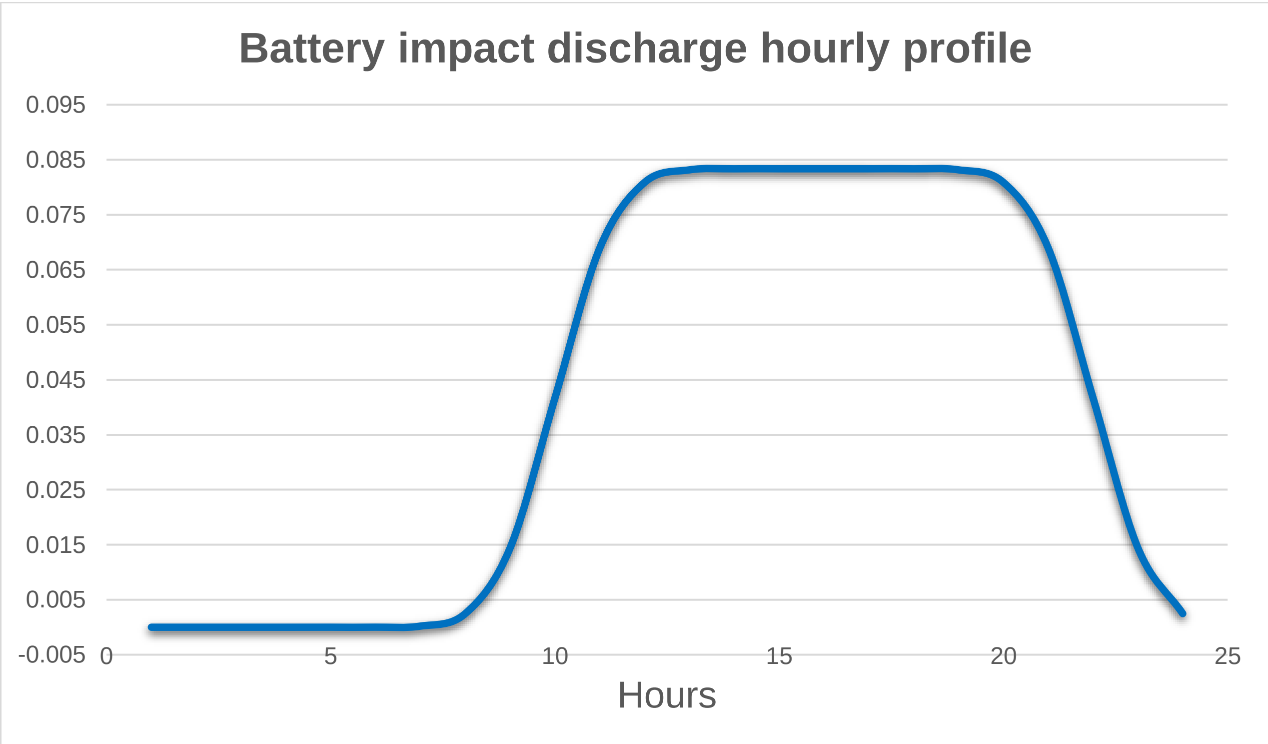
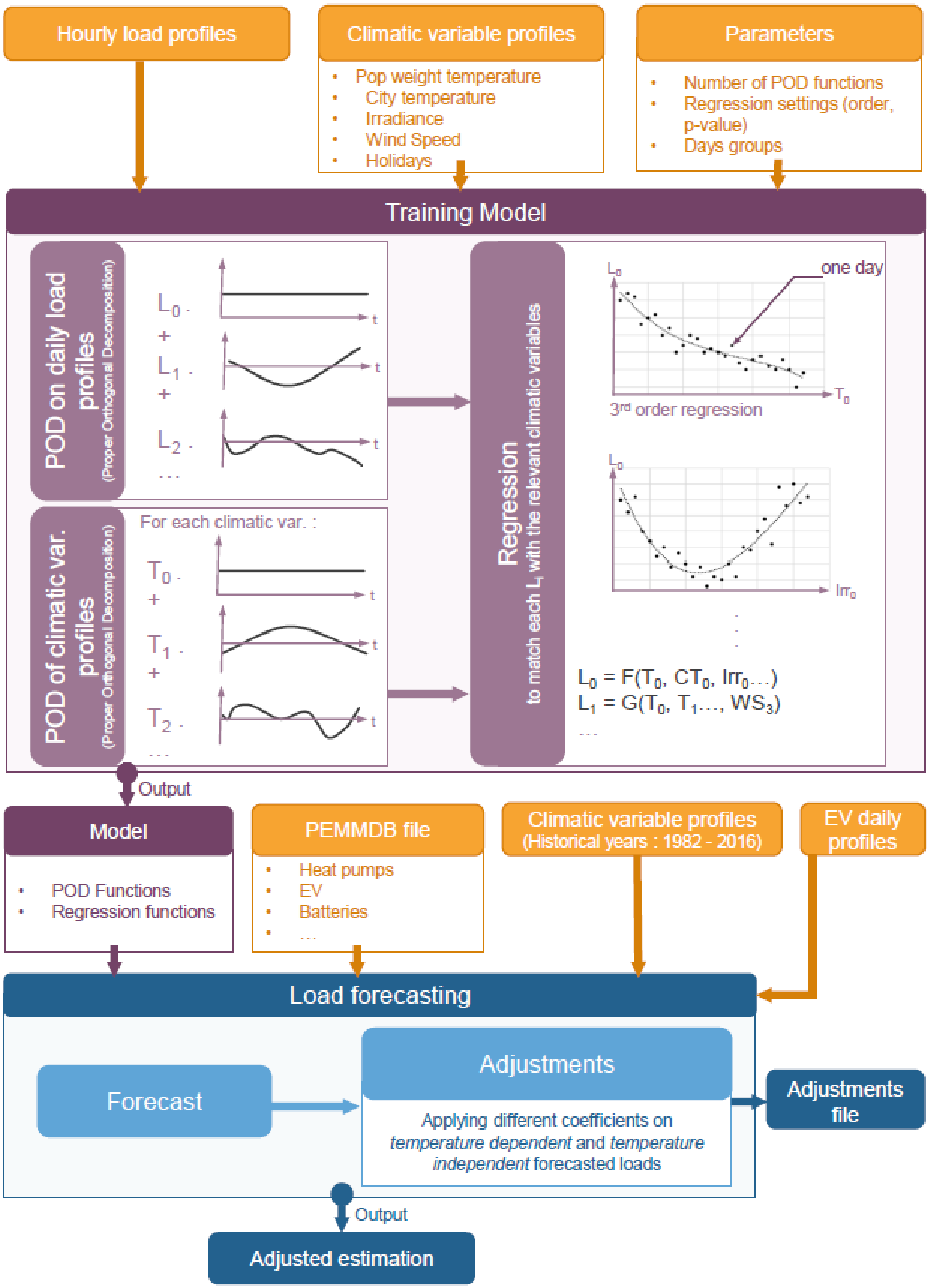


Figure 25 - Battery impact discharge hourly p

APPENDIX 1: MODEL TRAINING AND FORECAST

TRAPUNTA FLOWCHART



APPENDIX 2: POLAND HOURLY DEMAND FORECASTING METHODOLOGY

Polish methodology evolved from previous ENTSO-E tool SIMULA. Demand is impacted by the climate conditions (via e.g. air conditioning, electric heating). On the other hand some part of demand is climate independent, that is structural part of demand (e.g. load of industry processes). PSE methodology try to capture this distinction, still including the Climatic Years concept so the forecast is done in many different climatic conditions to make probabilistic analysis. To achieve all this goal we first of all detrend and de-seasonalize data and then create an autoregressive model, which include temperature as representative of climate condition. PSE excludes other climate variables due to collinearity and secondarity. After making a forecast, we use dedicated temperature dependent technological models to make EV and HP forecast adjustment, which is consistent with ENTSO-E methodology.

In the table below, a comparison of assumptions between Trapunta and PSE methodology is presented

PSE and TRAPUNTA methodology

Feature	TRAPUNTA	PSE Methodology	PSE Comment
Climatic parameters	possible: Temperature, City Temperature, Wind speed, Irradiance, Humidity	Average bidding zone temperature	We analyse using many climatic parameters (as in TRAPUNTA, like wind speed, irradiation) but we find out correlation between them or having the same seasonality. Due to collinearity and lack of new information we decide to use only average temperature as representative of climate variables.
Used method	SVD + Regression	Regression + Autoregresion	
Thermosensivity	Yearly	Monthly	Due to the significant differences of the thermosensitivity in winter and summer, we decided to use models for each month (12 models per year). It allows to better describe the complex nature of this phenomenon.
Technology submodels (EV, HP)	Dependent of model	Independent	Both, PSE and Trapunta profiles are climate-dependent
Output	Hourly demand in PECD Climatic Years	Hourly demand in PECD Climatic Years	

Table 3. Comparison of assumptions between Trapunta and PSE methodology

APPENDIX 3: BELGIUM HOURLY DEMAND FORECASTING METHODOLOGY

The Belgian approach is an evolved methodology inspired from the previous tool developed by ENTSO-E (SIMULA). This approach follows two main steps:

The first step consists in generating load profiles accounting for thermosensitivity based on a given set of temperature.

In a second step, three different types of components are taken into account to construct the hourly profiles: the growth factor (excluding electrification and additional base load), the additional baseload and finally additional electrification elements. The target yearly consumption is calculated via a stacking model divided by sector taking into account all drivers impacting the evolution of the total annual electricity demand (electrification, energy efficiency, macro-economic trends, etc)

- In order to reach the target yearly consumption, a growth factor is applied to the raw profile obtained in the first step. This growth factor encompasses mainly energy efficiency, economic growth among others. After applying the growth factor, the electrification elements and the based load are added on top as they are independent of this step 1 profile.
- The additional baseload is a constant value to be added on top of the profile generated in step one, it represents mainly the additional consumption of datacenters.
- The electric vehicles (EVs) and batteries are modelled via their amount at the target time horizon multiplied by a daily profile. Regarding the heat pumps (HPs) and air conditioning (AC), the profiles are built in function of the number of appliances, a daily profile, and the daily temperature from each climate year. Adding these result accounts for the electrification of each of these elements as a last step of the applied approach.

All elements added in the second step are following the same reasoning as applied in Trapunta and uses the PEMMDB data as source. The profiles of heat pump and air conditioning are based on ENTSO-E profiles. The only exception is the EV profile that comes from the e-mobility study realized by Elia in November 2020. This profile is a combination of two charging profiles described below (further information can be found in the Adequacy and Flexibility study 2022-32). Note that the share of V1G charging is increasing towards 2030.

1) ‘Natural’ charging: the electric vehicle profile overlaps with the evening electricity consumption peak. No smart meter nor incentives are present to optimise the charging of the vehicle. The observed pattern is one in which people charge their EVs when needed, mostly after work. It results that it coincides with doing it at the same time as they use other electric appliances (for cooking, entertainment, etc.);

2) ‘Optimised charging’ V1G: electric vehicles are combined with unidirectional smart charging technology (without the possibility of injections into the network) to optimise charging during off-peak periods;

APPENDIX 4: FRANCE HOURLY DEMAND FORECASTING METHODOLOGY

Drawing up load curve forecasts

Demand forecasts are prepared in two phases, as described below:

> Forecasts established for annual energy demand, for each year in the study period,
> Forecasts established for power demand, on an hourly basis, using as input data the annual energy demand forecasts calculated previously.

Each phase includes a retrospective analysis of past years, and an alignment with the years used as reference for simulations, as well as a forward-looking study designed to offer a realistic idea of possible future outcomes based on today's situation and current and future trends, including relevant shifts that may occur based on the determinants such as the electrification of space heating or the development of electric vehicles. Annual energy demand forecasts are calculated using an analytical approach and stacking model. This involves dividing electricity demand into sectors of activity. The following sector breakdown has been used (starting with the highest level of demand today): residential, tertiary, industry, energy (including network losses), transport and agriculture.

Each sector is then broken down into branches or end-uses. Energy demand for each branch or end-use is estimated by multiplying and adding together "extensive" variables (generated quantities, heated floor surface, appliances per home, etc.) and "intensives" ones (unit consumption per produced unit, per sq. m, per home, etc.). The demand figures thus calculated are then aggregated for each sector.

To provide input data for and exploit its forecasting models, RTE relies on data made available by research institutes (CEREN, BIPE, BatiEtude, GfK, etc.), public or semi-public institutions (INSEE, ADEME, etc.), trade associations and other sources. The results of statistical surveys and data drawn from RTE metering are used to align these variables with past data. Wherever possible, projections factor in information gathered from the economic actors in question. Sector information is updated regularly to take into account new end-uses, behavioural changes and the implementation of regulations designed to improve energy efficiency. Power demand forecasts are also calculated using a stacking method.

Each non-temperature sensitive branch or end-use for which energy demand forecasts have been drawn up is associated with an hourly load curve profile. A large percentage of the profiles are generated using measurements under real conditions: RTE metering for branches of industry connected to the transmission grid, measurement campaigns for some residential and tertiary end-uses, etc. Profiles of the branches and end-uses for which no measurements are available are recreated based on knowledge about the profile of the sector of activity in question.

The profiles of end-uses sensitive to weather conditions (heating and air conditioning) are calibrated using historical data. The calibration use the seasonality of the demand, building inertia, the influence of cloudiness, the fact that the heating is only triggered when a threshold temperature is reached. The method for calibrating heat-sensitive consumption profiles uses a coupling of an iterative dichotomy process with a linear regression solved by recursive least squares. The profiles are generated based on the PECD temperature datasets.

These profiles are updated on a regular basis to incorporate new information about the sectors and emerging end-uses, new technologies. Such updates require data, which RTE takes from the measurement campaigns and surveys carried out by different players.

Based on annual energy demand for each end-use or branch and the associated profiles, RTE calculates the anticipated load curve for the end-use or branch for the year under review. The demand forecasts thus calculated are then aggregated to produce the load curve for France. National load curves for past years, modelled by stacking end-uses or branches, are then aligned with the load curves measured for the most recent years.