FLEXBEAN
Flexibility for Energy Transition PROJECT

D1.2.6

Technical flexibility potential in Luxembourg

a sector-based model & analysis:
industry, tertiary sector, residential and e-mobility

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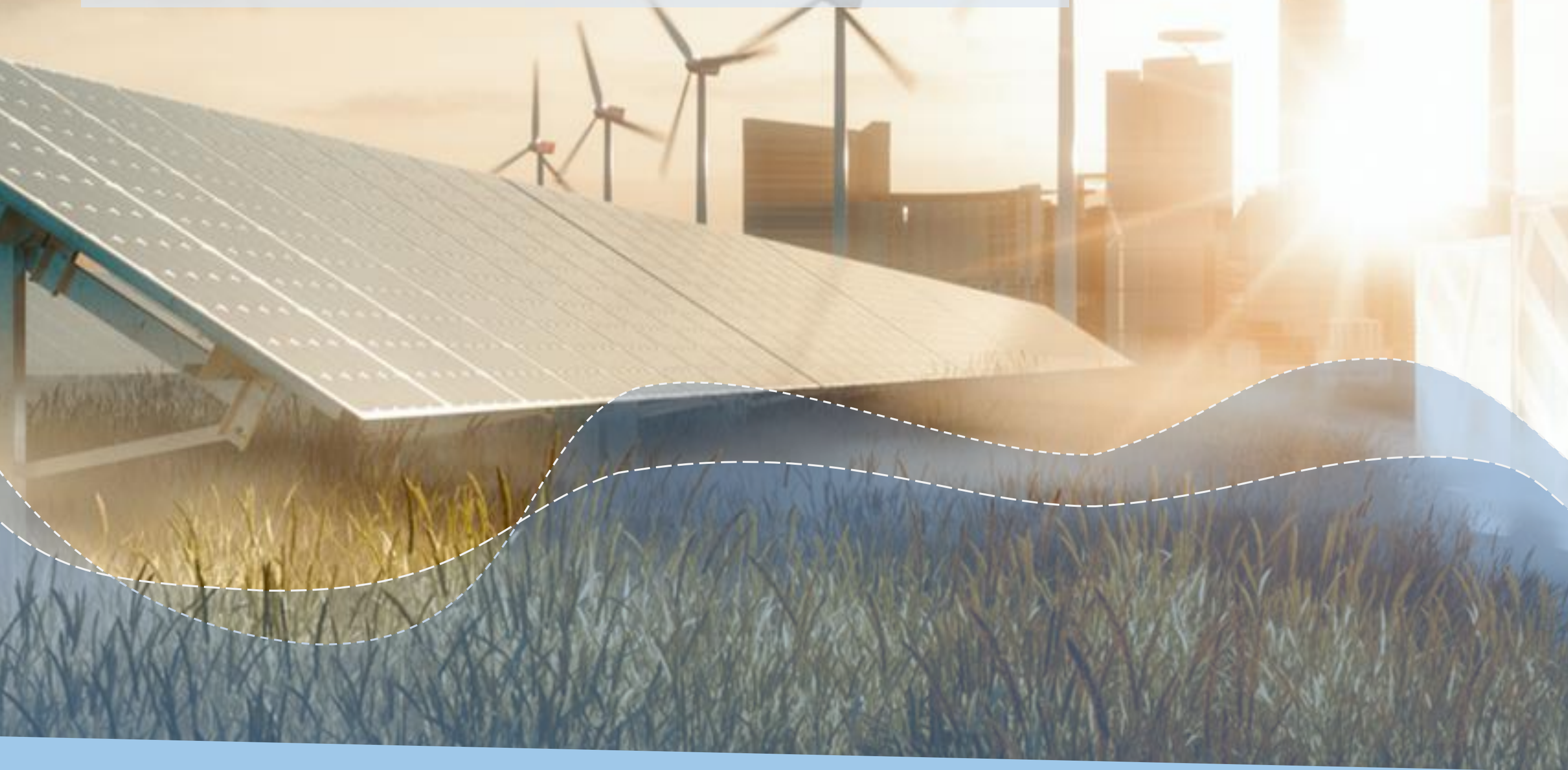

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Table of Contents

List of Tables

List of Figures

Abbreviations

AC	air-conditioning
aFRR	automatic Frequency Restoration Reserve
BRP	Balance Responsible Party
CDH	Cooling Degree Hours
COP	Coefficient of Performance
DC	direct current
DHW	domestic hot water
DSO	distribution system operator
ECMWF	European Centre for medium ranged weather forecasts
EV	electric vehicle
EWH	electric water heater
FCR	Frequency containment reserve
GHI	global, horizontal irradiance
HP	Heat Pump
HV	high voltage
HVAC	Heating, Ventilation and Air-Conditioning
LiDAR	Light Detection and Ranging
LV	low voltage
MFH	multi-family house
MW	mega watt
mFRR	manual Frequency Restoration Reserve
PNEC	plan national intégré en matière d'énergie et de climat du Luxembourg
PV	photovoltaic
PV BESS	photovoltaic battery energy storage system
SFH	single-family house
SGR	Smart Grid Ready
SH	space heating
SLP	Standard Load Profile
SoC	State of Charge
TSO	transmission system operator
V2G	vehicle-to-grid

Executive summary

Luxembourg's energy system is undergoing a profound transformation as renewable generation expands and electrification accelerates in heating, mobility, and industry. This transition brings significant challenges for grid management and infrastructure planning, but it also creates opportunities to leverage demand-side flexibility as a cost-effective and sustainable solution. This report provides a comprehensive assessment of the technical flexibility potential across four key sectors, industry, tertiary, residential, and e-mobility, covering the present situation and projections for 2030 and 2040.

The analysis is based on a detailed, sector-specific modeling framework that combines statistical data, historical weather patterns, and technology penetration scenarios. Results are provided with hourly resolution and spatial granularity down to the commune level, enabling insights into both national and local flexibility resources.

Industry could become a solid pillar of Luxembourg's flexibility landscape. Today, large industrial consumers can provide around -20 MW of upward flexibility, even up to -39 MW under optimistic assumptions – although often limited to relatively short durations. While this capacity is concentrated in a few energy-intensive sectors, the electrification of steam production in plastics manufacturing could temporarily add -15 to -55 MW of symmetrical flexibility between 2030 and 2040, offering a critical buffer during the energy transition.

The tertiary sector — comprising offices, retail, and services — offers substantial but highly seasonal flexibility from air-conditioning, ventilation and cooling processes. Air-conditioning and cooling systems dominate the technical potential in summer, with downward flexibility exceeding 188 MW during peak periods, while ventilation provides a steady year-round contribution. However, activation strategies must account for short durations and rebound effects to ensure reliable grid support.

In the residential sector, the rapid deployment of heat pumps and PV battery storage systems will fundamentally reshape flexibility dynamics. By 2040, heat pumps alone could deliver around 265 MW of downward flexibility and -123 MW upward (on average), depending on activation mode and temperature conditions. PV battery systems, assumed to reach 55% penetration in single-family homes by 2040, could add 300–400 MW of bidirectional flexibility, provided smart charging and grid-aware operation are implemented. Additional contributions come from electric water heaters and shiftable appliances, though their impact is comparatively modest. A common downside of all these assets is a short to modest duration for which the flexibility can be sustained. This requires smart, cascaded activation strategies, that shall further consider the compensation of rebound effects, that are inherent to flexibility activations from some assets, such as heat pumps and household appliances.

Electro-mobility introduces both challenges and opportunities. With an expected fleet of over 430.000 electric vehicles by 2040, smart charging could unlock up to 190 MW of flexibility from home charging alone, during the evening peak times. This is complemented by workplace and public charging resources, preferably over the day. This makes EVs a key lever for mitigating evening peaks and integrating renewable generation, provided that appropriate control mechanisms and incentives are in place.

Overall, the findings underline that demand-side flexibility can become a cornerstone of Luxembourg's energy transition strategy, deferring or even reducing the need for costly and time-consuming grid reinforcements and enabling higher shares of renewable energy. Realizing this potential will require coordinated action: establishing flexibility mechanisms of versatile use cases, incentivizing participation, and deploying digital control solutions. The next decade is critical to build the regulatory, technical, and market frameworks that will allow these resources to deliver their full value.

1. Introduction & Background – Demand Side Flexibility

In our future renewable-based energy system, flexibility on the demand side is necessary to react on fluctuating energy production from volatile renewable energy sources, such as wind and solar, but also to manage changing energy consumption patterns, e.g. due to electric vehicle charging or electrification of the heating sector via heat pumps. Flexibility use cases reach from classical “balancing” flexibility (or system flexibility) to network / grid flexibility to help (transport and distribution) grid operators to avoid grid congestions. Further, the growing volatility on the spot markets for energy becomes an important driver for flexibility to economically use the price spread on the energy markets (market arbitrage). Internal usage of flexibility in households, private companies or energy communities is another rising demand, e.g. to optimize grid tariffs (peak shaving), to increase the share of self-consumption from own electricity production, or to use periods of low spot market prices to reduce the energy bill.

Nevertheless, the results presented in the following chapters are focusing on grid flexibility and originate from the FlexBeAn Project, a joint project of CREOS, the Luxembourg Institute of Science and Technology (LIST) and the “Security and Trust” Institute (SnT), belonging to the University of Luxembourg.

Flexibility, in the understanding of this project, focused on demand side flexibility and can be defined as:

“Flexibility is the ability of consumers to adjust their electricity consumption, following an external signal, comprising an increase and/or decrease of power consumption. “

Such “external signals” can be manifold, reaching from dynamic electricity tariffs or grid fees, non-monetary incentives or direct load-control signals, to name the most important ones. The flexibility potentials that are reported in this document are mainly the technical potentials, taking into account also some practical aspects. Other than the theoretical potential, the technical potential considers technical restrictions which limit the potential and is therefore smaller than the theoretical potential. The economic potential would further reduce the potential to the share that is economically viable, but this is not subject of this study.

Within the FlexBeAn Project, the partners are evaluating the flexibility potentials for the sectors industry, tertiary sector, households and e-Mobility. In the following the methodology for the estimation of their potentials and the results are documented.

The project comprises potentials for today, 2030 and 2040 via a model that allows for spatial and temporally resolved results. The spatial resolution of the final model gives insights down to the level of communes, and hence, enables the allocation of flexibility in low voltage level and could be aggregated up to the distinctive high-voltage areas. The temporal resolution of one hour over a full year, allows findings regarding fluctuation of flexibility potentials over the seasons, across week-day and week-ends, as well as representing the diurnal cycle, if relevant.

1.1. Stakeholder overview

Demand-side flexibility involves a range of stakeholders, either as providers of flexibility, as actors with a need for flexibility, or as intermediaries facilitating its use.

Flexibility providers are found across sectors, including large industrial facilities, tertiary sector companies, households, and users of electric mobility. Their main interest is to reduce costs, optimise their own energy use, or obtain revenues from providing flexibility services.

Distribution system operators (DSOs) seek flexibility primarily to manage local and regional grid constraints and to avoid costly reinforcements at low- and medium-voltage levels.

Transmission system operators (TSOs) could also use flexibility to overcome grid constrains, and further require flexibility to maintain overall system stability and security of supply, for example to balance load and generation across the network.

Balance responsible parties (BRPs) and **energy suppliers** are interested in flexibility as a tool to balance their portfolios and to manage the risks arising from volatile energy markets.

Aggregators and energy service companies act as intermediaries, bundling small-scale and distributed flexibility resources and making them accessible to system operators or market actors.

Successful mobilisation of flexibility requires that all parties derive tangible benefits: providers expect fair remuneration and minimal disruption to processes or comfort, while DSOs and TSOs demand reliable, predictable and verifiable flexibility. This interaction of needs and roles forms the basis for the following chapters, which address flexibility needs, flexibility services and the corresponding use cases.

1.2. Types of flexibility services

In the energy sector, demand-side flexibility is typically categorised according to the purpose and the context in which it is activated. Three main types can be distinguished:

1. **Grid-oriented flexibility (network flexibility):**

   Flexibility activated to relieve local or regional grid constraints, for example to avoid overloading distribution or transmission lines, manage voltage issues, or defer grid reinforcements. DSOs are the main users of this type of flexibility, but TSOs also require location-specific measures to maintain secure grid operation.

2. **System-oriented flexibility (balancing services):**

   Flexibility mobilised to maintain the real-time balance between electricity generation and consumption at the system level. TSOs are responsible for these services, which are typically procured via balancing markets (e.g., frequency containment reserve, frequency restoration reserve, replacement reserve).

3. **Market-oriented flexibility:**

   Flexibility used to respond to price signals on wholesale or retail markets. This includes shifting consumption to periods of low prices, avoiding periods of high prices, or providing arbitrage opportunities across time. BRPs and energy suppliers are the main actors using this type, but end-users may also directly benefit from dynamic tariffs or time-of-use pricing schemes.

In practice, the same technical flexibility source may serve different types of services depending on contractual arrangements and the activation signal. For instance, a residential EV wall box can be curtailed for network purposes, activated by an aggregator for balancing, or shifted in response to dynamic tariffs. This illustrates the need for clear definitions of services and use cases.

1.3. Flexibility Use Cases and markets

Flexibility can be activated for a variety of purposes and through various mechanisms. While the same technical resource may serve different applications, the relevant use cases can be grouped into three main domains:

Grid-oriented use cases (network flexibility):

- ***Congestion management:*** avoiding or mitigating overloads in distribution or transmission grids, particularly at times of high demand or high decentralised generation.
- ***Voltage support:*** maintaining voltage within allowed limits, especially in low- and medium-voltage networks with high shares of distributed generation.
- ***Deferral of grid reinforcement:*** using demand-side measures as a cost-efficient alternative to conventional network expansion. This requires the recurring use of demand-side flexibility to reduce the need for physical grid upgrades.

Procurement of flexibility for these types of use cases is typically not standardised at European level but some DSOs or TSOs procure flexibility through local flexibility markets, bilateral contracts, or pilot schemes. Increasingly, DSOs establish local flexibility tenders or platforms to access such services.

System-oriented use cases (balancing services):

Flexibility mobilised by the TSO to maintain the system balance between generation and consumption. The products which deliver these flexibility services are well-defined and harmonised at EU level:

- *Frequency Containment Reserve (FCR):* very fast automatic response to stabilise frequency deviations (within seconds).
- *Automatic Frequency Restoration Reserve (aFRR):* automatic activation within minutes to restore frequency.
- *Manual Frequency Restoration Reserve (mFRR):* manually activated reserve for longer duration balancing (up to hours).
- *Replacement Reserve (RR):* slower, longer-term reserves, where implemented.

Market-oriented use cases:

- *Wholesale market arbitrage:* shifting demand to benefit from price spreads on day-ahead or intraday markets.
- *Portfolio balancing by BRPs:* adjusting load to match contracted supply and demand.
- *Dynamic tariffs and retail products:* household or commercial consumers responding to time-of-use or real-time pricing.

While system-oriented products (FCR, aFRR, mFRR, RR) are well established and market-oriented products are evolving, the core interest of this report lies in grid-oriented flexibility. These are essential to support DSOs (and TSOs) in managing local and regional network constraints, even though service definitions and mechanisms are less harmonised and often still subject to pilot projects.

The distinction between grid-oriented, system-oriented and market-oriented flexibility use cases highlights that demand-side flexibility can serve very different purposes. In the context of this report, the focus lies on network flexibility, as it is directly relevant for the secure and efficient operation of Luxembourg's electricity grids. The importance of systematically identifying such needs has also been recognised at European level: under Article 32 of the Electricity Regulation (EU 2019/943), transmission system operators (TSOs) and distribution system operators (DSOs) are required to carry out a regular assessment of flexibility needs. A dedicated methodology for this assessment has recently been established at EU level ("Methodology for the analysis by TSOs and DSOs of the flexibility needs at national level").

1.4. Scenarios of potentially high flexibility needs

Against the background of a future assessment of flexibility needs, this section presents scenarios of potentially high flexibility needs. These scenarios describe typical situations where flexibility could play a key role in addressing **grid challenges**. They provide the framework against which the technical flexibility potentials assessed in later chapters can be evaluated.

Grid congestions mainly occur during periods of high consumption and low local generation, or in case of high local generation and low consumption. In these situations, flexibility could particularly be useful to solve these congestions. The following scenarios are of relevance, structured by their period of occurrence, weather conditions and the grid voltage level where they cause congestions. They have been set up based on Luxembourg's gross generation, consumption data from smard.de and experience of Creos network development experts.

Table 1 – Potential flexibility needs and their characteristics (focus on grid-oriented flexibility)

Time period	Cause	Voltage Level	Grid Area	Weather
Summer / Midday (especially May – August 13:00 to 15:00)	**High PV generation** on sunny days can lead to excess PV injection at times of low consumption	Mainly Low and Medium Voltage	Residential areas and rural medium voltage lines	Sunny weather

Winter / Evening (17:00 to 20:00) on very cold days	**High consumption** when heat pump consumption overlaps the usual evening peaks.	Low Voltage	Residential areas	Very cold weather
Winter / Midday (8:00 to 18:00) on very cold days	**High consumption** from **tertiary sector heat pumps** which may run intensively throughout the day (future scenario)	Medium and High Voltage	"Zones industrielles" with a lot of office buildings, shops and industry (tertiary sector and industry flex can be useful here)	Very cold weather
Transition periods / Midday (13:00 to 15:00 in April, May & September)	**Simultaneous high wind and PV generation**. Especially during holidays (April/May) when consumption is also relatively low.	Medium and High Voltage	Rural (in the north of Luxembourg) and HV import lines (all flexibility sources can be helpful here)	Sunny and windy weather
Summer / very hot days (14:00 to 18:00)	**Suspended lines have a higher line sag** on hot days due to the expansion of the metal lines. This is likely to happen on days with **high PV generation**	Medium and High Voltage	Rural (in the north of Luxembourg) and HV import lines (all flexibility sources can be helpful here)	Extremely warm weather

The scenarios will later be used as reference cases when evaluating technical flexibility potentials and their temporal and spatial availability against the potential use cases (10.2). In line with (DSO entity & ENTSO E, 2024), flexibility needs should distinguish network needs, which must be satisfied at specific places and times, from broader system-level needs that can be met from anywhere. Besides above-described network needs, also **system needs,** for instance related to load and RES forecast errors, residual load variations, or RES integration, become increasingly important. These needs are required at national level, or even cross-national level, as Creos has delegated its balancing responsibility to Amprion. Although Amprion is currently taking care of these needs for Creos, a look at them shows how important flexibility is becoming in the future. Already today, Luxembourg requires up to 100 MW of balancing energy due to forecast errors of the BRP. Also, the maximum ramp-up and ramp-down capacities (load differences in one hour) are around 100 MW in both directions (positive and negative). These values relate to the situation of today and will grow in the future. For the RES integration, the Creos scenario report 2024 estimated that excess generation could reach about 1.400 MW on the HV transmission grid in 2040. These numbers indicate how important demand-side flexibility will become in the future.

1.5. Definition - Technical Flexibility Potential

In this project, the focus is on the technical flexibility potential of demand-side resources in Luxembourg. This concept refers to the maximum amount of flexibility that can be mobilised from a given sector or technology under realistic technical and operational constraints. It is distinct from the theoretical potential, which represents the absolute maximum flexibility if all loads could be controlled without restriction – which is typically larger than the technical potential. Further, it differs from the economic potential, which considers e.g. price signals, incentive schemes and behavioural responses, and limits to the amount that is reasonable from an economic perspective (typically smaller than the tech. potential).

Our analysis of technical potential is grounded in sector-specific models and data sources:

- **Industry and tertiary sector:** flexibility is estimated using energy consumption statistics combined with technology-specific flexibility ranges (e.g. load shifting in cooling, HVAC, or industrial processes).
- **Residential sector:** a bottom-up modelling approach was applied for heat pumps, water heaters, white ware, and PV-battery systems. Technical restrictions such as demand profiles, device capacities, and storage sizes were explicitly considered.
- **E-mobility:** flexibility was derived from empirical charging datasets, assessing how charging profiles can be shifted in time while ensuring mobility needs are met. No changes in mobility- or charging habits were considered, as for example by economic incentivisation.

Across all sectors, we distinguish between load reduction, load increase (load shifting or storage, where applicable) as forms of flexibility. In each case, technical feasibility is constrained by device operation, user comfort, and physical storage (thermal or electrical).

The resulting values therefore represent a realistic but upper-bound estimate of the flexibility that could be made available to system and network operators if suitable incentives and activation mechanisms were in place. The technical flexibility potential however does not take into account potential future behaviour changes.

2. Flexibility Model

The technical flexibility potential is estimated by a meta-model of hybrid sub-models for each sector and asset type, using partially statistical and physical modelling approaches. Each sub-model and the respective results are documented in own chapters of this report.

2.1. Model Structure

The FlexBeAn project set out the objective to estimate the technical flexibility potential arising from certain assets from different sector. Based on data availability, available methods and interests, this has been narrowed down to the following assets, processes or devices:

- Industry Sector – diverse processes in large-scale industries
- Tertiary Sector – Cooling, ventilation and air-conditioning processes
- Households – Heat pumps, PV Battery systems, white ware and (larger) water heaters
- (Private) Electro-mobility – home charging, public charging and charging at workplace

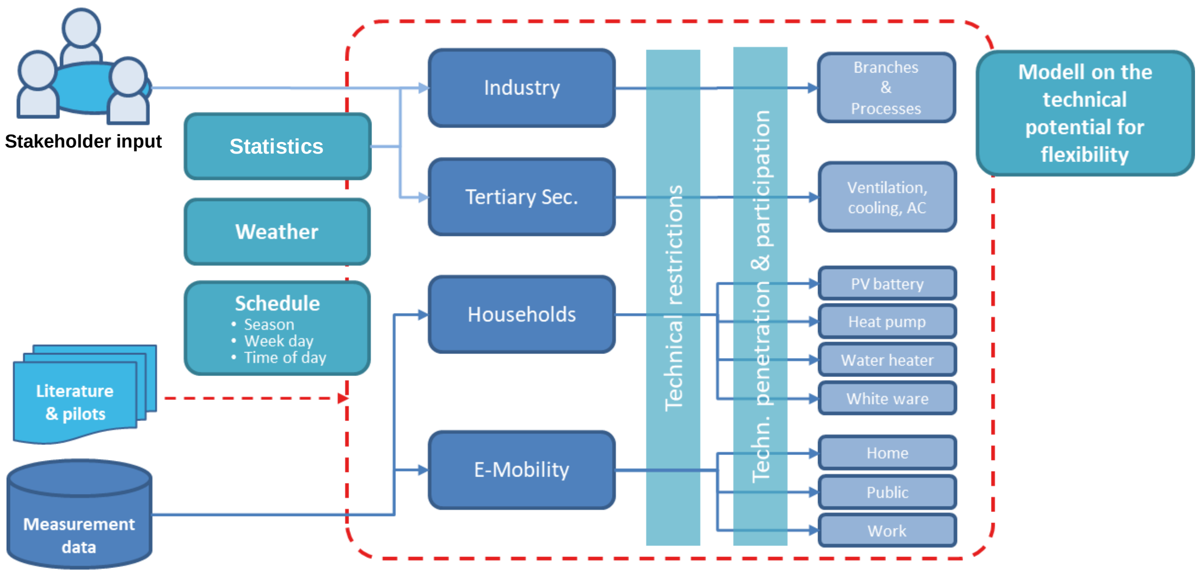


Figure 1 – Schematic view of the model structure

The sub-models are based on various inputs, ranging from national statistical data, literature values and models, measurement data (e.g. for public charging and white ware), stakeholder inputs and historical weather data. This enables the model to represent fluctuating flexibility potentials, depending on seasons, weekly profiles, the daily cycle or outdoor temperatures, to name the most important influences.

Technical potentials respect technical restrictions of the potentials (as far as practically possible). Further, based on future scenarios the technology penetration, specifically of rapidly growing technologies, is estimated for the time horizons 2030 and 2040 (e.g. e-mobility, heat pumps and PV battery systems).

2.2. Input parameters

The following chapters give a brief overview on some of the most influential input parameters and data sources.

2.2.1. Historical weather data

The energy demand, production and flexibility potential of a) residential heat pumps, b) PV battery systems and c) tertiary sector flexibility from cooling- and air-conditioning, depends strongly on weather conditions. The respective sub-models use historical weather data as main input data. Concretely, the ambient temperature and global horizontal irradiance.

The meteorological data are historical “reanalysis data” from the European Centre for medium ranged weather forecast (ECMWF). Within the model, the data sets from 2020 until 2024 have been saved and could be chosen as inputs. A first analysis step assessed the different yearly data to give insights in their statistical representativeness – to identify outliers, extreme weather conditions as well as representative years.

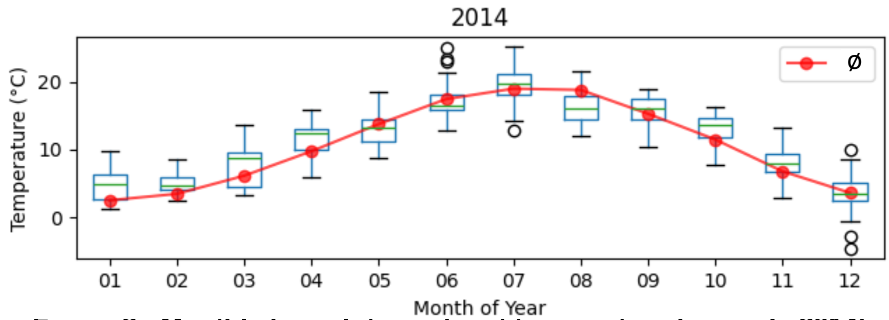


Figure 2 - Monthly box-plots, ambient temperature (example 2014)

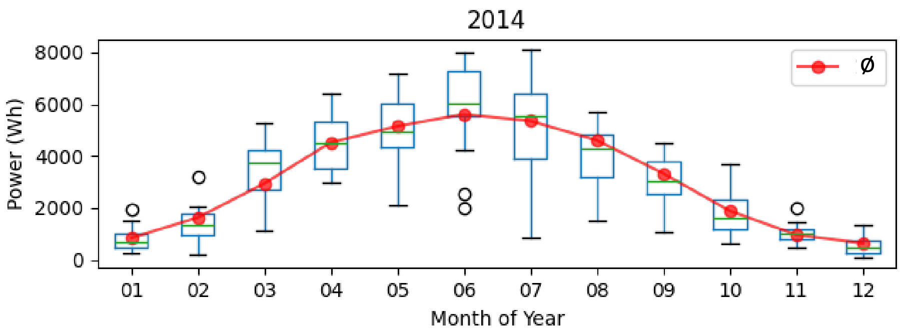


Figure 3 – Monthly box-plots, solar irradiance (example 2014)

In Figure 2 and Figure 3, two examples are given: the boxplot for each month show the mean (green line), the 50% median values in the blue box and the min / max represented by the black bars. The Red line represents the mean of the years 2000 – 2024.

The following years could be used to represent moderate or rather extreme conditions, regarding these parameters:

Ambient temperature data:	**Solar irradiance (GHI):**
moderate: 2002, 2009, 2014, 2016, 2019	moderate: 2005, 2008
high temperatures: 2022	high yearly irradiance level: 2003, 2020, 2022
low temperatures: 2004 summer, 2010 winter	low yearly irradiance level: 2002, 2024

2.2.2. Statistical key parameter

The FlexBeAn model and individual sub-models used different statistical data as input to the model. The main sources of these are :

Statistiques.lu (STATEC)
Parameter: Inhabitants (per commune), household data, building structure, energy related data

data.public.lu – common platform to share data for public use, from different sources
Parameter: e.g. registered cars / EVs (SNCA), renewable energy sources (ILR)

Geoportail
Parameter: divers geospatial data, e.g. commune borders, LIDAR data to characterize buildings, tertiary sector activity data

The individual input data are introduced as .csv files to the model in dedicated folders and could easily be updated.

2.2.3. Electrical load data

Electrical load profiles of households are integrated in the FlexBeAn model to enable the calculation of self-consumption and surplus production of photovoltaic systems within the sub-model for residential PV battery systems. Although, aggregated load profiles for Luxembourg are available, these kinds of profiles are useless to estimate the energy balance of individual systems.

The FlexBeAn model uses artificially set up load profiles for households of different household compositions and combines them in such manner to obtain a representative yearly electricity demand. The artificial load profiles are built by an application for creating synthetic residential load profiles. It uses a desire-driven agent simulation to model the behaviour of the residents in detail and generate load profiles with the high temporal resolution for residential energy consumption, primarily electricity and domestic hot water (Pflugradt et al., 2022).

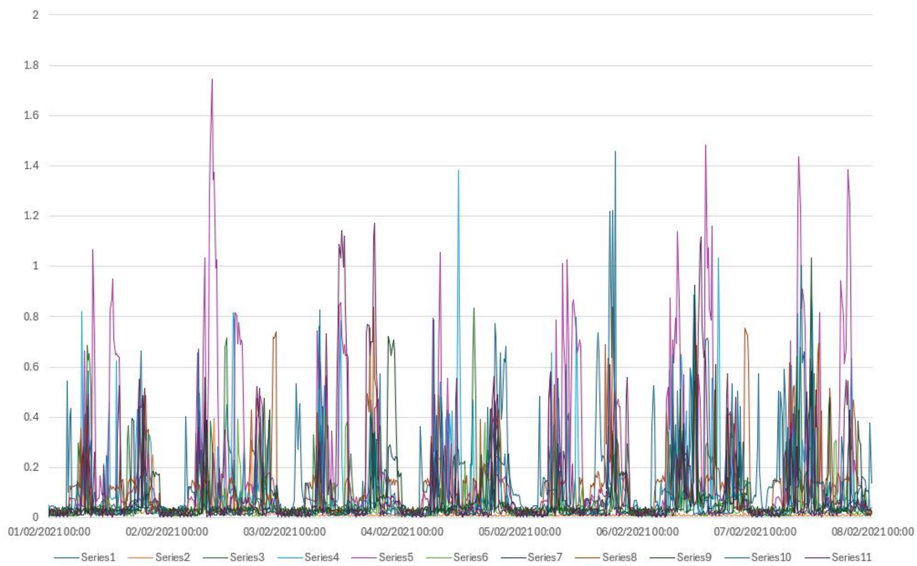


Figure 4 – Example of electricity load profiles for households, quarter-hourly values, one week

The load generator models different household compositions, such as the examples listed below, from which 11 are chosen for the FlexBeAn model: Couple, both working (CHR1), Family, one child (CHR3), Family, both working, 3 children (CHR5), single man, shift worker (CHR10), Couple over 65y. (CHR11), to give a basic impression.

Avg. electricity consumption of lux. household: **3.600 [kWh]**

The composition of different household profiles to assemble a representative set of households was not targeting to obtain a representative sample of the society! But the probabilities by which the model chooses a profile are defined in a manner that the average yearly electricity consumption of the household set lies around 3'600 kWh/a, which corresponds to the average Luxembourgish household.

Table 2 – Probabilities for different household electricity profiles to assemble representative sets

CHR01	CHR02	CHR03	CHR04	CHR05	CHR06	CHR07	CHR08	CHR09	CHR10	CHR16
10 %	8 %	23 %	8 %	10%	3 %	5 %	7 %	7 %	7 %	12 %

2.2.4. Assumptions & Limitations

Obviously, modelling a complex matter such as demand side flexibility across sectors, technologies, time horizons and spatial domains requires simplifications of reality and assumptions. In the individual chapters, describing the modelling approaches for the sectors and technologies, the limitations and main assumptions are transparently described. Anyhow, here are some main assumptions that are valid across different sectors:

The scenarios for 2030 and 2040 define technology penetration rates for the most relevant technologies, which are in this context, heat pumps, electric vehicles and residential PV batteries. Obviously, uncertainties are inherent to future projections. But there are further influential factors, mainly regarding future energy demand, that are kept constant within this model:

- The electricity demand of households, industry and tertiary sector are considered stable
- The building structure, relevant for the residential and tertiary sector modelling, remain unaltered

Further assumptions, limitations and uncertainties are described within the different chapters.

2.3. Output parameters & Characterization of flexibility

The output of the FlexBeAn model is the technical flexibility potential, defined as the deviation from a baseline load profile under the technical and operational constraints of the considered technology. Flexibility is expressed consistently with the ENTSO-E and DSO Entity methodology (DSO entity & ENTSO E, 2024) from a generation perspective:

- **Upward flexibility,** corresponds to the possibility of increasing net generation or reducing consumption, as in our context for demand side flexibility.
- **Downward flexibility,** corresponds to the possibility of decreasing net generation or increasing consumption.

To characterise the flexibility potential of a flexibility source, several (interrelated) parameters are used:

- **Power [MW]:** the maximum instantaneous deviation from the baseline load
- **Energy [MWh]:** the total amount of energy that can be shifted over the activation period
- **Duration [h]:** the time span over which the power deviation can be sustained

Since the potentials reported here represent an upper bound of a large set of distributed resources, considering max. power for each resource, the aggregated maximum power values are often only available for a limited time. In practice, system operators (or aggregators) are interested in combining or cascading the activation of individual assets to spread flexibility over longer periods. Such strategies require careful design to ensure that the desired quantities are met for the intended temporal and spatial resolution. Along with the consideration of rebound effects (e.g. increased heating demand after curtailment of a heat pump) are mitigated, and that additional resources are activated to compensate for such rebounds.

The modelling results are provided with an hourly resolution, either as:

- complete **time series** of baseline and flexibility profiles, or
- representative **daily profiles,** considering weekly or seasonal specialties, derived from statistical or model-based approaches.

When interpreting hourly potentials, it is important to note that the values represent **instantaneous flexibility**: activation in a given hour is only possible if the resource has not been used for flexibility in the preceding period. Sustained activation may therefore reduce the available potential in subsequent hours and induce rebound effects.

Other flexibility characteristics, which are technically relevant for some applications e.g. common in balancing services, such as ramp rates and dynamic response times, were not explicitly considered in this study.

Flexibility potentials are allocated to the 100 communes of Luxembourg, enabling spatial aggregation to higher grid levels. Although the present report does not detail the mapping to high-voltage (HV) zones, the allocation provides a consistent basis for such analyses.

3. Industry Sector

To achieve the energy policy targets, the installed capacity of renewable technologies continues to grow in European countries due to their carbon-neutral characteristics during the usage stage. On the other hand, coal and gas are gradually being decommissioned. This combination is increasing the uncertainty of the power system and reducing its flexibility. Consequently, modern power systems require an upgrade in their design and new flexibility sources to maintain an economic and secure operation of the power system. Demand-side flexibility has a big potential to become a flexible source by applying Demand Response. Demand Response is defined as the capability of adjusting the load by the end-use customer from their normal consumption pattern in response to an external signal. Industries in particular show great potential to offer demand response because of their size and energy usage.

The aim of this section is to analyse the demand-side flexibility potential of the Luxembourgish industry. This section has been structured into distinct subsections. The initial section outlines the key metrics used to evaluate demand response measures. In the second section, we give an overview of the share of industrial sectors within the Luxembourgish territory resulting from a systematic literature review. They are categorized into ten industrial sectors and further analysed according to the identified metrics. In the third section, we apply the findings from the second section to Luxembourgish industrial consumption profiles to estimate the country's total demand response potential. Finally, the last section presents the key conclusions of the study.

Please note that there is a full version of this section (Industry Flexibility) available as individual report on the FlexBeAn Website as well as the websites of the partners.

3.1. Key metrics for industry sector flexibility assessment

To harness the full potential of demand response as a dependable grid resource, it is crucial to establish a quantitative framework that evaluates the resource's capacity, performance variability, and predictability, all supported by empirical data (Liu et al., 2022). Researchers have proposed several theoretical metrics to quantify and assess demand response performance. In this section, we define and visually present (see Table 3 and Figure 5) the key metrics required to measure demand response potential.

Table 3 – Definition of demand response metrics

Metric	*Definition*
Capacity	Capacity refers to the change in the power output (in kW or MW) required to reach after the full activation time (Artelys Optimization solutions, 2023).
Duration	Duration refers to the period of time (minutes or hours) for which the demand response provider must deliver the full requested change of power level (Faria et al., 2015), (Artelys Optimization solutions, 2023). It can also be referred to as active duration (Tristán et al., 2020).
Direction	Direction refers to the power change direction of the offered demand response action. An upward bid refers to a reduction of power consumption from the system. Conversely, a downward bid refers to an increase in power consumption in the system (Artelys Optimization solutions, 2023)
Location	Location refers to the actual geographic or network-specific positioning of demand response resources within the power grid (Plaum et al., 2022) This metric assesses where flexible loads are situated in relation to grid infrastructure, such as substations, transmission lines, and generation sources, which is crucial for effective grid management.
Preparation time	Preparation time refers to the time period required by the demand response provider to start delivering the flexibility after it has been (Tristán et al., 2020) (Artelys Optimization solutions, 2023).

Ramping period	Ramping period refers to the period of time after the preparation period during which the input/output of the active power is being increased/decreased until reaching the full requested power change (De Vos et al., n.d.), (Artelys Optimization solutions, 2023).
Full activation time	Full activation time refers to the period of time elapsed from the notification until the full delivery of the requested active power. It is equivalent to the sum of preparation and ramping periods (Artelys Optimization solutions, 2023).
Deactivation period	Deactivation period refers to the period of time between the end of the active duration of the flexibility provision and the return to the original consumption state (Tristán et al., 2020).
Recovery time	Recovery time refers to the period of time that must elapse before the flexibility can be activated again (Tristán et al., 2020)
Availability	Availability is the period of time for which the flexibility is available. It can be specified as daily availability (specific hours for which the flexibility is available during the day), as well as seasonality (if there are seasonal changes in the flexibility due to weather, holidays, maintenance periods, etc.) (De Vos et al., n.d.),(Heleno et al., 2015). Moreover, it should also specify the maximum number of times the demand response action can be executed over a specific period of time (usually referred to as daily maximum activations, but it can also be weekly, monthly, yearly, etc.) (Tristán et al., 2020)

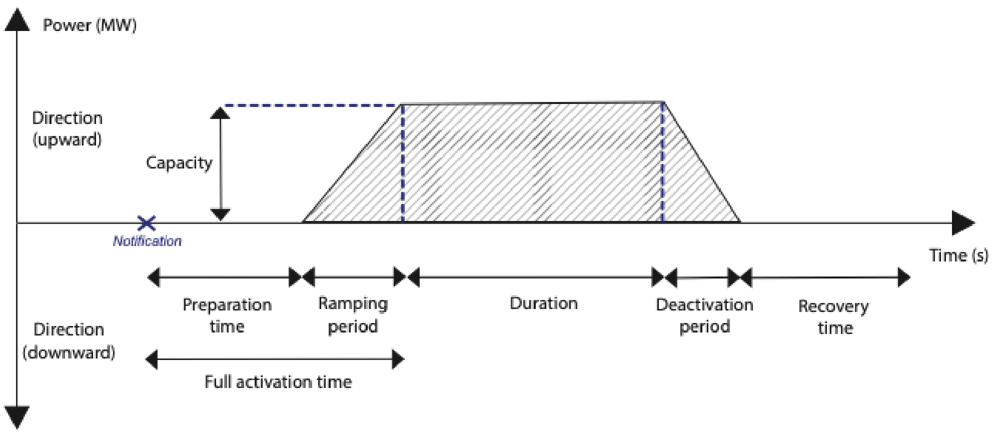


Figure 5 – Representation of demand response metrics

3.2. Demand response in industrial facilities

Within our systematic literature review, we identified relevant articles from ten different industrial sectors. Each of those sectors is characterized by its distinctive manufacturing systems. In this section, we give a short explanation of the manufacturing procedures and we identify the processes that can provide demand response measures.

3.2.1. Refineries

An oil refinery can offer demand response by adjusting feedstock mass flow and strategically scheduling self-generation units such as gas turbines and Combined Heat and Power (CHP), with flexibility duration constrained by storage capacity (Golmohamadi, 2022) (Sofana Reka & Ramesh, 2016) (Gholian et al., 2013)(Alarfaj & Bhattacharya, 2019). Load-shifting in key units (e.g., distillation, hydro treatment, gas separation) has been shown to reduce power consumption by up to 6.2% for 2 hours, lowering electricity costs by 6.5 % (Sofana Reka & Ramesh, 2016), while participation in frequency control schemes enables power reductions of around 7.1% (Noor et al., 2015).

3.2.2. Steel and iron

Steel production relies on blast furnaces and electric arc furnaces, with the latter being the main focus for demand response due to its high energy use (≈0.525 MWh/t) (Shoreh et al., 2016). Demand response can be achieved by rescheduling or interrupting furnace operation, where melting scrap lasts approximately 45 minutes and must be reheated within 15 minutes (Feta et al., 2018). Studies show a 6.5% load reduction potential in steel plants (Gong et al., 2020), while a Dutch case demonstrated that 10 MW of load can be reduced for 30 minutes with an availability of 97%. If the capacity is increased to 20 MW, then, the availability is reduced to 65%. On the other hand, regarding the load increase capability, they discovered that 20 MW of load can be increased for 45 minutes (Zhao et al., 2017).

3.2.3. Cement

Cement plants transform limestone, clay, and shale into cement through four main processes: Crushing, Kiln Feed Preparation, Clinker Production, and Finish Grinding. Around 25% of the energy use is electrical (111–160 kWh/t) and 75% thermal (Golmohamadi, 2022) (Ghalandari et al., 2019) (Summerbell et al., 2017). Table 4 shows the electricity consumption of each of the processes.

Table 4 - Consumption of cement manufacturing processes (Golmohamadi, 2022)

Process	Consumption (kWh/ton)
Crushing	5 – 20
Kiln Feed Preparation	27 – 38
Clinker Production	39 – 45
Finish Grinding	52 - 57

Demand response potential is highest in cement mills due to their intermittent operation, supported by silo storage, while Finish Grinding offers some flexibility but is constrained by output needs. However, clinker production is inflexible as interruptions risk equipment damage (Golmohamadi, 2022). Studies show significant potential: A UK plant achieved 1 MW load shifting (30% of total power), reducing electricity costs by 4.2% (Summerbell et al., 2017), while a South African pilot demonstrated 2–3 hours of load shifting in cement mills, cutting costs by 6% and indicating up to 23% sectoral flexibility (Golmohamadi, 2022), (Lidbetter & Liebenberg, 2013).

3.2.4. Glass

Glass manufacturing is highly energy-intensive, with furnaces consuming 70–80% of total thermal energy (Seo et al., 2020) (Sardeshpande et al., 2007). Adjusting furnace input can significantly shift power demand, with studies showing 20–25% load reduction possible for 20–30 minutes without affecting product quality (Sardeshpande et al., 2007) (S. I. P. . FfE, 2022). A dynamic optimization strategy further demonstrated that demand response actions could raise electric boosting power from 1.94 MW to 7.82 MW during low-price periods or reduce it from 2 MW to 0 MW during high-price periods, cutting energy costs by 30%. Since boosting accounts for 20% of plant power, this corresponds to a 60.6% load increase and 20% load decrease potential (Seo et al., 2020).

3.2.5. Pulp and paper

Pulp and paper production is energy-intensive, with refineries being the main consumers. Adjusting refiner speed allows demand response, and studies show the sector can reduce load by about 7% (Herre et al., 2020) (Gils, 2014). Paper mills with electric boilers can also provide fast frequency reserves, offering up to 30 MW of symmetrical flexibility by ramping to full power within 3 minutes, cutting electricity costs by 2.3–7.4% seasonally (Herre et al., 2020). A dynamic simulation further showed that flexible units like stock preparation, winders, and storage (980 kW, 36 kW, and 5 kW) can each provide up to 30 minutes of flexibility, yielding notable economic savings (Rodríguez-García et al., 2016).

3.2.6. Food

The food industry is highly diversified, with refrigeration alone accounting for about 16% of its energy use (Alcázar-Ortega et al., 2012). Cooling processes offer strong demand response potential, as they can be interrupted until critical food temperatures are reached. A Spanish cured ham factory showed that reducing cooling system power by 22.9% was feasible without affecting product quality, allowing shutdowns of up to 2 hours and achieving 5% annual electricity savings (Alcázar-Ortega et al., 2012). Similarly, in the sugar industry, using bagasse in boilers enabled demand response, with optimization models showing electricity cost savings of up to 18.65% (Hannan et al., 2019).

3.2.7. Data centers

Data centers are highly energy-intensive, with cooling systems accounting for approximately 70% of total use (Sun & Lee, 2006). Demand response strategies include load shedding (temporary IT shutdowns or temperature set-point changes), load shifting (rescheduling IT tasks), and load migration (moving workloads geographically). Studies report significant flexibility: 25% demand response potential at the IT level (10–12% at building level) (Ghatikar et al., 2012), up to 400 kW increase or 325 kW reduction (Cao et al., 2022), and maximum load reductions of 30–32% through workload dispatching, temperature adjustments, or optimized scheduling (Cioara et al., 2018) (Tang et al., 2014) (Tang & Dai, 2012). Reported impacts include peak reductions of 11–12%, cost savings of 12–15% (Bahrami et al., 2019), and flexibility from HVAC, storage, and delay-tolerant tasks enabling ±15% load changes (Cupelli et al., 2018). Dynamic server load adjustments further achieved a 20% reduction for 50 minutes with 30% cost savings (Li et al., 2015).

3.2.8. Aluminium

Aluminium production begins with bauxite refining into alumina, followed by electrolytic reduction in smelters, the most energy-intensive step requiring around 15.37 kWh/(kg of Al) (Obaidat et al., 2018). Potline power can be rapidly adjusted (~1 MW within seconds) by controlling rectifier voltage, but pot thermal balance must be maintained for safety (Zhang & Hug, 2015). Studies show the industry can provide up to 25% power reduction for 4 hours (Shoreh et al., 2016), while optimized scheduling of electrolytic reduction can yield ~0.7% electricity cost savings (Zeng et al., 2020).

3.2.9. Textile

Textile manufacturing converts fibres into yarn through blending, aligning, twisting, and shaping, with specifications depending on the final fabric (He et al., 2021). Production involves equipment such as spinning machines, looms, and dryers, operating as a continuous but stable load (Cai et al., 2023). Since subprocesses are relatively independent, demand response can be applied without disrupting production, limited only by inventory capacity, allowing flexibility for 30–60 minutes (Cai et al., 2023). Regarding the capacity, by summing all shares of the flexible equipment represented in Table 5, we can conclude that 15% of the load is flexible in the textile sector.

Table 5 - Main electrical equipment of the textile industry (Cai et al., 2023)

Equipment	*Share of load (%)*
Weaving machine	**10**
Opening machine	**2**
Dewatering machine	**2**
Warping machine	**1**
Turning machine	**1**

3.2.10. Water treatment plants

Wastewater treatment plants are energy-intensive, with electricity making up 25–50% of operating costs (Kirchem et al., 2018). Aeration and pumping account for 75% of total use and offer the main demand response potential (Aghajanzadeh et al., 2015). Studies show aeration can be shut down for up to 2 hours, or 1 hour in pilot trials, without harming performance, with ramping times of 10–60 s, deactivation of 5–60 s, and recovery in 15–30 min (Aghajanzadeh et al., 2015) (Schäfer et al., 2017). Such actions can reduce energy use by 24.4% or increase it by 19.9%.

3.3. Industrial flexibility in Luxembourg

By combining the theoretical flexibility potential of different industrial sectors reported in the literature with the annual consumption profiles of Luxembourgish industries, we were able to quantify the theoretical flexibility potential of the Luxembourgish industry.

3.3.1. Literature review results

Table 6 presents the average reported capacities, expressed as the percentage of power reduction from peak demand, along with the minimum and maximum reported flexibility values for the identified actions. Moreover, Table 7 presents how long the identified flexibility can be maintained within each industrial sector.

Table 6 - Reported industrial demand response capacity potential

Sector	Capacity (%)		
	Minimum	Average	Maximum
Oil refinery	6.20	6.65	7.10
Steel and iron	6.50	10.29	14.07
Cement	23.00	26.50	30.00
Glass	20.00	31.40	60.60
Paper	7.00	7.00	7.00
Food	14.00	25.50	37.00
Data Center	11.50	23.43	68.00
Aluminium	25.00	25.00	25.00
Textile	15.00	15.00	15.00
Water treatment	15.00	19.70	24.40

Table 7 - Reported industrial demand response duration potential

Sector	Duration
Oil refinery	2 hours
Steel and iron	20 - 45 minutes
Cement	2 hours
Glass	25 minutes
Paper	30 minutes
Food	2 hours
Data Center	15 minutes – 11,5 hours

Aluminium	4 hours
Textile	30 minutes – 1 hour
Water treatment	1 - 2 hours

3.3.2. Industrial flexibility in Luxembourg

Using this information, we estimated the demand response potential of Luxembourgish industries by combining literature-based flexibility data with annual consumption profiles provided by CREOS. For each of the largest industrial facilities in Luxembourg, we identified their industrial sector using NACE codes, retrieved their annual consumption profile, and applied the reported flexibility capacities to construct three scenarios: a pessimistic case (minimum reported flexibility), an average case (mean flexibility), and an optimistic case (maximum flexibility). Table 8 summarizes the aggregated industrial demand response potential (upward - load decrease), broken down by geographical location, based on the high-voltage transmission grid.

Table 8 - Industrial demand response potential in Luxembourg

Region	Average (MW)	Pessimistic (MW)	Optimistic (MW)
Centre	2,6	1,4	4,5
North	2,7	1,5	3,8
West	3,8	1,9	9,0
East	4,2	2,0	8,9
South-East	4,0	2,8	7,0
South-West	3,0	1,7	5,8
Total	**20,2**	**11,3**	**38,8**

Based on the reported flexibility durations in the literature (see Table 7), we estimated how long the Luxembourgish industry could sustain its flexibility, assuming that all available flexibility is activated simultaneously. Figure 6 describes the resulting aggregated flexibility duration of Luxembourg.

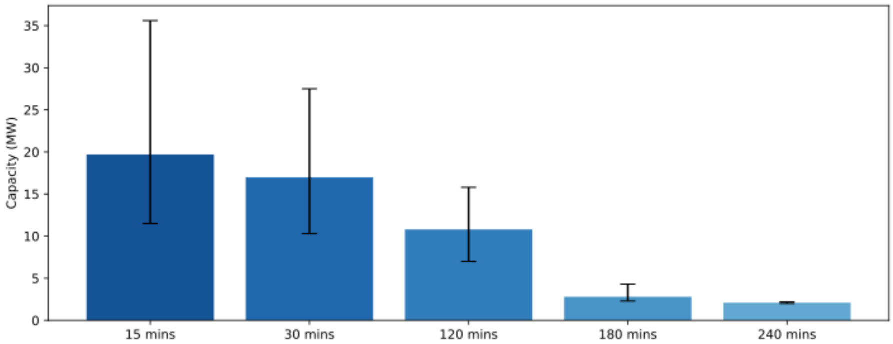


Figure 6 – Available duration of the upward (load reduction) flexibility

3.3.3. The case of plastic industry

Based on discussions and data exchanges with two major Luxembourgish plastic manufacturing companies, it was confirmed that they currently do not possess any demand-side flexibility, as they are unwilling to modify their existing consumption profiles. However, this situation is expected to change due to the electrification of steam production, driven by European carbon-neutrality regulations, which will gradually replace gas-fired boilers with electric boilers. During the transition period, when both gas and electric boilers are operational, a window of cross-sectoral flexibility will emerge. In this phase, companies will be able to increase or decrease their electricity consumption without altering total steam output by compensating with gas.

To estimate the national flexibility potential of the plastic manufacturing sector, we combined data obtained from direct collaboration with two major Luxembourgish plastic manufacturing companies and information provided by Creos Luxembourg S.A. The two companies supplied detailed steam production data, while Creos provided comprehensive gas consumption data for these companies as well as for all other plastic manufacturers in Luxembourg. By analysing the data from the two companies, we determined the share of their total gas consumption used in gas boilers for steam production, which is the primary source of cross-sectoral flexibility during the transition period.

This information was then used to approximate the share of gas used for steam production in other Luxembourgish plastic manufacturing companies. As no direct steam production data were available for the remaining companies, we defined three scenarios to reflect different possible levels of flexibility potential:

- **Pessimistic scenario**: This scenario assumes that all other plastic manufacturers have a share of gas used for steam production equal to that of the company with the lowest observed share among the two firms studied. Consequently, it represents the minimum flexibility potential of the sector, as it assumes that most of the gas consumption in these companies is used for processes that are not electrifiable or cannot be shifted, limiting the possible demand response.
- **Optimistic scenario**: In this scenario, we assume that all other companies exhibit a share of gas used for steam generation equal to the company with the highest observed share. This represents the maximum flexibility potential, as it implies that a significant proportion of gas consumption is dedicated to steam production, which can be progressively electrified and thus offers a larger capacity for demand-side flexibility during the transition phase.
- **Average scenario**: This scenario uses the mean of the two observed shares as a representative value for the rest of the plastic manufacturing companies. It provides a balanced and more realistic estimation of the national flexibility potential, lying between the two extreme assumptions of the pessimistic and optimistic cases.

The flexibility potential of the plastic industry will largely depend on the pace of technology adoption, the installed capacity of electric boilers, and the degree of simultaneity in boiler acquisitions across companies. In this assessment, we assumed a gradual transition from gas to electric boilers, with installations meeting 25% of peak steam demand by 2030, and 75% by 2040. Gas boilers are expected to be progressively phased out, reaching complete decommissioning by 2050. The resulting aggregated flexibility potential of the major Luxembourgish plastic manufacturing companies is presented in Table 9. Notice that the reported flexibility is symmetrical, meaning that the flexibility potential represents both upward and downward flexibilities.

Table 9: Projected flexibility potential of the plastic industry (in MW).

Year	Gas	Elec.	Optimistic	Mean	Pessimistic
2024	100%	0%		0	
2030	100%	25%	27.4	20.8	15.2
2035	75%	50%	54.8	41.5	30.5
2040	50%	75%	54.8	41.5	30.5
2045	25%	100%	27.4	20.8	15.2
2050	0%	100%		0	

Gas: Capacity of gas boilers, Elec.: Capacity of electric boilers.

Importantly, as long as gas boilers remain operational, no additional inflexible electrical load will be introduced to the grid. However, once gas boilers begin to be phased out, not only will the available flexibility decrease, but an extra non-flexible load will also be added to the system. Nevertheless, if flexibility is properly incentivised and effectively utilised, it could provide CREOS with valuable additional time to plan and invest in grid reinforcement.

3.4. Conclusion

The results from the industrial flexibility analysis demonstrate that Luxembourgish industries possess a significant theoretical demand response potential, estimated at approximately 20 MW on average in 2024, with an optimistic scenario reaching up to 39 MW. However, the duration of this flexibility varies substantially across industrial processes, ranging from as little as 15 minutes to several hours.

Since our analysis could only be based on electricity consumption values within the CREOS grid, it should be noticed that large scale industrial customers in the SOTEL grid were not considered. Further, the analysis was limited to large scale consumers, neglecting medium and small-scale industrial consumers, that could potentially provide additional capacities.

In the medium to long term, the plastic manufacturing sector is expected to provide temporary additional flexibility between 2030 and 2050, primarily due to the electrification of steam production. The actual magnitude of this contribution will depend on the rate of electric boiler adoption and the degree of simultaneity in investments across companies, ranging from 15,2 MW to up to 54,8 MW. This flexibility is expected to diminish once gas boilers are fully phased out, at which point additional inflexible electric loads will be introduced into the system. Although temporary, this flexibility can be particularly valuable for CREOS, as it provides a critical window of opportunity to prepare the power grid, allowing time for necessary infrastructure upgrades such as capacity expansions, transformer replacements, and network reinforcements.

Finally, unlocking this potential will require active engagement from industrial stakeholders. Insights from the FEDIL workshop revealed that many companies remain sceptical about the economic viability of demand response, express concerns regarding technical and organizational disruptions, and are constrained by contractual obligations. Building trust, enhancing awareness of market opportunities, and providing targeted support mechanisms will therefore be essential to encourage industrial participation and to facilitate the transition towards a more flexible and resilient electricity system.

4. Tertiary Sector

The tertiary sector includes a wide range of services such as trade, finance, insurances, engineering etc. and similar office related services, as well as schools, hospitals, restaurants, hotels, craftsmen and retail stores. It holds significant opportunities for demand-side flexibility. Most of the relevant energy consuming processes that the above-mentioned services within the sector have in common, are related to buildings. For the tertiary sector, the specific energy consumption categories considered for this flexibility analysis, include Air Conditioning (AC), Ventilation, and Cooling (e.g., refrigeration of warehouses and server room).

- Air-Conditioning (AC): representing cooling needs in buildings during warmer months.
- Ventilation: essential for fresh air circulation in buildings and typically operated year-round.
- Cooling (e.g., refrigeration): either used in commercial settings like supermarkets or food storage, but also for server rooms and cooled warehouses.

These categories are considered due to their substantial load profiles, potential for temporal adjustment, and relevance to grid flexibility. Other energy uses, such as lighting or computing, are less commonly included in flexibility assessments due to their smaller contribution to peak demand or limited adjustability (Schlomann et al., 2004) (Schlomann et al., 2013).

4.1. Methodology for tertiary sector flexibility assessment

A schematic overview of the flexibility modeling process is shown in Figure 7.

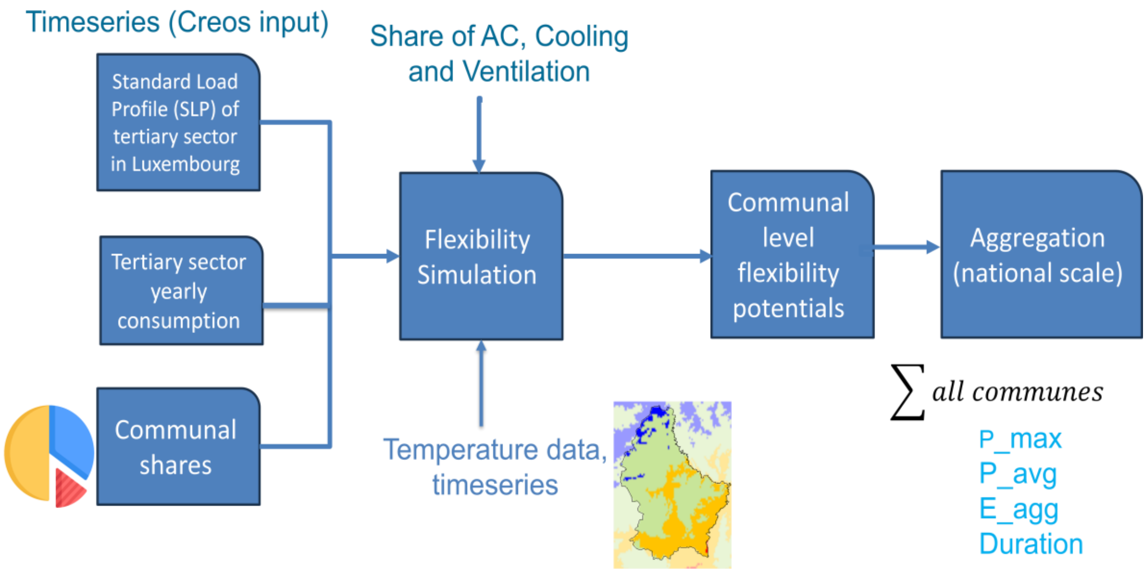


Figure 7 – Schematic overview of the tertiary sector flexibility modeling

The methodology for assessing flexibility in the tertiary sector involves several steps, which are explained below:

Starting point is the total yearly electricity consumption of the tertiary sector as documented by the national statistics[1]. This sets the baseline for further analysis and ensures the results are based on reliable data.

The total electricity demand is split into shares that correspond to specific categories, according to literature values, for air-conditioning, ventilation and cooling. Since national values were not available, shares from Germany are used as a reference, where air-conditioning accounts for 2%, ventilation 12%,

[1] LUSTAT Data Explorer • Final energy consumption according to the different uses and energy forms

and cooling 8% of the electricity demand of the tertiary sector (European Commission, 2002) (Schlomann et al., 2013).

4.1.1. Allocation Over Time Using the Standard Load Profile (SLP)

These shares represent proportions of the yearly electricity consumption. However, to allow for an analysis of the available flexibility across seasons and days, these shares need to be distributed over time to achieve hourly results throughout the year. This temporal allocation is achieved using the Standard Load Profile (SLP) of the tertiary sector (provided by Creos[2]), which represents the typical distribution of the sector's energy demand across the year. The SLP captures the variations in energy use due to seasonal, weekly, and daily patterns, ensuring a more accurate representation of when electricity is consumed within a certain sector. Linking the annual shares to the SLP allows for a time-sensitive assessment of demand, which is crucial for modeling flexibility potentials.

4.1.2. Temperature dependency

Using the above-described constant shares for each process, the yearly energy consumption as a reference for the total electricity demand and the SLP for daily and weekly variations is a valid basis for the analysis but should be adapted for seasonal variations: The energy consumption of some energy-consuming assets, like air-conditioning and cooling, depends on the ambient temperature, which means their demand changes with weather conditions. To include this, the model uses the approach of "Cooling Degree-Hours".

Cooling Degree Hours (CDH) are calculated to show how much cooling is needed when temperatures rise above a set level (here is 18°C). These values are combined with yearly demand shares to create a temperature-sensitive load profile that matches more realistic seasonal patterns.

For air-conditioning systems, all the demand is assumed to depend on temperature. For cooling systems, only part of the demand (30%) is considered temperature-sensitive, since not all cooling demand is fully affected by weather conditions.

4.1.3. Flexibility potential estimation

The share of demand that can be considered flexible is analysed based on minimum and maximum boundaries for flexibility (e.g., thermal comfort levels for AC or critical refrigeration needs). Flexibility is expressed in terms of upward flexibility, which is the ability to reduce demand (e.g., cycling AC systems off temporarily), and downward flexibility, which is the ability to increase demand (e.g., pre-cooling buildings).

The analysis considers how technology and operational constraints affect these adjustments. Studies suggest that these loads could provide downward flexibility up to 75% of the nominal power, while upward flexibility could mean temporarily reducing the total demand in ideal cases (Heitkoetter et al., 2021) .

4.1.4. Allocation of tertiary sector activities to the communal level

In order to spatially allocate the tertiary sector activities, and by this the related electricity consumption and flexibility potential to the communes, weighting factors have been derived. Basis for the weighting factors are the building footprints in the cadastral plan marked as "commercial", which have been identified using the publicly available data from "geoportail.lu". This only gives 2D information on the buildings footprints and require further processing to allow an estimation of the usable floor area. The building footprints have been intersected with LiDAR data, which give height information, were averaged over the area and were processed with surrounding LiDAR points, to approximate a building height. Considering an average storey height and subtracting standardized shares for non-usable areas (such as walls etc.), the usable floor area for each commercial building has been estimated. The weighting factor for tertiary sector activities per

[2] https://www.creos-net.lu/en/pro-space/electricite/fournisseurs-delectricite/synthetic-profiles

commune is defined to be the share of commercial building floor area on the total national floor area of the sector.

4.2. Scenarios for technology penetration

Unlike the rapidly growing technologies such as heat pumps, e-mobility, or photovoltaics, the electricity demand in the tertiary sector as well as the technology penetration of the relevant technologies, is comparably stable. For the time being, no scenarios for technology penetration for 2030 or 2040 concerning tertiary sector flexibility were considered. Hence, the results presented in the following chapter are based on the yearly electricity consumption of the sector from 2021 and the mentioned technology share from German studies for air conditioning, ventilation, and cooling. However, future integration of scenarios is feasible and could be achieved through extrapolation or scenario-based modeling. Such an approach would need to consider differences between new and existing buildings, as new buildings often have higher energy efficiency and different HVAC system configurations, which could significantly influence flexibility potential. It would also need to account for the increasing impact of electrified heating via heat pumps, which is expected to become a major contributor to electricity demand in the tertiary sector by 2040, as projected in national and European energy plans.

4.3. Results for individual processes

This section provides an example by analysing the power and energy flexibility potentials of key technologies in the tertiary sector of Luxembourg City based on electricity consumption data from 2021, with particular emphasis on a representative summer month (using meteorological data from July 2008). The final paragraph of the chapter summarized the flexibility potential on national level.

4.3.1. Demands and power flexibility potentials of air-conditioning

Air-conditioning (AC) systems have significant potential to provide demand-side flexibility. Flexibility can be achieved through various operational strategies that allow shifting or modulating energy usage without compromising occupant comfort or operational requirements. A key approach is pre-cooling, where buildings are cooled to a lower temperature than usual during periods of low electricity demand or low pricing, anticipating the future cooling load. Another strategy involves the use of cold-water storage systems, where excess cooling is stored during off-peak hours and utilized during peak periods to reduce active AC operation, as well as the temporal modulation or even deactivation of chillers, benefiting from the inertia of the buildings. These methods enable temporal adjustments in cooling demand, contributing to grid stability and energy cost optimization.

The flexibility potential calculated in this analysis assumes that the adjustment (e.g., pre-cooling or storage utilization) is activated for a single hour. This approach aligns with values found in the literature, where flexibility potentials from AC systems are quantified in terms of their suitable duration. Pre-cooling for one hour is considered a practical and effective method for reducing demand during subsequent peak hours without causing significant thermal discomfort for building occupants. Providing flexibility for longer periods is theoretically possible but becomes increasingly complex, as extended modulation or deactivation of AC systems can lead to noticeable impacts on indoor comfort and may require more advanced control strategies or additional thermal storage capacity. Studies have indicated that the one-hour timeframe offers a balance between meaningful grid support and maintaining operational efficiency.

However, it is essential to account for certain limitations when implementing such strategies. One of these is the need for a regeneration period following the activation of flexibility. For example, after pre-cooling or drawing from cold water storage, the system might require a certain amount of time to return to its normal operating state or to recharge the storage before the next flexibility request can be accepted. This regeneration period ensures that the system is not overused and that critical cooling needs are not compromised. The duration of the regeneration period, as well as the maximum number of flexibility activations per day, depends on the specific AC system design and operational constraints and is normally contractually defined in demand side management schemes. For our analysis, we consider this to be 1 hour.

Another critical aspect to consider is the potential for rebound effects. When cooling demand is reduced temporarily through flexibility measures, there may be a subsequent increase in demand as the system compensates for the heat gains or re-stabilizes indoor temperatures. For example, after reducing cooling output for an hour, the system might need to work harder in the following hours to restore the desired thermal conditions. This rebound effect could create additional peaks in demand.

In this analysis, rebound effects have not been explicitly modelled, as the current focus is on estimating short-term flexibility potential (e.g., one-hour activation) rather than multi-hour or continuous activation strategies. For a one-hour activation, studies suggest that systems often return to their normal operational patterns after the activation period, with only limited rebound, especially when pre-cooling or thermal inertia strategies are used. However, for longer activation periods, such as several consecutive hours (e.g., 11–15h in summer), rebound effects become more relevant and can significantly influence the net flexibility. In such cases, coordinated activation across multiple customers and temporal distribution of activations would be essential to avoid creating new demand peaks. Therefore, it is important to quantify rebound effects in flexibility use cases to provide a realistic evaluation of the benefits and limitations of AC flexibility and incorporated suitable activation strategies (e.g. temporal and spatial distribution of the activation).

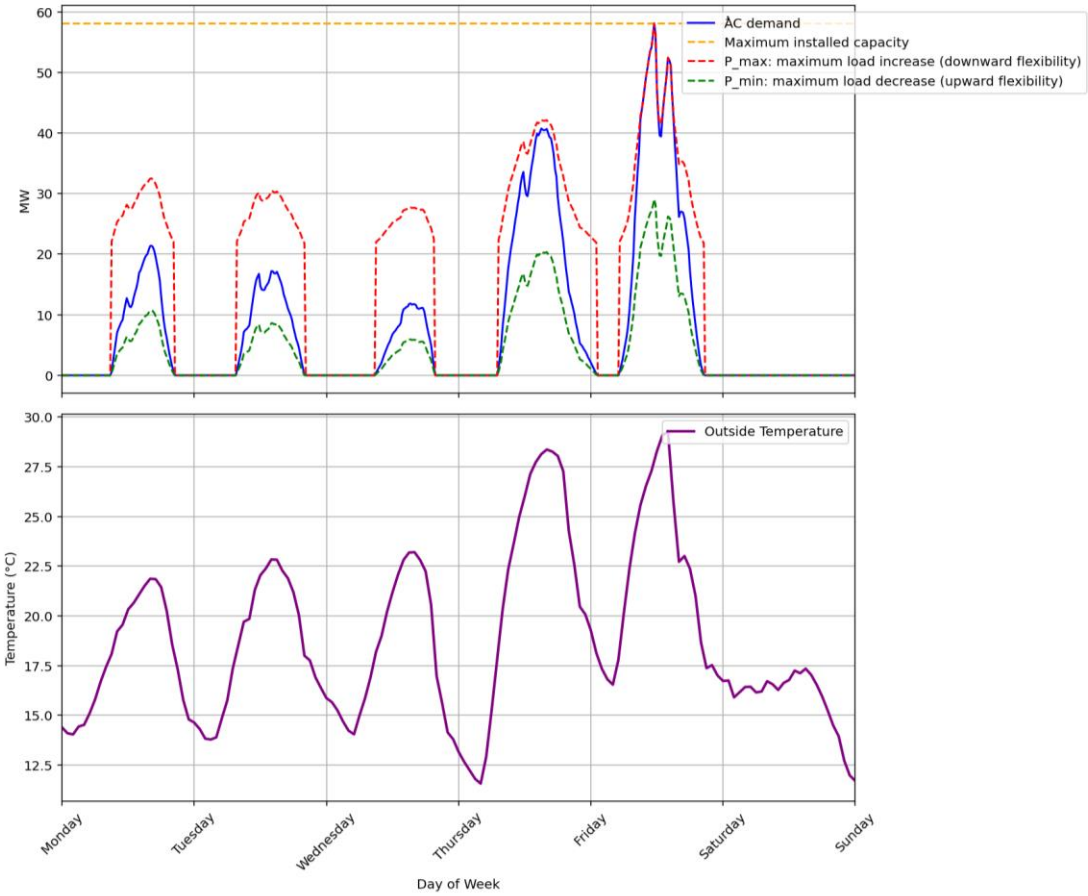


Figure 8 – a) Demands and power flexibility potentials of AC from tertiary sector in Luxembourg City (summer week) – b) Temperature data

Figure 8 provides a comprehensive visualization of the interaction between AC demand and its flexibility potential in the context of the tertiary sector in Luxembourg City, scaled with the 2021 yearly electricity consumption of the sector, with particular emphasis on a summer week (temperatures from first week of July 2008). It highlights the dynamic behaviour of AC systems, influenced by external temperature conditions. The AC demand, as temporally distributed by the model based on the cooling-degree hours from 2008, is observed only between the months of May and October, corresponding to the warmer periods of the year, and is zero for the rest of the year. Further, the model only considers a flexibility potential whenever there is cooling load.

The upper graph illustrates the fluctuations in air-conditioning demand over time and the range of possible adjustments to either increase or decrease demand as needed. The blue line represents the actual AC demand throughout the month, which has been calculated considering external temperature variations. This accounts for the temperature-dependent nature of AC systems, where cooling demand rises during periods of high ambient temperatures and decreases during cooler periods. As a result, the demand profile approximates real-world seasonal and daily patterns, with peaks in demand closely tied to high-temperature periods.

The red and green lines depict the flexibility boundaries for the AC systems. The red line, labelled as "P_max," represents the maximum potential for load increase for 1 hour, or downward flexibility. In our model, this flexibility is capped at 75% of the maximum installed capacity, rather than the full maximum. Downward flexibility occurs when additional cooling can be scheduled or performed within this limit. This is typically achieved during times of reduced external demand or when pre-cooling strategies are applied (Heitkoetter et al., 2021).

The green line, labelled "P_min," represents the maximum potential for load decrease, or upward flexibility. Upward flexibility is achieved by temporarily reducing AC usage, such as cycling systems off or reducing their output. This helps to decrease energy demand during peak times and is crucial for balancing grid loads during high-stress periods.

The orange line at the top of the chart indicates the maximum capacity of the AC systems. This represents the limit of the systems, beyond which no additional cooling can be achieved. Since this capacity is unknown, it has been simplified in the model to be the peak load of AC consumption during the year.

The bottom part of Figure 8 shows the outdoor temperature profile for Luxembourg City during the selected summer week, which serves as the input for determining temperature-dependent AC demand. Daily temperature fluctuations are evident, with peaks reaching above the 18°C threshold used for calculating CDH.

Overall, the graph shows that while there is considerable variability in AC demand, the flexibility potential of these systems is substantial. The inclusion of temperature considerations ensures that the demand profile is more realistic and closely aligned with actual seasonal and operational variations. These flexibility potentials demonstrate how AC systems in the tertiary sector can be integrated into broader energy management strategies, particularly during summer months when cooling demand is highest, as well as solar energy production.

Insights on national level

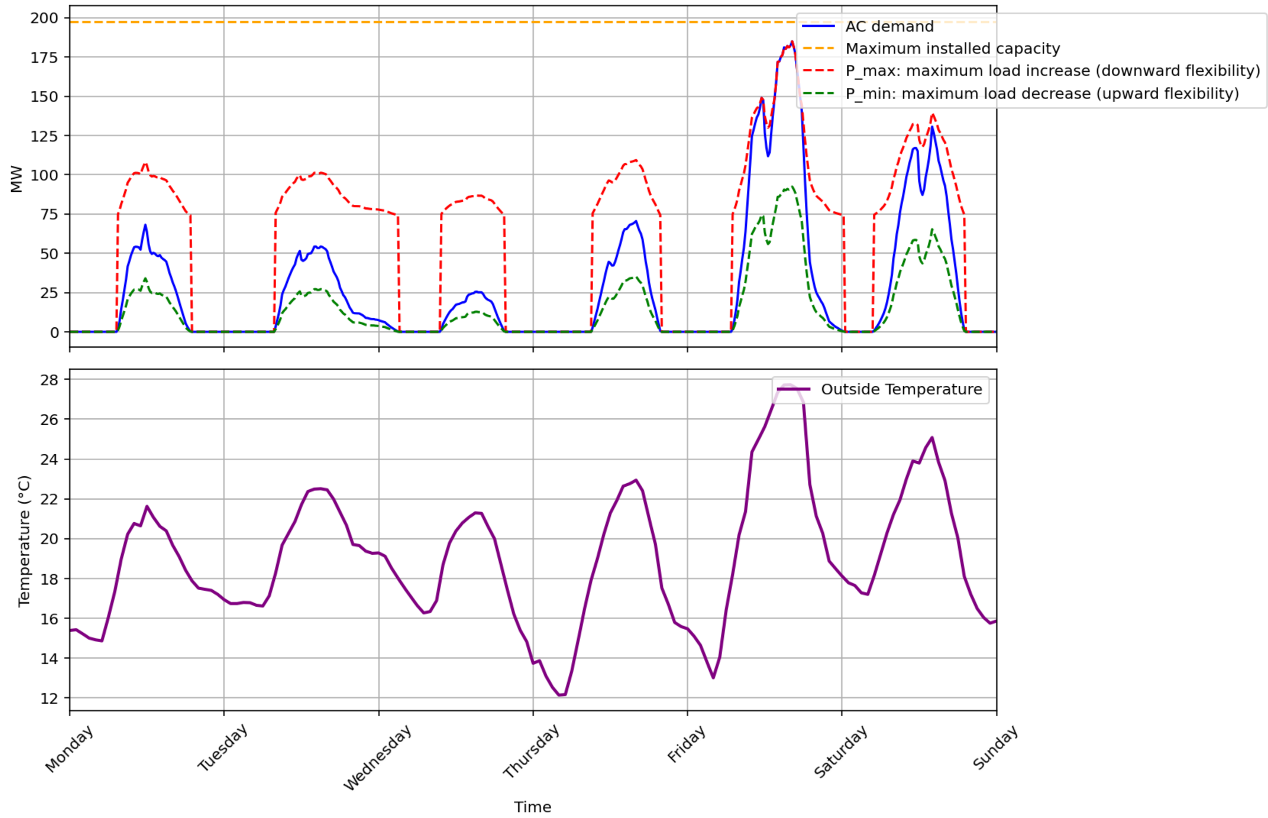


Figure 9 – a) Aggregated demands and power flexibility potentials of AC from tertiary sector in Luxembourg in a summer week – b) Temperature data

Figure 9 provides a detailed visualization of the modelled, aggregated demands and power flexibility potentials of AC systems in the tertiary sector of whole Luxembourg during a week in August. At the national level, by aggregating individual results for all communes in Luxembourg using the same assumptions and modeling approach, the flexibility potential from AC systems in the tertiary sector can be estimated for the entire country. During the cooling period (May to October), the aggregated daily cycle shows that the downward flexibility potential for 1-hour ranges from 0 MW during inactive periods to approximately 74 MW depending on demand peaks and system constraints, with the averages given in Table 10. Similarly, the upward flexibility potential for 1-hour ranges from 0 MW to approximately -99 MW and the monthly averages reported below. This insight provides a high-level perspective on the role of AC systems in grid flexibility at a national scale.

Table 10 - Average downward- and upward- flexibility per month (1h shift) – from AC systems in tertiary sector

Monthly averages	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*
Downward flexibility [MW]	0	0	0	0.9	17	20	17	21	5	0.65	0	0
Upward flexibility [MW]	0	0	0	-0.1	-5.5	-6.6	-11	-6.5	-1.3	-0.04	0	0

Figure 10 displays the aggregated upward flexibility potentials of AC systems across Luxembourg for the year 2021, alongside their corresponding monthly averages. The grey bars represent the hourly upward flexibility potential, while the green bars indicate the monthly average upward flexibility.

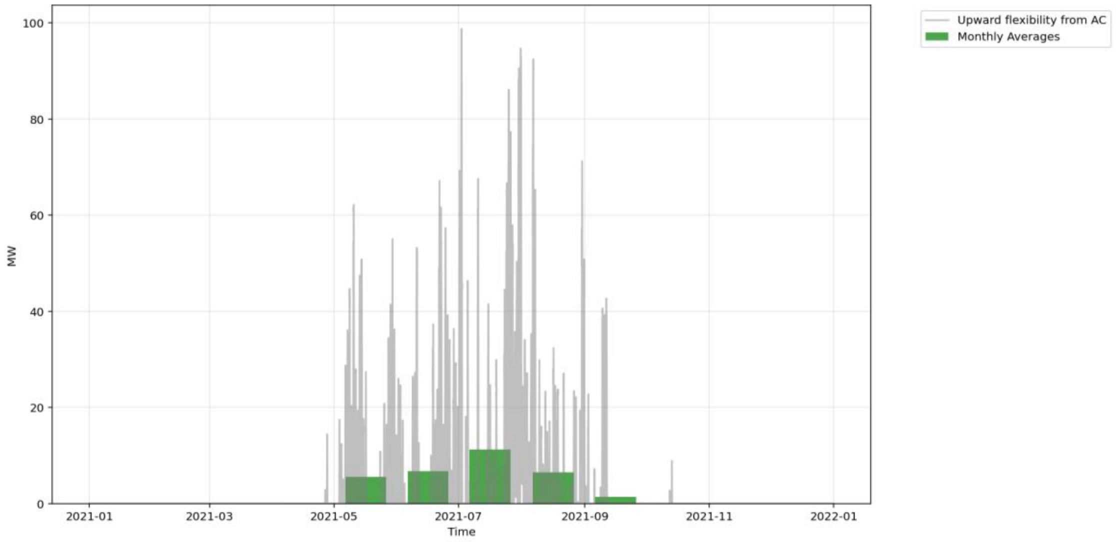


Figure 10 – Upward flexibility from AC systems in tertiary sector – monthly

4.3.2. Energy Flexibility Potentials for Air-Conditioning

Figure 11 illustrates the energy flexibility potentials of AC systems of the tertiary sector in Luxembourg city scaled by yearly consumption data, showcasing results for the first week of July.

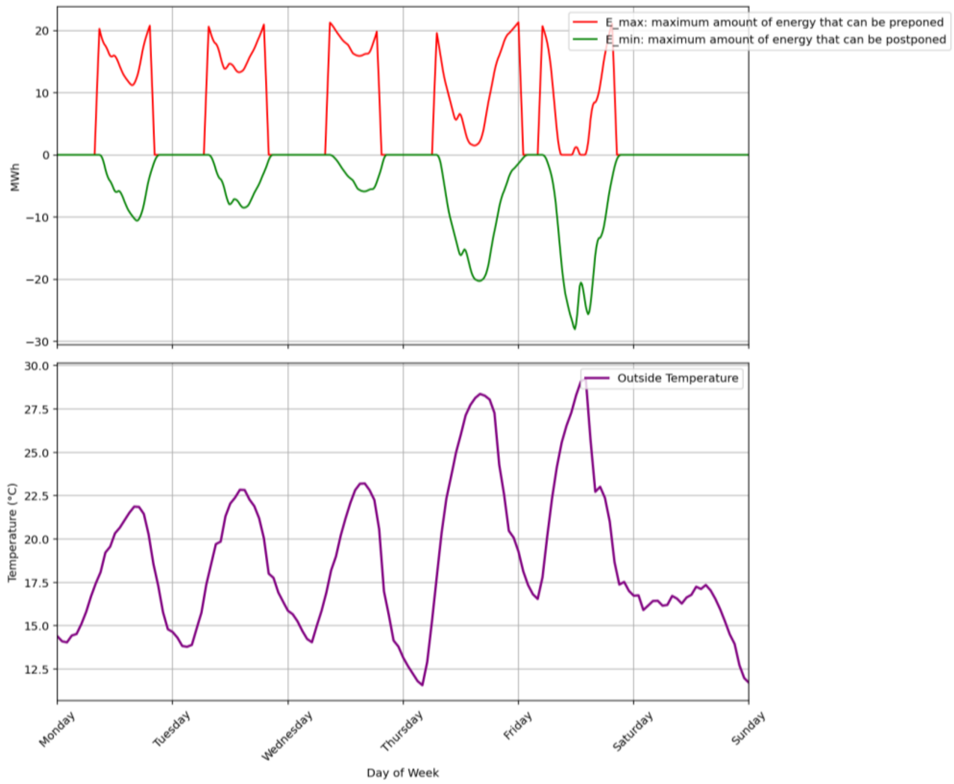


Figure 11 – a) Energy flexibility potentials of AC from tertiary sector in Luxembourg City (week in July) – b) Temperature data

The chart evaluates the maximum amounts of energy that can be preponed or postponed, which are represented by the curves E_max (t) and E_min (t), respectively.

The red line represents E_max (t), which is the maximum amount of energy that can be preponed at a given time t. Preponing refers to increasing demand to shift energy consumption to earlier periods, such as pre-cooling a building. This value is calculated by integrating the load flexibility over the future time interval [t, t+Δt]. It reflects the upper boundary of energy flexibility based on operational and comfort constraints.

The green line represents E_min (t), which is the amount of energy that can be postponed by decreasing demand at a given time t. Postponing means delaying energy consumption, such as cycling off air conditioning systems temporarily without compromising thermal comfort. This value is derived by integrating downward load flexibility over the past time interval [t-Δt, t]. The Δt in both calculations is considered to be 1 hour (Heitkoetter et al., 2021).

The bottom part of Figure 11 shows the outdoor temperature profile for Luxembourg City during the selected summer week.

As can be seen, the energy flexibility curves exhibit significant variability throughout the week, reflecting changes in AC demand driven by external temperature fluctuations. Peaks in E_max (t) occur during periods of lower AC demand, typically in the early morning or late evening, indicating opportunities to shift cooling loads forward in time. Conversely, E_min (t) peaks during high demand periods, such as early afternoon on hot days, revealing the potential to delay energy use and alleviate stress on the grid.

To illustrate a practical application, we highlight Friday as a representative sunny summer day, where the outside temperature peaks near 28°C. Around noon, both high cooling demand and strong solar irradiance are expected. In such a case, the upward flexibility potential (E_max (t)) around midday allows for preponing cooling loads to coincide with the solar production peak, thus enabling maximised self-consumption of locally generated PV electricity. This synergy between AC demand and PV output is particularly relevant in the summer, where demand-side flexibility can directly support grid integration of renewable energy. The visible asymmetry between the upward and downward flexibility on such days reflects the system's ability to absorb surplus solar generation by advancing loads, reinforcing the role of AC systems in balancing midday solar peaks.

4.3.3. Demands and Power Flexibility Potentials for Cooling

Cooling processes in the tertiary sector encompass various applications, including refrigeration in the retail sector, cooled warehouses, temperature regulation for server rooms or process cooling. Unlike air conditioning systems, which are entirely temperature-sensitive, cooling demands are only partially dependent on ambient temperatures. This is because such cooling loads are present year-round, but demand tends to increase during warmer periods due to higher heat loads on the systems and a drop in their operational efficiencies. This partial temperature-sensitive load pattern of cooling processes significantly defines the characteristics of the flexibility potential of these systems.

Figure 12 provides an analysis of the demands and power flexibility potentials for cooling in the tertiary sector of Luxembourg City during a summer week (here, first week of July). The temperature-sensitive part of the cooling demand is derived from the same underlying methodology used for AC calculations, which is applied to 30% of the total cooling demand in the tertiary sector. Unlike the AC demand, only this portion of the cooling demand is considered to vary with the temperature fluctuations.

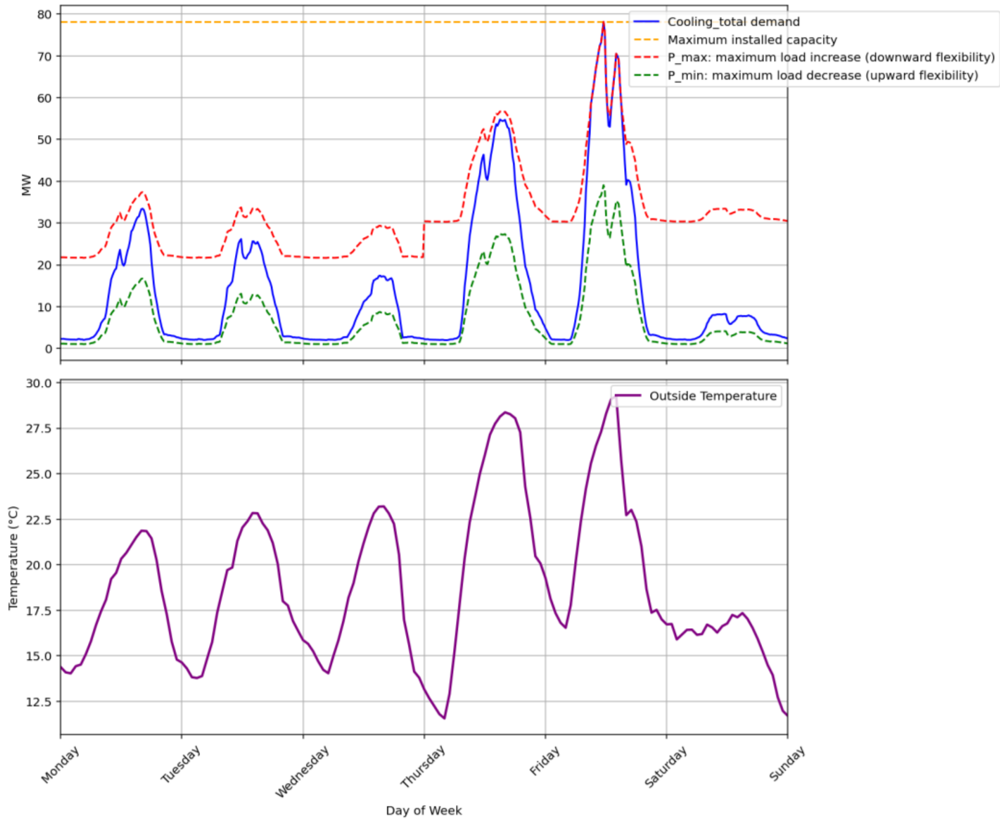


Figure 12 – a) Demands and power flexibility potentials of Cooling from tertiary sector in Luxembourg City (meteo-data: first week of July 2008; consumption data: 2021) – b) Temperature data

The orange line at the top of the chart indicates the maximum capacity of the cooling systems. For cooling, this represents the limit of the systems, beyond which no additional cooling seems reasonable. Since the installed maximum capacity is unknown, and an increase of actual power should be related to the demand during that period, it has been simplified in the model to be the peak load of cooling consumption during the respective month.

Figure 12 indicates the "total cooling demand", which includes both the temperature-sensitive (30%) and the non-temperature-sensitive (70%) portions of the cooling demand. Correspondingly, the total flexibility potential is calculated as the sum of the flexibility contributions from both the temperature-dependent and non-temperature-dependent components, thereby providing a comprehensive overview of the sector's cooling needs and associated flexibility.

Insights on national level

Figure 13 illustrates the aggregated demands and power flexibility potentials of the cooling systems in the tertiary sector of whole Luxembourg during the a week of August. Cooling demand patterns throughout the week are presented alongside upward and downward flexibility potentials, providing a comprehensive view of how cooling loads and flexibility vary over time. By extending this methodology nationally and aggregating data across all communes in Luxembourg, the flexibility potential of cooling systems can be evaluated at a countrywide scale. The downward flexibility potential from Cooling ranges from 0 to approximately 96 MW, depending on demand peaks and system constraints, with the averages given in Table 11. Similarly, the upward flexibility potential of cooling systems ranges from -3 MW to approximately -133 MW and the monthly averages reported below.

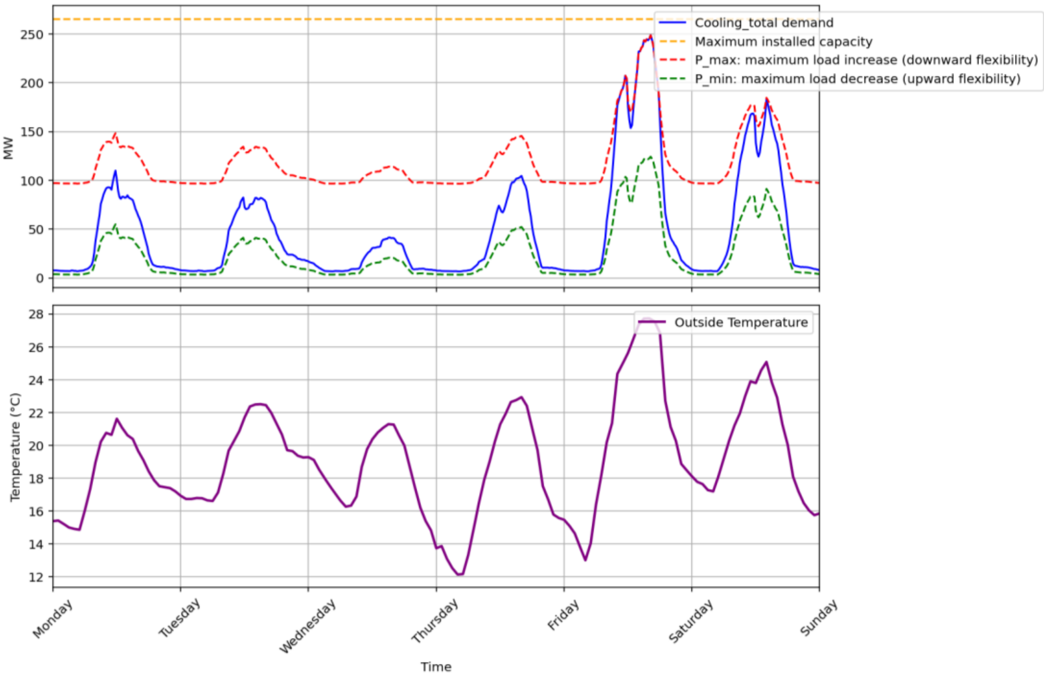


Figure 13 – a) Aggregated demand and power flexibility potentials of cooling from tertiary sector in Luxembourg, in a summer week (meteo-data: first week of August 2008; consumption data: 2021) – b) Temperature data, first week of August 2008

To guide practical applications of this potential, a set of concrete use cases can be defined. These include: (i) summer days with high solar production and elevated temperatures, where midday downward flexibility can support PV self-consumption or reduce curtailment; (ii) winter periods during cold spells and high system load, where even modest upward flexibility can ease grid stress; and (iii) windy days with excess renewable generation, where short-term downward flexibility can help absorb surplus wind power. Systematically assessing flexibility performance under such targeted scenarios will help align flexibility modelling with actual system needs and improve its integration into energy planning and grid operations.

Table 11 - Average downward- and upward- flexibility for each month – from cooling systems in tertiary sector and a one hour shift

Monthly averages	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*
Downward flexibility [MW]	5	5	5	12	53	55	80	79	40	5	5	5
Upward flexibility [MW]	-8	-8	-8	-7	-14	-15	-20	-15	-9	-7	-8	-8

Figure 14 displays the aggregated upward flexibility potentials of cooling systems across Luxembourg for the year 2021, alongside their corresponding monthly averages. The grey bars represent the hourly upward flexibility potential, highlighting the strong seasonality of cooling-related flexibility, which becomes prominent primarily between late spring and early autumn. Peaks in flexibility occur during heatwaves and high cooling demand days, with maximum values exceeding 133 MW in some instances. In contrast, the colder months show very limited or negligible upward flexibility due to the lack of active cooling demand. The green bars indicate the monthly average upward flexibility, reinforcing the concentration of flexibility during the warmer months. This seasonal pattern aligns with ambient temperature trends and illustrates the potential role of cooling flexibility in supporting the electricity system during summer peaks, especially when combined with solar PV generation.

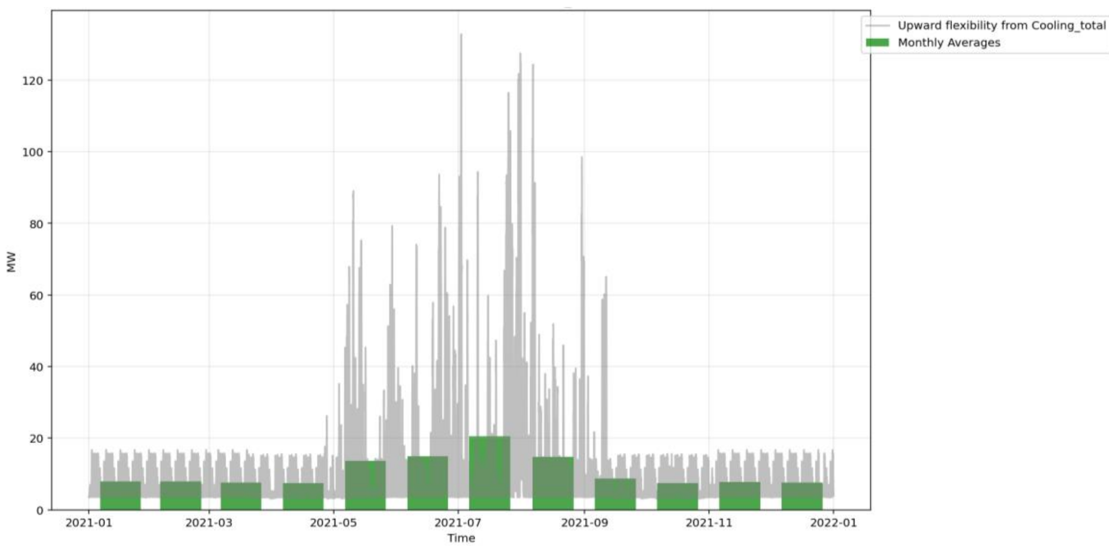


Figure 14 – Upward flexibility from cooling systems in tertiary sector – monthly averages

4.3.4. Energy Flexibility Potentials for Cooling

Figure 15 illustrates the energy flexibility potentials of the cooling systems in the tertiary sector of Luxembourg City, as analogue to the power flexibility. The chart evaluates the maximum amounts of energy that can be preponed or postponed. Unlike for the AC systems, the cooling systems are considered to have a permanent part load throughout the year and hence, could provide a certain degree of upward and downward flexibility anytime, across the season. This results in a relatively stable downward energy flexibility potential, at least during the colder and moderate seasons. The warmer periods show temporal fluctuating upward potentials. The methodology for deriving these values, based on flexibility integration over time intervals, is consistent with the approach used for AC systems, adjusted to account for the mixed sensitivity to temperature.

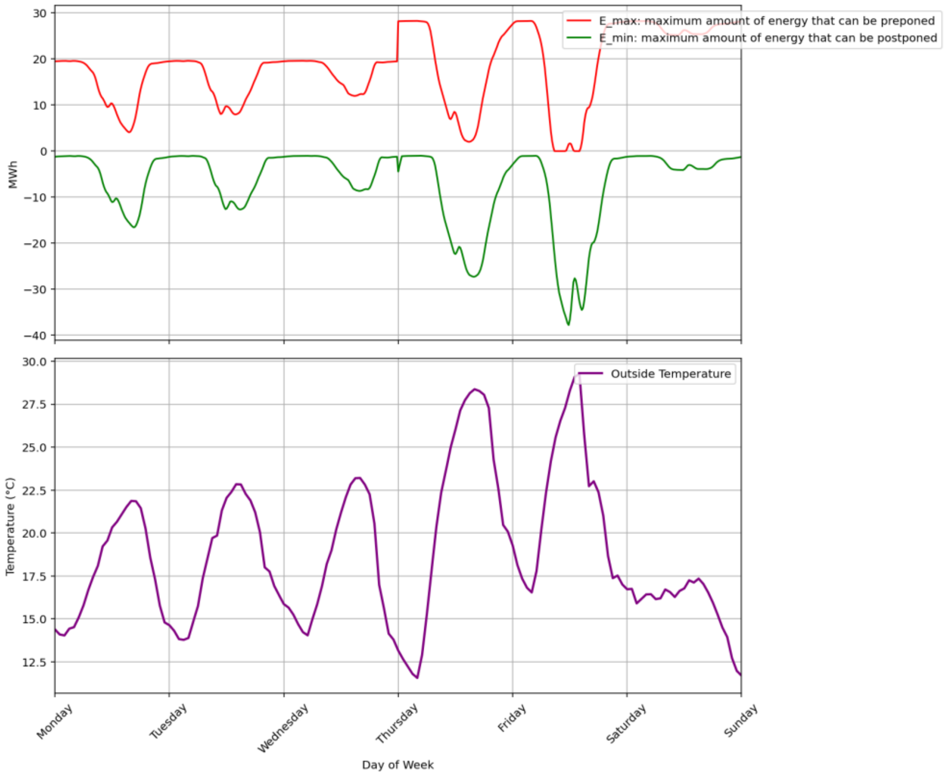


Figure 15 – Energy flexibility potentials of Cooling from tertiary sector in Luxembourg City in July

4.3.5. Demand and Power Flexibility Potentials for Ventilation

Figure 16 illustrates the demands and power flexibility potentials of ventilation systems in the tertiary sector of Luxembourg City, based on the example of a week of July. The chart displays the ventilation demand and its associated upward and downward flexibility potentials for 1 hour, along with the maximum installed capacity for these systems.

Unlike cooling systems, ventilation demand is considered independent of temperature. This independence is reflected in the smoother, more consistent patterns in both demand and flexibility potential over time. The ventilation systems account for 12% of the total energy consumption in the tertiary sector, providing a significant but steady contribution to overall energy use.

The ventilation demand, shown as the solid blue line, follows a daily cycle corresponding to typical activity levels in the tertiary sector – induced to the model by the standard load profile of the sector. Peaks are observed during working hours, while lower demand is seen during nights and weekends. The consistency in the pattern reflects the stable nature of ventilation needs throughout the year, influenced by operating hours of the service sector and occupancy schedules of the buildings.

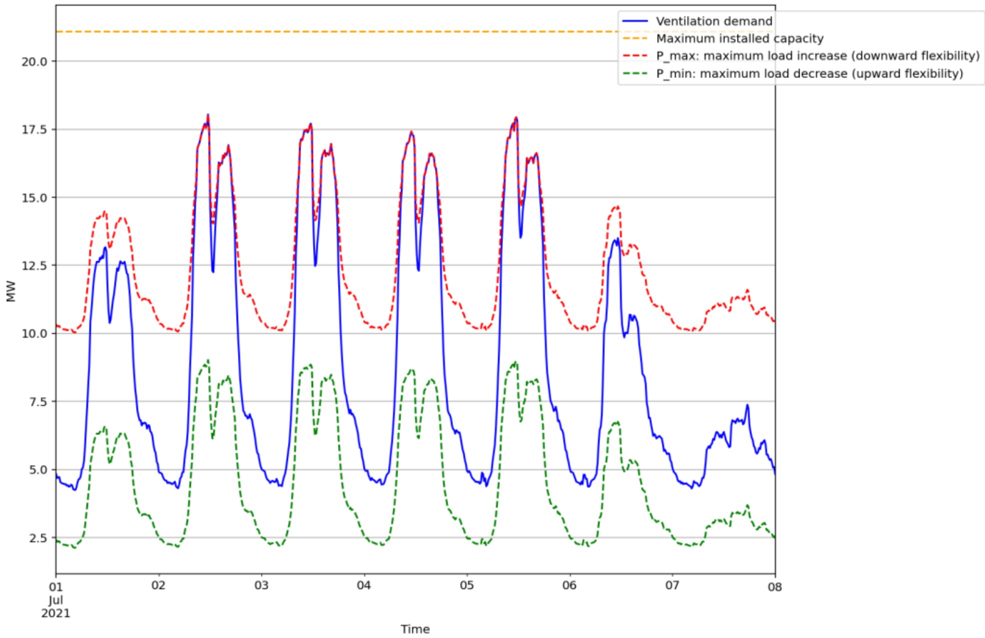


Figure 16 – Demand and power flexibility potentials of ventilation from tertiary sector in Luxembourg City (meteo-data: first week of July 2008; consumption data: 2021)

Insights on national level

Figure 17 illustrates the aggregated demands and power flexibility potentials of ventilation systems in the tertiary sector across Luxembourg at a national level (first week of August). The chart expands upon the city-level analysis to represent the cumulative impact of ventilation systems across all communes, reflecting their significant contribution to energy consumption and flexibility.

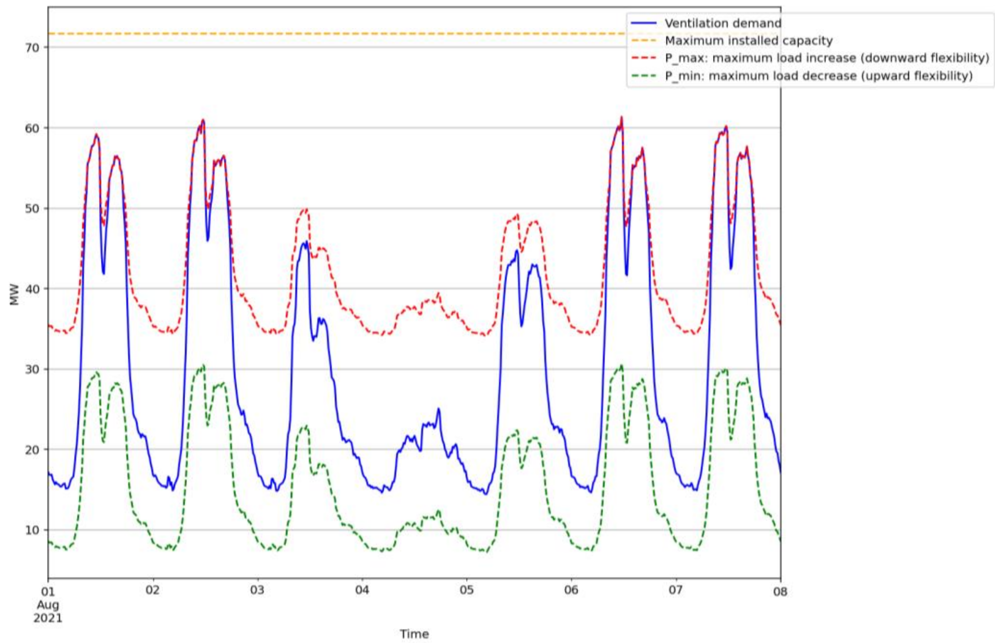


Figure 17 – Aggregated demands and power flexibility potentials of ventilation from tertiary sector in Luxembourg in the first week of August

Ventilation systems, accounting for 12% of the total energy consumption in the tertiary sector, are modelled independent of temperature fluctuations. The downward flexibility potential from ventilation ranges from 0 to approximately 20 MW, with the averages given in Table 12. Similarly, the upward flexibility potential from ventilation systems ranges from -6.5 MW to approximately -36 MW and the monthly averages reported below.

Table 12 - Average downward- and upward- flexibility for each month – from ventilation systems in tertiary sector for a one hour shift

Monthly averages	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*
Downward flexibility [MW]	10	10	11	12	12	12	12	12	12	11	11	11
Upward flexibility [MW]	-17	-17	-16	-15	-15	-15	-15	-15	-15	-16	-17	-16

Figure 18 displays the aggregated upward flexibility potentials of ventilation systems across Luxembourg for the year 2021, alongside their corresponding monthly averages. The grey bars represent the hourly upward flexibility potential, while the green bars indicate the monthly average upward flexibility.

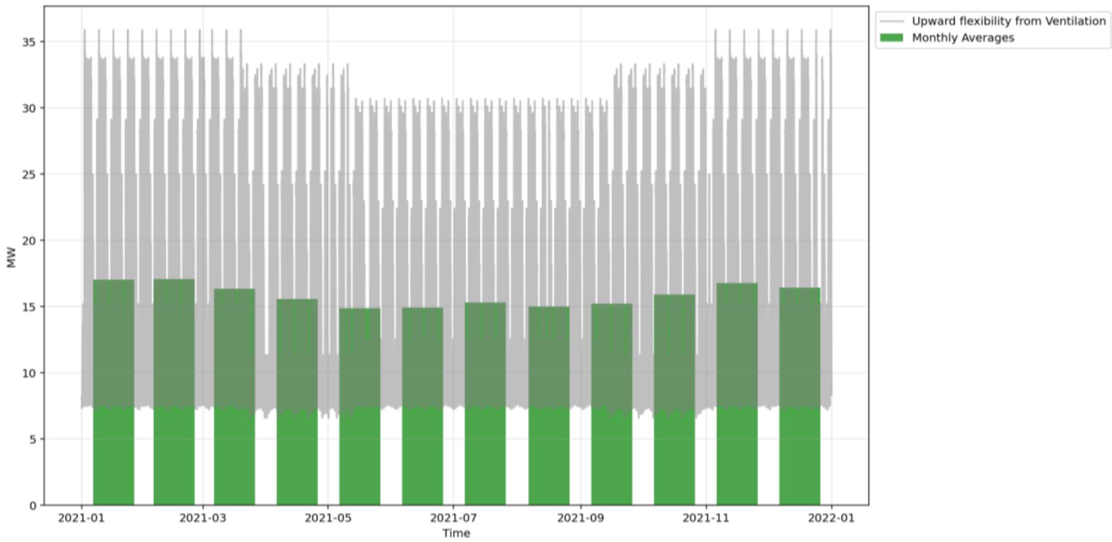


Figure 18 – Upward flexibility from ventilation systems in tertiary sector – monthly averages

The ventilation demand is considered to be independent of the temperature and follows a nearly uniform pattern over the year, resembling the standard load profile of the service sector. Consequently, the ventilation demand is evenly distributed throughout the year. Despite accounting for 12% of the total energy consumption in the tertiary sector, the average magnitude of ventilation demand over the year is lower than that of AC and cooling, which are more sharply distributed during periods with temperatures exceeding 18°C. As a result, the average magnitude of the power flexibility potential for ventilation is also lower compared to AC and cooling systems.

4.3.6. Energy Flexibility Potentials for Ventilation

Figure 19 illustrates the energy flexibility potentials of ventilation systems in the tertiary sector of Luxembourg City during a summer week (based on consumption data form 2021). The energy flexibility patterns follow a consistent daily cycle, mirroring the ventilation demand pattern. The upward flexibility potentials peak during working hours, aligning with higher ventilation demand due to building occupancy, and drop during nighttime and weekends when activity is reduced. The absence of seasonal variations in demand shows a stable and predictable energy flexibility potential throughout the year.

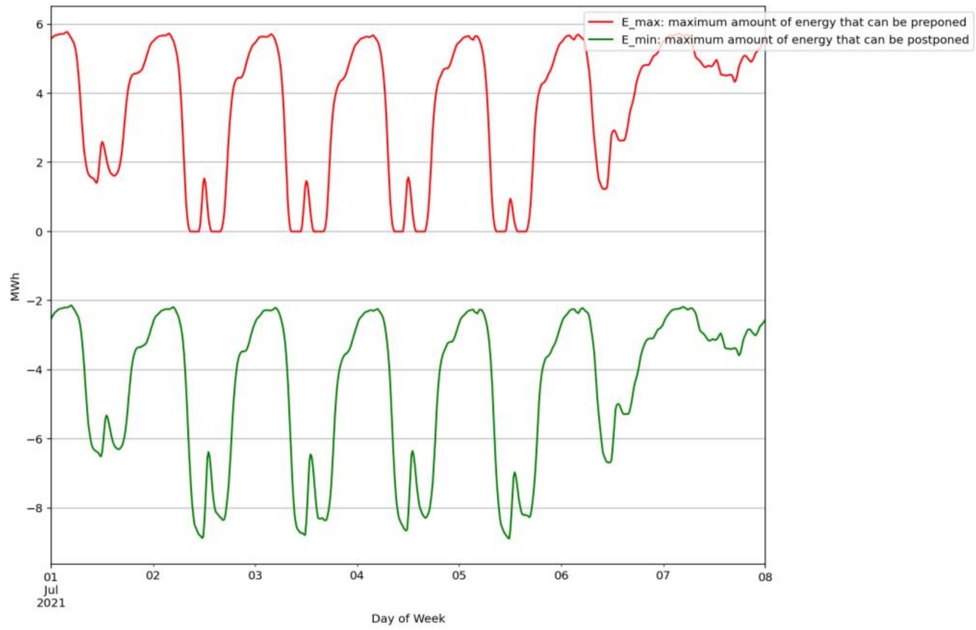


Figure 19 – Energy flexibility potentials of ventilation from tertiary sector in Luxembourg City (summer week)

4.4. Overall Results - Tertiary sector flexibility on national level

Figure 20 illustrates the aggregate demand and power flexibility potentials of AC, ventilation, and cooling systems in the tertiary sector of Luxembourg, representative for a summer week. The combined demand profile and flexibility potential for these flexibility-relevant processes are shown to provide insights into their contribution to demand-side management strategies.

The blue line represents the sum of AC, ventilation, and cooling demand, which shows a distinct daily cycle with peaks occurring during periods of high operational activity, typically aligned with daytime working hours. These peaks are influenced by both external temperature variations (affecting AC and temperature-sensitive cooling) and year-round operational requirements (ventilation and non-temperature-sensitive cooling).

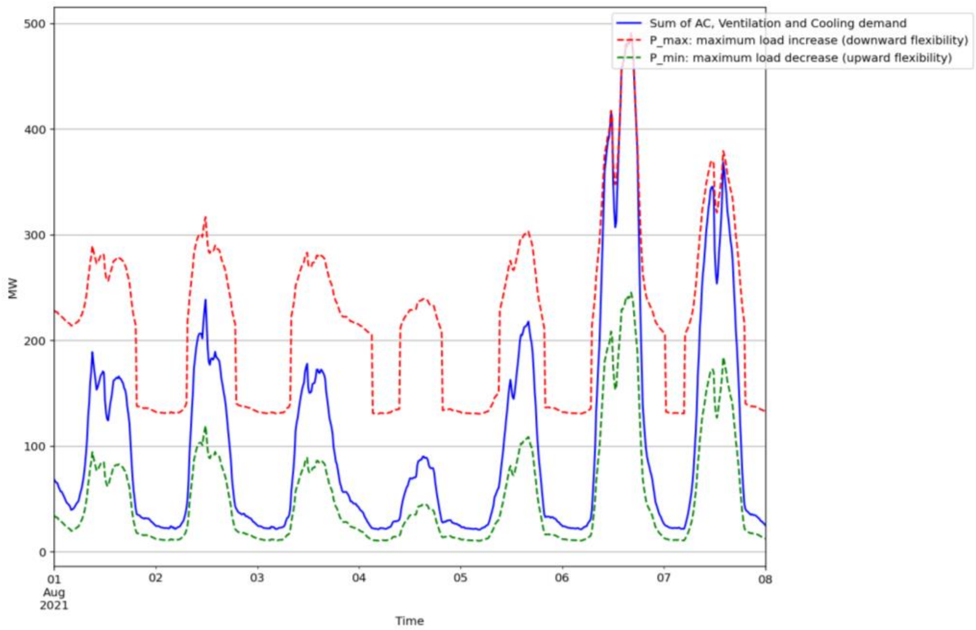


Figure 20 – Aggregated demands and power flexibility potentials from air conditioning, ventilation and cooling demand in the tertiary sector (meteo data: first week of August 2008; consumption data: 2021)

The red dashed line (P_max) illustrates the maximum potential for load increase, or downward flexibility, which could involve pre-cooling buildings, ramping up ventilation systems, or increasing cooling loads during off-peak hours when grid demand is lower or electricity prices are more favourable. However, to practically realise such flexibility, there must be a net economic benefit for the customers. Simply consuming more energy at lower prices is not sufficient unless it replaces consumption that would otherwise occur during higher-priced periods. This highlights the importance of actual load shifting, not just temporary load addition. The green dashed line (P_min) represents the maximum potential for load decrease, or upward flexibility, corresponding to opportunities for reducing demand by modulating system operation during periods of grid stress or high prices.

Figure 21 provides a comparative analysis of aggregated electricity demands and power flexibility potentials of the tertiary sector in Luxembourg. The figure includes two representative days: a summer day with high ambient temperature and irradiance (left), and a winter day with low temperatures and heating needs (right). The top panels display the aggregated load profiles alongside their flexibility envelopes, while the bottom panels show the corresponding outdoor temperature curves for each day.

In the summer profile (left), demand shows a pronounced diurnal cycle, sharply increasing in the late morning and peaking in the afternoon (around 15:00–17:00), in response to rising temperatures that reach up to 29°C. The blue curve indicates the total electricity demand, while the red and green dashed lines depict the potential for downward and upward flexibility, respectively. High daytime cooling demand drives significant flexibility margins, reflecting the sector's capacity to either pre-cool (downward flexibility) or temporarily reduce load (upward flexibility). These patterns align with typical summer energy dynamics, where solar generation potential is also high.

In contrast, the winter profile (right) shows a more flattened and consistent demand curve throughout the day, with outdoor temperatures ranging from -7°C to -0.5°C. Although cooling loads are minimal, baseline electricity demand from ventilation and other non-seasonal operations persists. Consequently, flexibility margins are present but lower in magnitude and less dynamic compared to summer. This reflects the reduced ability to shift loads without compromising heating quality during colder periods.

Together, these two profiles demonstrate the seasonal variability of both load shapes and flexibility potential in the tertiary sector. Summer days offer higher and more dynamic flexibility opportunities, especially when synchronized with solar generation. Winter days, while more constrained, still provide stable baseline loads that can contribute to flexibility schemes, particularly when complemented by wind energy availability.

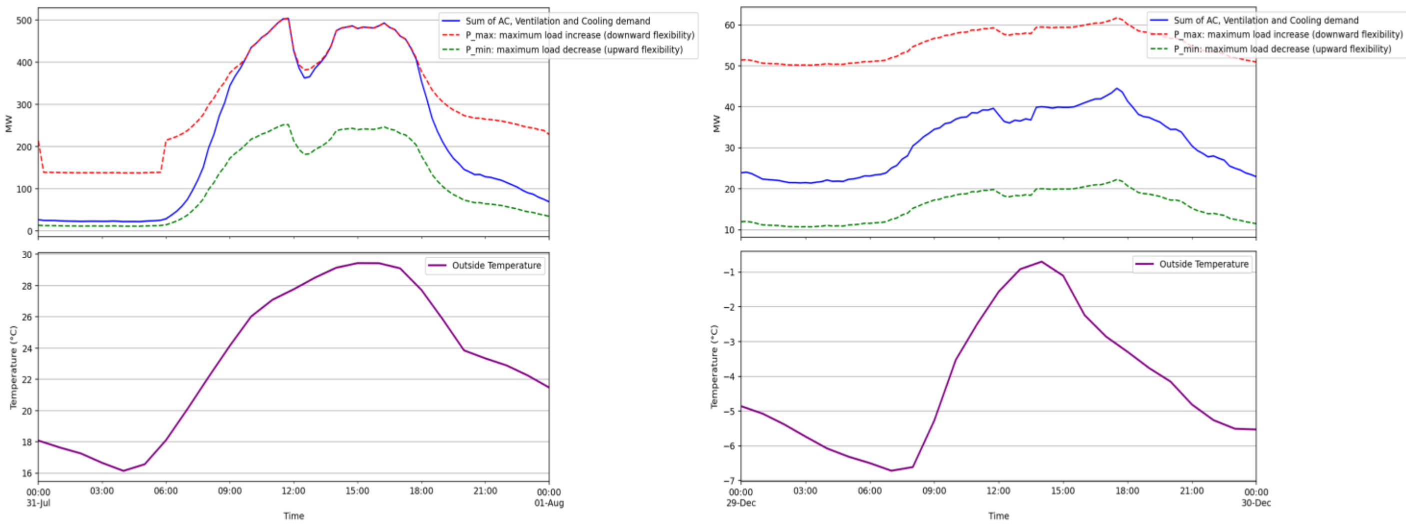


Figure 21 – Comparison of aggregated electricity demands and flexibility potentials in the tertiary sector in Luxembourg for a typical summer day (left: July 31) and a typical winter day (right: December 29)

The aggregate demand profile demonstrates a combination of temperature-sensitive components (AC and part of the cooling load) and non-temperature-sensitive components (ventilation and the remaining cooling load). This dual dependency results in a demand profile that is both seasonally variable (due to temperature effects) and consistently present throughout the year. Finally, the model results in an estimation of upward and downward flexibility from tertiary sector, based on the previously described assumptions and simplifications, using temperature data and tertiary sector electricity demand, as given in Table 13. The yearly average downward flexibility potential from ventilation, cooling, and AC in Luxembourg's tertiary sector, is approximately 48 MW, with a maximum of 189 MW, depending on demand peaks and system constraints. Similarly, the average upward flexibility potential from the same processes, is approximately -29 MW, with a yearly maximum of about -262 MW during peaks in summer.

Table 13 - Resulting flexibility potentials from tertiary sector in Luxembourg, considering modelled electricity demand from air-conditioning, cooling and ventilation (for a duration of 1 hour)

	Yearly average	*Yearly maximum*	*Yearly minimum*
Downward flexibility	48 MW	189 MW	0 MW
Upward flexibility	- 29 MW	- 262 MW	-9,6 MW

Specifically, due to the nature of the temperature sensitive demands of air-conditioning and cooling processes, the maximum available flexibility in the tertiary sector appears only in summer periods and is rather volatile. Hence, a reliable and plannable utilisation of flexibility should either be oriented along the average available flexibility (compare Table 14 and Figure 22) or needs to be well aligned with the fluctuating demand of the relevant processes.

Table 14 - Average downward- & upward- flexibility per month – by AC, cooling & ventilation in tertiary sector (for a duration of 1h)

Monthly averages	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*
Downward flex. [MW]	16	16	17	25	83	88	109	112	57	17	16	17
Upward flex. [MW]	-25	-25	-24	-23	-34	-37	-47	-36	-25	-24	-25	-24

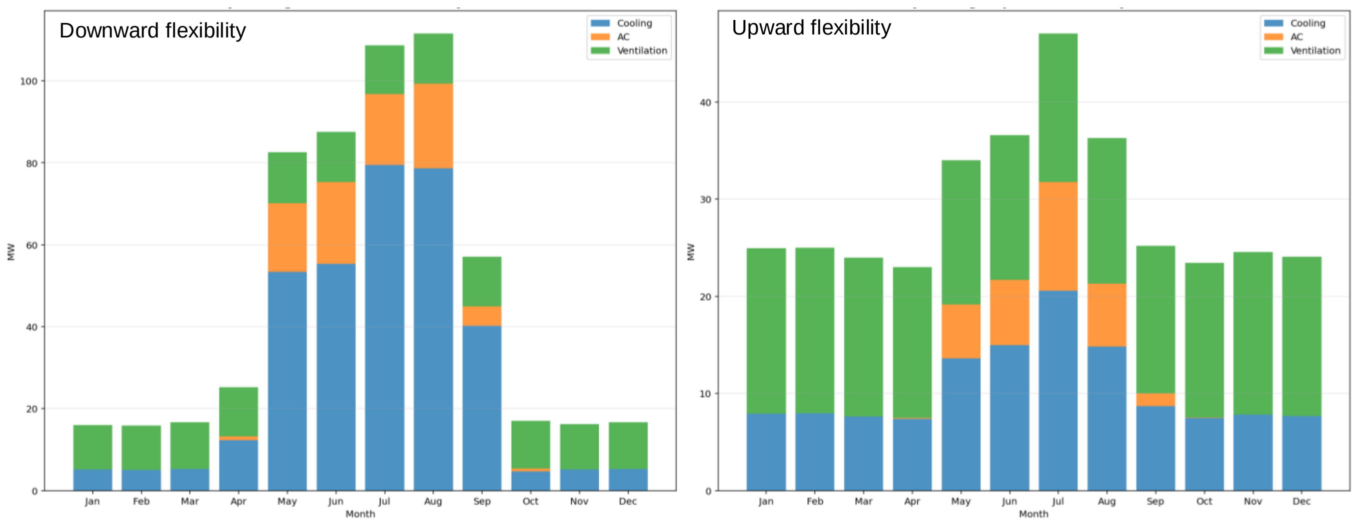


Figure 22 – Flexibility potentials for cooling, air-conditioning and ventilation in tertiary sector – monthly averages – for a 1 hour duration

Figure 22 presents the monthly average downward and upward flexibility potentials for three temperature-sensitive components, i.e. cooling, AC, and ventilation in Luxembourg during 2021. The left panel shows the downward flexibility, representing the potential to increase electricity consumption (e.g., through pre-cooling), while the right panel illustrates the upward flexibility, indicating the potential to temporarily reduce electricity use during peak periods. Overall, these results highlight the dominant role of cooling loads in shaping seasonal flexibility, especially for downward adjustments, while ventilation systems provide a reliable source of upward flexibility throughout the year.

5. Residential Sector – Heat Pumps

Heat pumps are important components of Europe's and Luxembourg's climate change mitigation policy as a backbone of the energy transition in the build environment. The national energy and climate action plan (NECP - 2021-2030, published 2018) foresees steep growth rates for the implementation of this technology (MEA & MECD, 2018).

This development will cause further growth in electricity demand, specifically during the heating period, which adds to the peak consumption during winter. Besides rising electricity demand and peak power for the distribution grid, heat pumps have the potential to be used as flexibility providing assets. A high degree of automation is possible with limited effort and, if correctly implemented, without comprising user comfort.

In the following chapter the ability of heat pumps to provide flexibility by switching "on" or "off", following an external signal, or increasing their instant power consumption and adapting the amount of heat that could be stored, is explained and the influencing factors are described.

5.1. Methodology for the heat pump flexibility assessment

The methodology to estimate flexibility from residential heat pumps consist of 4 main steps:

1. Estimation of the heat demand of residential buildings and the possible Coefficients Of Performance (COP) for heat pump systems in each commune, under given temperature conditions (for a full year, in hourly resolution)
2. Setting up a representative portfolio of heat pump systems in combination with building types. Eight standard heat pump system types are defined. By randomization of some design factors, for each of the eight standard heat pump system types, 100 variations per type are created.
3. The potential heat pump flexibility is modelled for five possible flexibility activation types
4. The resulting flexibility characteristics for all eight building groups are upscaled and aggregated to the individual communal level

5.1.1. Estimation of the heat demand and coefficient of performance

The heat demand of residential buildings consists of two main components, the space heating demand and domestic hot water demand. While the domestic hot water demand mainly depends on the number of inhabitants, the space heat demand is strongly dependent on the outdoor temperature and the building envelop. Following a methodology published in "Nature - Scientific Data" by (Ruhnau et al., 2019) the annual heat demand of all residential buildings in Luxembourg can be broken down to daily heat demand for space heating and domestic hot water, for a specific year, using the meteorological data (ambient temperature and wind speed) of the given period. The approach is partially based on a method from (BDEW Bundesverband der Energie- und Wasserwirtschaft e.V. et al., 2016) and is combined with hourly profiles from (BGW Bundesverband der deutschen Gas- und Wasserwirtschaft, 2006) to obtain temperature-dependent hourly heat demand values.

Using different types of statistical data from Luxembourg (STATEC (Klein & Peltier, 2017)), the hourly heat demand for all communes is estimated, differentiating single-family- (SFH) and multi-family-houses (MFH), as well as domestic hot water- and space heating-demand. The meteorological data for 2008 from the European Center for Medium-ranged Weather Forecasts[3] have been used.

Electric heat pumps provide heat using a process which extracts heat from a heat source (e.g. the ambient air or the ground), elevates the temperature level via a thermo-dynamic process and releases the heat to a heat sink, for example a floor heating system, heating radiators or for domestic hot water. The ratio of

[3] ECMWF - https://www.ecmwf.int/

the amount of heat delivered to the building and the electricity necessary to run the heat pump is described by the coefficient of performance, the COP. This COP is the main “efficiency parameter” of the heat pump and depends mainly on the temperature difference of the heat sink and heat source.

For the estimation of heat pump flexibility, it is essential to calculate the electricity demand of heat pumps under the given temperature conditions throughout the year. This is done via the method proposed by (Ruhnau et al., 2019) and the hourly temperatures for all communes in the given year. Taking into account the main parameter influencing the COP of a heat pump, besides the outdoor temperature, it is possible to estimate the theoretical COP for different combinations of heat pumps and heating distribution systems. The model differentiates air-sourced and ground-sources heat pumps, single- and multi-family buildings and floor heating systems vs. radiator heating, to calculate the COPs under given temperatures, which results in a matrix of COPs for each commune and hour of the year:

Table 15 - Matrix of categories defining the COPs of heat pump & building

Single-family house (SFH)				Multi-family house (MFH)			
air sourced heat pump		ground sourced h.p.		air sourced heat pump		ground sourced h.p.	
floor heating	radiator heating	floor heating	radiator heating	floor heating	radiator heating	floor heating	radiator heating

5.1.2. Defining a representative heat pump system portfolio

In order to model the normal operation of the heat pumps and the potential for flexibility provision, a mathematical model is set up, consisting of the following main components: the heat pump (air-sourced or ground-sourced), a buffer storage for domestic hot water demand (DHW) and a storage for space heating (SH), an electric back-up heater, and a heat distribution system (floor heating or radiators). The design and dimensioning of those components depends on design parameter linked to statistical values for the residential sector in Luxembourg [based on versatile statistics by STATEC]:

- avg. inhabitants per flat: 2,5
- avg. number of flats in MFH: 4
- avg. dwelling size SFH: 139 m2
- avg. dwelling size MFH: 67.7 m2

Further, the thermal nominal power was estimated using a simplified design parameter (specific heat demand), considering an energy efficiency standard which is a mix of modern buildings and existing, far less efficient buildings.

The design rules of the model establish connections between the different system design parameters: e.g. the storage volume for space heating depends on the thermal nominal power of the heat pump and the type of distribution system; the volume of the domestic hot water storage tank, is defined by the number of inhabitants. This results in 8 standard building types and heat pumps systems, indicated in Table 2 (partially adapted from (Fischer et al., 2016)).

Table 16– Main design parameter for 8 standard building characteristics

		Single-family house				Multi-family house			
		air-sourced HP		ground-sourced HP		air-sourced HP		ground-sourced HP	
design parameter	**unit**	**floor h.**	**radiator**	**floor h.**	**radiator**	**floor h.**	**radiator**	**floor h.**	**radiator**
therm. power	kW_{th}	9.73	9.73	9.73	9.73	16.25	16.25	16.25	16.25
Vol., storage SH	liter	361	661	361	661	544	1007	544	1007
Vol., stor. DHW	liter	138	138	138	138	375	375	375	375
Inhabitants	/	2.5	2.5	2.5	2.5	10	10	10	10
floor area	m^2	139	139	139	139	270.8	270.8	270.8	270.8

spec. heat demand	kW/m²	0.07	0.07	0.07	0.07	0.06	0.06	0.06	0.06

These eight standard buildings & heat pump system combinations serve as the basis for the randomisation. In order to avoid having only 8 buildings in the model, which could lead to very distinct characteristics in the results and sharp marginal values, some characteristics of the buildings are randomized within predefined boundaries. The values of each standard building type for “inhabitants”, “floor area” and “specific heat demand” are used as mean values and are varied following an individually defined distribution to generate for each building category a set of 100 buildings. This results in 800 buildings, 100 for each standard building type, which depicts a statistical distribution, representative for the building types in Luxembourg. In a later step, described in 2.1.4, the share of each building type is individually defined for each commune.

5.1.3. Modelling of heat pump flexibility

Flexibility from heat pumps can be used in different ways. Already today, in some European countries, energy provider offer specific heat pump tariffs, while (in return) the supplier could block the heat pump operation via a control signal, e.g. for up to 2 hours, evtl. more than once a day (three time per day in Germany). If not using a control signal, some suppliers have implemented fixed blocking hours in which the heat pump will not start.

Since 2024, Germany implemented a new regulation[4] to reduce the electricity consumption from heat pumps once network constrains are met. The allows the grid operator to limit the power take up of heat pumps to 4.2 kW via an EMS or smart meters but needs to proof that network capacity is constrained. Hence, this option is a smarter approach to avoid gid congestions during winter periods, due to intensive heat pump operation, but is not an option for a more general flexibility provision.

Some manufactures have implemented more advanced control options, as proposed with the “smart grid ready” of “SG Ready”-label (Bundesverband Wärmepumpen e.V., 2020), which offer besides the “blocking” or deactivation of a heat pump, also the option to switch-on.

Within the FlexBeAn Project, heat pump flexibility is modelled for the following 5 activation types (Fischer et al., 2016), which are geared to the above-mentioned options:

- **Blocking signal for 2 hours** *(Off-2h)* – heat pumps receiving this signal will switch off, respectively are blocked from switching on for the duration of 2 hours.
- **“SG Ready – Off”** *(SGR-Off)* – running heat pumps will be switched off within their normal operation mode, until the lower temperature set points of the space heat- or domestic hot water storage are underpassed
- **“SG Ready – On”** *(SGR-On)* – heat pumps will be switched on within their normal operation mode, until the upper temperature set points of the space heat- and domestic hot water storage are reached
- **“SG Ready – On, Space Heating storage temperature elevated”** *(SGR-On-SH)* - heat pumps will be switched on with increased temperature set points for the space heating storage (of 60°C)

1. [4] Gesetz über die Elektrizitäts- und Gasversorgung (Energiewirtschaftsgesetz - EnWG) - § 14a

- **“SG Ready – On, back-up heater”** *(SGR-On-SH-BH)* - heat pumps will be switched on at increased temperature set points for space heat storage ***and*** the electrical back-up heater is activated

Although the activation types above are defined under the SG-Ready label, this label is not a detailed technical standard or norm. The detailed interpretation and implementation fall to the individual heat pump manufacturer and can be quite different.

To estimate the available flexibility for each of the 8 pools of 100 heat pump / building types, in hourly resolution over a full year (based on historical meteorological data), for each time step the current status of the heat pumps are set, in dependence to the operational conditions: e.g. if a heat pump is currently running or switched off, the state of charge of the buffers, etc. This initialisation step is based on rules depending on the outdoor temperature defining the share of operating heat pumps, but underlies randomness regarding which of the systems is chosen to be running. Hence, the results are not to 100% deterministic and show a low degree of stochasticity.

Further, heat pump types, configurations, control strategies and the hydraulic implementation of buffer storages (if any) are highly divers. The model tries to represent a common set up and is based on scientifically proven methods and assumptions, adapted to the Luxemburgish context. Nevertheless, the presented results are based on models which are partially based on assumptions and simplifications of reality, which causes uncertainties.

5.1.4. Upscaling to communal level

The above-described methods allow to estimate the available flexibility for five activation types, for a set of 800 representative buildings, in hourly resolution over a full year, for each commune in Luxembourg with the given temperature conditions of a specific year. In the next step, the flexibility parameter will be aggregated to a representative set for the heat pump systems and building type, which could be expected in each individual commune:

Air-sourced- / Ground-sources heat pumps

Heat pumps using the ambient air as heat source and the ones using a geothermal collector are the most common types in Europe, and Luxembourg. Water-based heat pumps can be neglected for the case of Luxembourg. How the market in Luxembourg is split between air-source and ground-sourced heat pumps is not published, but the sales figures[5] from Germany show a clear tendency towards air-sourced systems. While the growth rate for ground-source heat pumps almost stagnated over the last 10 years, air-sourced heat pumps saw huge growth rates. Hence, the aggregated market shares over the last seven years were about 16% to 84% for air-sourced systems – not considering the installations before 2017. Although, sales figures from Luxembourg are not available, this tendency is confirmed by the numbers of subsidised heat pump installations by the AEV[6]. Due to conditions and changes in the support schemes, these numbers have to be interpreted carefully, but previously subsidised installation had about 28 % share of ground-sourced heat pumps, recent installations (up from 2022) showed on 9.2 % for ground-sourced systems.

In some regions, the possibilities for geothermal drillings are restricted, or even excluded, mainly for reasons of ground water protection. These restrictions are publicly accessible in the geographical information system “GeoPortail”[7]. As depicted in Figure 23, these restrictions reach from the exclusion of geothermal drilling, over conditions for heat transfer media and drilling depth, to a simple requirement for authorisation.

[5] https://www.waermepumpe.de/presse/zahlen-daten/absatzzahlen/ (last accessed October 2024)
[6] Administration de l’Environement – information by mail in March 2025
[7] https://map.geoportail.lu

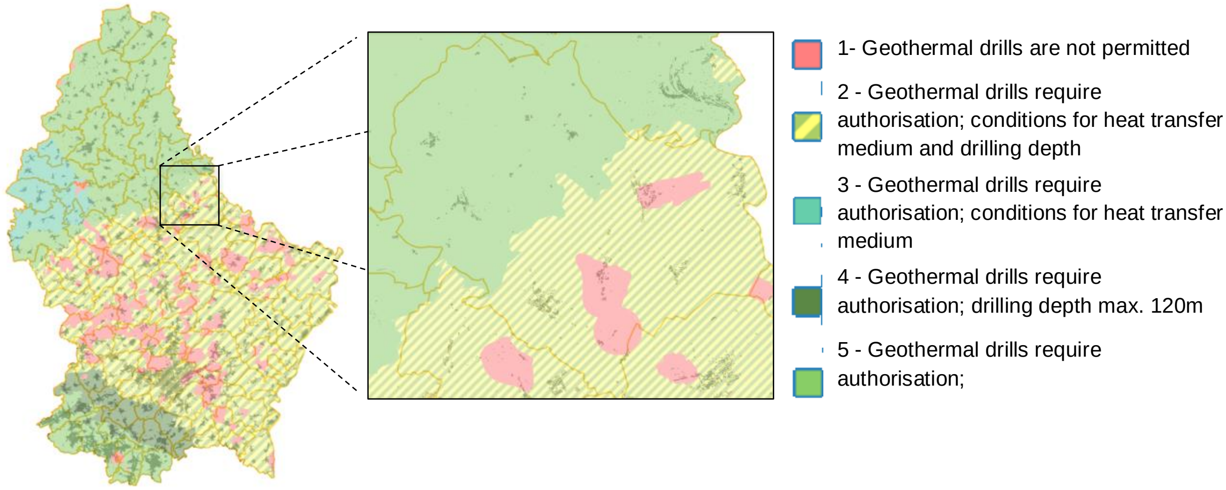


Figure 23 - Restrictions for geothermal drillings [geoportail.lu / AGE]

To assign the individual share of both heat pumps types per commune, the cadastre parcels of each residential building have been intersected with the drilling restrictions, to estimate the share of parcels falling into either restriction area. Taking into account the statistics on the share of ground-sourced to air-sourced heat pump sales in Germany and the restrictions in Luxembourg, the following assumptions are taken for the share of parcels in each commune falling into either of above categories:

Table 17 - Share of heat pump types assigned to drilling restriction areas

CAT.		Share of AS heat pumps	Share of GS heat pumps
1	Geothermal drilling not permitted	100 %	0 %
2 & 3	Authorization required – stricter limitations	90 %	10 %
4 & 5	Authorization required – lower limitations	80 %	20 %

A potential share of both heat pump types is calculated per commune, reaching from e.g. 99% air-sourced for Sandweiler, to 80% air-sourced heat pumps in all 20 communes that have no further restrictions.

Single-family- / multi-family-houses

The share of single-family house (SFH), to multi-family houses (MFH) per commune is defined by the amount of flats in SFH and apartments in MFH, as analysed and published in (Klein & Peltier, 2017) via STATEC. Those numbers vary largely across the country. Example: while the urban capital, City of Luxembourg, has almost 80% of their flats as apartments in MFH and only a share of 20% SFH, the rural area of Kiischpelt states the other extreme, with 88% of the dwelling as SFHs and only 12% of the flats in MFHs.

Floor-heating / radiator heating

Heat pumps work more efficient with low supply temperatures, as it is possible if combined with floor heating systems. But also modern low-temperature radiators enable the efficient usage of heat pumps and even older radiator could (under certain conditions) be used in heat pump systems, although the COP would not be optimal. Nevertheless, for this study it has been assumed that most heat pumps would be combined with floor heating systems and a share of floor- to radiator systems of 70% / 30% has been considered.

These statistical data, assumptions and model results are used to aggregate an individual potential for the flexibility per commune, considering the regional specifications – in hourly resolution over a full year.

5.1.5. Characterisation of the flexibility provision

Requesting flexibility from a pool of heat pumps will lead to a heterogenous reaction from those systems. The example given below in Figure 24 shows a group of 100 heat pumps being asked to “switch on”, following their normal operation mode (SGR-On activation signal) at an ambient temperature of 12°C, so at rather low heat demand. The heat pumps being currently switched off will react, by switching on until their upper temperature set points are reached, which takes (in this example) between 1 and 20 minutes at those conditions, on average 10 minutes. Hence, there is an increased power consumption by those heat pumps up to almost 400 kW (t=0), which drops down over time. Even the power consumption of a single heat pump might not be totally constant, but might show a higher initial consumption, indicated by the P_max in Figure 24, while the y-axis shows the cumulated average power of each HP. In order to characterize this flexibility provision by a pool of 100 heat pumps to a certain activation signal at a given time and temperature condition, the following characteristics are introduced (modified from (Fischer et al., 2016)) and explained based on the example below:

Maximum power (P_{max}): aggregated peak response after a trigger signal is send

Shiftable energy (E_{agg}): aggregate energy content below the curve (blue area) - can be consumed by the pool of heat pumps over the full period of an activation

Maximum duration ($Dura_{max}$): time until the consumption of the activated pool falls back to normal (baseline)

Average duration ($Dura_{avg}$): average duration of the flexibility provision of a heat pump in the pool. It is the sum of durations of all reacting heat pumps, divided by the number of HPs reacting

Mean power (P_{mean}): a virtual power, describing the power for the average duration of an activation, which represents the same amount of shifted energy (E_{agg}), but at constant power (E_{agg} = red area)

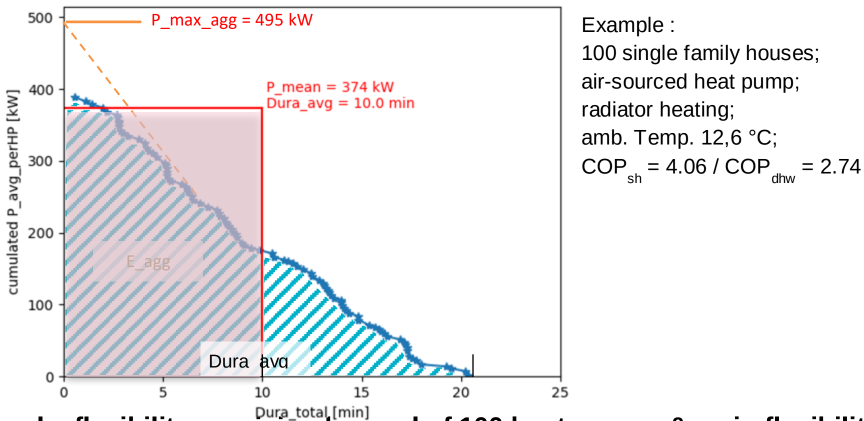


Figure 24 – Example, flexibility provision by pool of 100 heat pumps & main flexibility characteristics

5.2. Scenarios – heat pump penetration today, 2030, 2040

The electrification of the heat demand is an essential part of the decarbonisation strategy in the residential sector. Although the share of heat pumps on the currently used heating systems is still relatively low, the expected growth rates are rather high. The numbers reported by STATEC, Statista and referred to by CREOS in the scenario report (Delbrassinne & Michels, 2023), indicate a share of about 2% of the residential buildings being heated by electrical heat pumps in 2020, for about 147.000 residential buildings.

In coherence to updated assumptions of the PNEC, as of 2024, STATEC adapted the projections for heat pump implementation and CREOS refers to this publication in the latest update of their scenario report (2025). Hence, the modelling of flexibility from residential heat pumps is based on the following absolute numbers, that have been defined under consideration of the (STATEC, 2024) publication:

Table 18 – Projections - heat pumps in residential sector (based on STATEC)

	2020	2030	2040
Number of heat pumps in residential buildings	3.007	48.000	98.000
Number of residential buildings	147.000	160.500	174.000
Share of heat pumps	2 %	30 %	56 %

In the results sections under 5.4.1 and 5.4.2 for communal and national level, only results for the 2040 scenario are presented, which represent the upper limit of the technical potential. Flexibility results are scaled down to 2030 and today (for power and energy) in chapter 5.5.

5.3. Results – example for a set of 100 houses

The heat pump flexibility model developed in FlexBeAn runs simulations for 8 typical building types and heat pump systems, in sets of 100 buildings for each type (as explained in 5.1.2). This chapter gives an overview on representative results for the 5 activation types for one group of 100 buildings. The most common combination of building type and heat pump system has been chosen, which are *Single-family-houses with air-sources heat pump and floor heating system*.

Besides the differences due to the versatile activation types, the available flexibility is mainly dependent on the outdoor temperature, since it defines the heat demand and influences the COP. Hence, the results vary over time and with the seasons. To give an overview, the following graphs show results for each activation type for a single moment in time as well as for a one full month:

Activation signal " SGR-Off " – flexibility by a pool of 100 heat pumps

Sending a "Smart-Grid Ready Off" signal (SGR-Off), as described in 5.1.3, to a group of 100 heat pumps in our model will result in switching off the systems that are currently running until their lower temperature set-points are reached. As depicted in Figure 25 a) for a winter day at about 3°C, there would be 39 heat pumps switching off for an average duration of 17 minutes (min. 1 minute / max. 33 min.), which results in a load reduction of about -200 kW. This load reduction continuously sinks with heat pumps switching on again, being dropped to -100 kW after app. 18 minutes, and reaching the baseline consumption again after 33 minutes. This corresponds to 56 kWh of energy shifted (E_{agg}). The virtual "mean power", if all heat pumps would be switched off for the average duration of 17 minutes, shifting the same amount of energy (E_{agg}), would correspond to -193 kW.

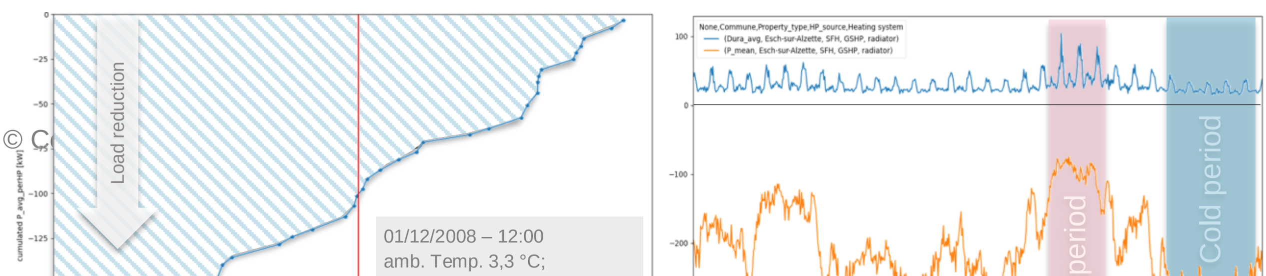


Figure 25 - a) load reduction over time by activation signal SGR Off; b) possible load reduction and average duration based on December 2008 meteorological data (example of 100 heat pumps; SFH, air-sourced HP, floor heating)

The evolution of the flexibility (mean power) over the full month of December can be seen in Figure 25 b), orange line. The meteorological data of Dec. 2008 show a relatively warm period around the 22nd with average temperatures about 6°C, and a cold period around the 29th of December with temperatures about -5°C and reach down to -7. During those warm periods the available upward flexibility (via SGR-Off) of this pool of 100 buildings goes down to about 120 kW (P_{mean}) and heat pumps would remain switched off for 20-50 minutes on average. During the cold periods, the flexibility expressed in power (P_{mean}) is much higher, on average around 320 kW, while the average duration of a heat pump providing that flexibility is shorter, about 12 minutes.

Activation signals "SG Ready – On" & "SG Ready – On, SH elevated" comparison – for pool of 100 HPs

Under certain circumstances, the grid operator might be interested in increasing the present power consumption of heat pumps in an area, which is possible with activation signals such as Smart-Grid Ready-On ("SGR-On"). Of 100 heat pumps receiving this signal on a moderate winter day (3°C) 61 heat pumps are reacting by switching on and will run until their upper set point temperatures are reached. In the pictures below (Figure 26) the flexibility provision of the "SGR-On" signal is compared to the "SGR-On - SH elevated" signal, which results in an increased temperature set point for the space heating buffer storage of 60 °C. Figure 26a) indicates the differences between both modes: "SGR-On" results in 250 kW downward flexibility for a short duration of 7 minutes, on average, until most heat pumps switch off again. The increase of the temperature set points for space heat storage cause a prolonged activation, up to 56 minutes in the mean, at similar power. This elevated mode of operation gives a relatively stable flexibility provision for a period of about 40 minutes, according to the simulation.

Figure 26b) shows the changes in flexibility potential over a full month, based on Dec. 2008 meteorological data. The downward potential of a pool of heat pumps during the warmer period in this winter month lies between 270 kW (SGR-On-SH) and 310 kW, while during the colder period it drops to about 180 kW, on average, but with large fluctuations. The main difference between both activation types remains the average duration of an activation, which remains relatively stable across the period, and lies around 10 minutes for SGR-On and 60 minutes for SGR-On-SH, which also results in a larger difference in terms of the potentially shifted energy.

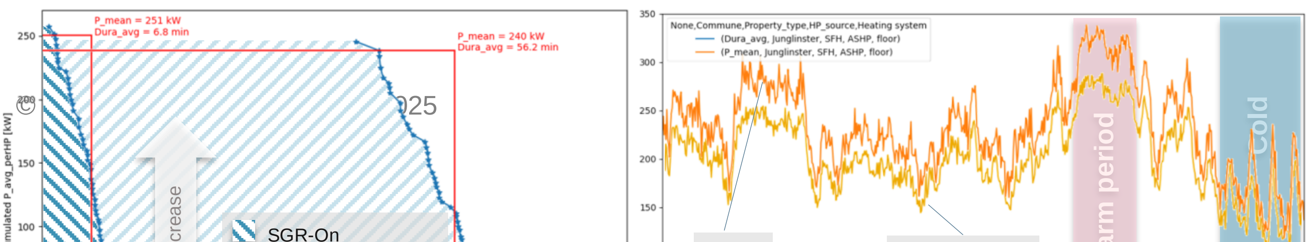


Figure 26 - a) load increase over time by activation signal SGR On & SGR-On-SH elev.; b) potential load increase over full month (SGR-On; SGR-On-SH-elev.)

Activation signal "SG Ready – On, back-up heater" – for a pool of 100 HPs

If an even higher temporary power consumption is desired, the activation signal "SGR-On-back-up heater" could further use the electric back-up heater to heat up the buffer storages to an elevated space heat temperature. Simulated for the same moderate winter day as the previous examples and the same building pool, this results in almost 400 kW of increased power consumption for an average duration of 50 minutes Figure 27a).

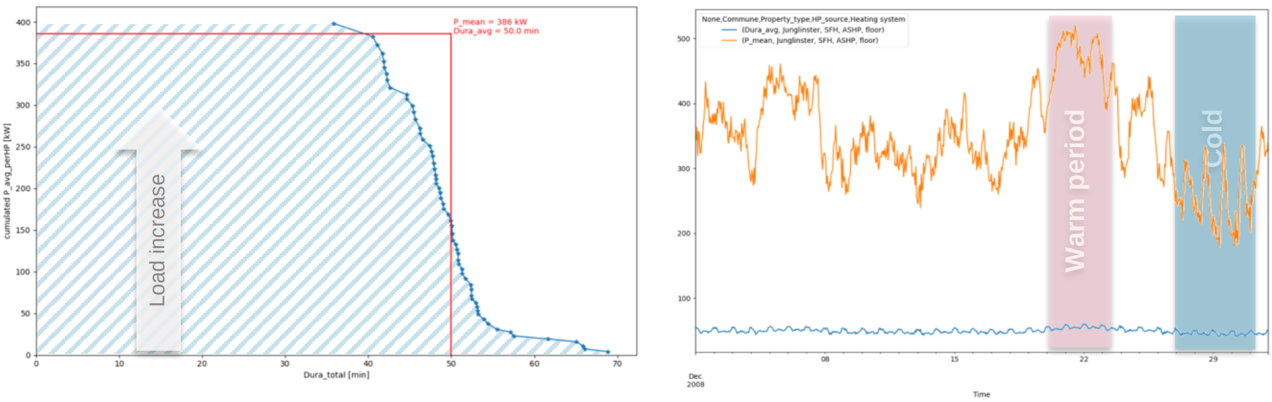


Figure 27 - a) load increase over time, by "SGR-On, back-up heater" b) potential load increase over full month ("SGR-On-back-up heater")

As expected, this activation mode differs from both previous types mainly in the higher aggregated power of the flexibility (Pmean) and the lower duration, as obvious from Figure 27 a) already, while the general characteristics over the monthly period with changing temperatures remains similar. It should be noted that the activation of the electrical back-up heater drastically reduces the efficiency of the overall heat pump system.

Activation signal "Off-2h" - 2 hours blocking signal applied to a pool of 100 HPs

Sending a "blocking signal" of up to a duration of 2 hours (as explained in 5.1.3) is a conventional approach, as done in some European countries. The results and its interpretation differs from the previous activation signals, since it blocks the heat pumps from starting for the full duration of the signal, often regulatory limited to a max. duration of up to 2 hours. The simulation results for a moderate winter day (3°C) show that 39 heat pumps would be running and could react by switching off (blue line / area), resulting in a load reduction of 178 kW. In case of the "SGR-Off" activation signal, this load reduction would only last for a short period, but the up to 2 hours blocking signal would prevent all heat pumps from starting for the full duration. The model considers this load reduction as permanent over the full period, since in the meantime, in the baseline consumption case, other heat pumps would start while the 39 running systems would switch off at some point.

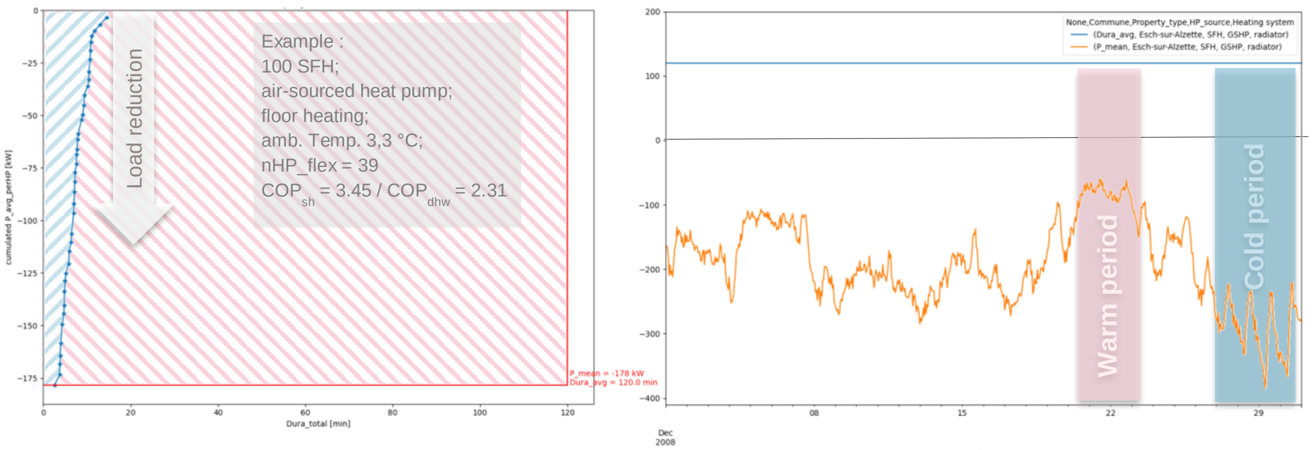


Figure 28 - a) load reduction over 2h via blocking signal b) potential upward flexibility over winter month

Analysing the varying flexibility potential over a full winter month, based on December 2008 weather data, the Figure 28 shows about 300 kW load reduction potential (upward flexibility) of these 100 houses during the colder period, while the lower heating demand in the warmer period results in a upward potential of about 100kW. Considering the blocking signal would prevent heat pump starts over a duration of 120 minutes and assuming the heating demand as stable, this results in a relatively high theoretical energy shifting potential of about 200 - 600 kWh for the full duration.

The drawback of this type of flexibility activation is that a high "rebound effect" can be expected, which means the effect that the operation of the heat pumps is just postponed and will result in a higher power consumption than in the baseline case after the signal. Assuming that a pool of heat pumps is blocked for 2 hours during a cold winter period, it is very likely that most heat pumps will start operation as soon as the blocking signal is lifted, which might cause an increased power consumption in a similar magnitude as the decreased power flexibility during activation. In case of our example of 100 buildings for a day at -3 °C ambient temperature, this could mean that the blocking signal results in a upward flexibility of about -300 kW, but could be followed by an increase of the baseline consumption of about +200kW after the blocking signal is lifted.

5.4. Results – national and communal level

The full technical potential of flexibility provision from residential heat pumps will remain a theoretical number since it describes the complete activation of the full potential and it is unrealistic that all heat pumps would participate in demand side management schemes, would be equipped with the necessary control and communication equipment and would all be activated at the same time. But the results presented in the following chapter represent this technical potential as an upper limit for the amount of heat pumps in residential buildings, as defined for 2020, 2030 and 2040 scenarios in chapter 5.2.

The current model does not consider energy efficiency gains, which will decrease the energy demand and flexibility potential of heat pumps. Further, no climate change effect on rising ambient temperatures has been accounted for.

The flexibility for each activation type (5.1.3), characterized by the power (P_{mean}), the shiftable energy (E_{agg}) and the duration ($Dura_{avg}$) of the flexibility response, are aggregated on communal and national level. The results represent the average of a single activation of all available heat pumps at the given level (commune or national). For each commune, the results from the 800 buildings (100 buildings per 8 building types) are individually aggregated, taking into account the share of building types, heat pump technologies and heating distribution system for each commune, as described under 5.1.4.

5.4.1. Communal level

As an example, the commune Junglinster has been chosen, being a medium sized municipality of both, rural and urban character (8622 inhabitants, 2080 single-family houses, 680 apartments). Using the 2040 scenario data, results in a 56% share of heat pumps on the heating systems in residential buildings.

The shiftable energy (E_{agg}) and the power flexibility (P_{mean}) shown in Figure 29 are indicating the monthly average for a single point in time – a single activation of flexibility, for the specific activation type. Depending on exterior temperatures and heat demand over the daily cycle, the available flexibility varies throughout the month. To visualize those fluctuations, the blue bar in Figure 29 shows the monthly average, while the orange line indicates the range of the minimum and maximum of the value.

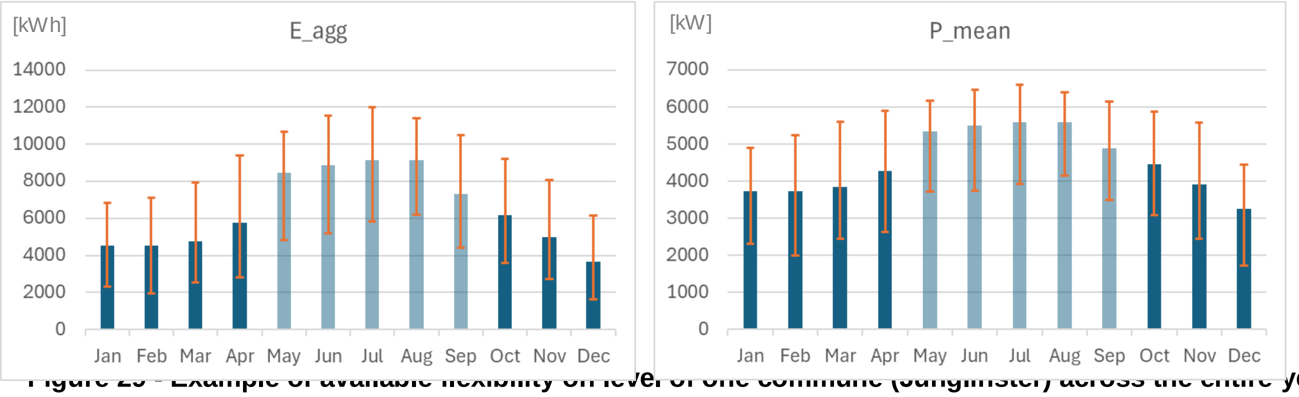


Figure 29 - Example of available flexibility on level of one commune (Junglinster) across the entire year (scenario 2040), in terms of shiftable energy (left) and power (right) for activation type "SGR-On-SH" – activation of a pool of heat pumps with increased temperature set points for the buffer storage

Figure 29 should give an example for the bandwidth of variations of the available flexibility within a month as well as throughout the seasons. Outside the classical heating period, an activation of the heat pumps may result in high flexibility potential, here May to September, but a usage of this downward flexibility appears questionable. Since heating systems are switched off at this period, only domestic hot water demand is given, and the stored energy in the space heating storage would be wasted. For ecological reasons this option is excluded, and those months were greyed out in the graph.

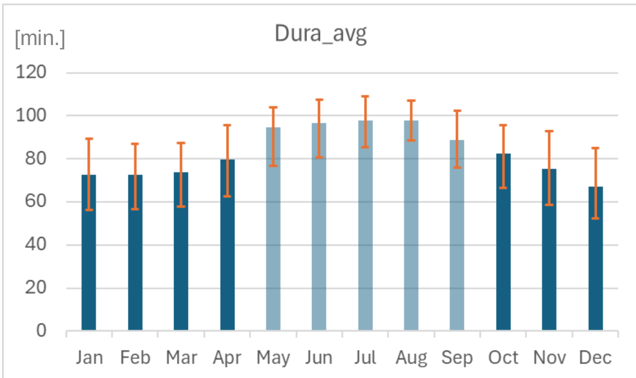


Figure 30 – Example Junglinster, scenario 2040, activation type "SGR-On-SH" - average duration of the flexibility provision by a pool of 100 heat pumps

The average duration for an activation in the above example (Junglinster – SGR-On-SH) reaches from 98 minutes in summer, to 67 minutes in winter (Figure 30). The average power flexibility reaches from almost than 5.600 [kW] (in the irrelevant summer period) to about 3.260 [kW] during winter. This results in a shiftable energy, during the heating period, between 3.680 [kWh] and 9.100 [kWh], which could be preponed.

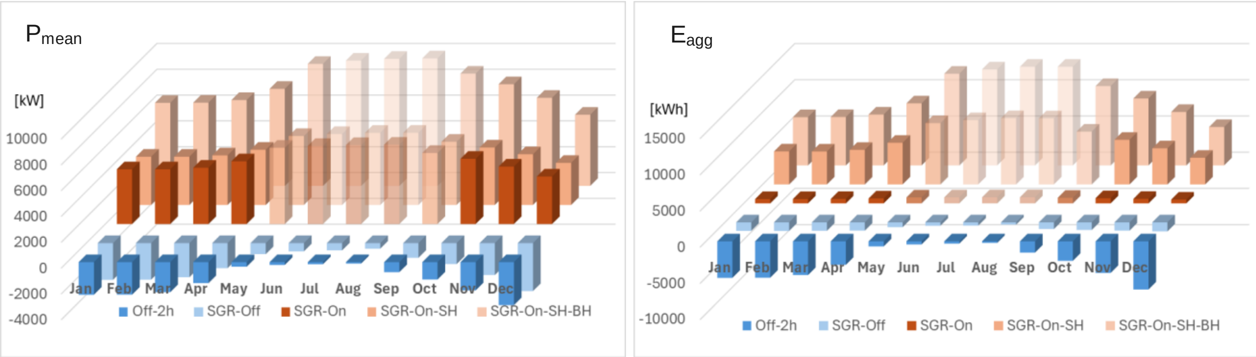


Figure 31 – Comparison of different activation types for the example of Junglinster, regarding average shiftable energy and average power flexibility (downward flexibility red colors, upward flexibility, blue colors)

To give a complete overview on the flexibility on communal level for the 2040 scenario, Figure 31 shows a comparison of all activation types – downward flexibility in red colours, upward flexibility in blue. Upward flexibility ("Off-2h" and "SGR-Off") reaches power flexibility between 1.350 [kW] and 3.700 [kW] at cold temperatures and show strong dependency on temperatures. This results also in higher shiftable energy potential during winter periods (up to 1.250 kWh for "SGR-Off"), specifically for the 2 hours blocking signal (reaching 6.650 kWh), with the before mentioned risk of a high rebound effect**.**

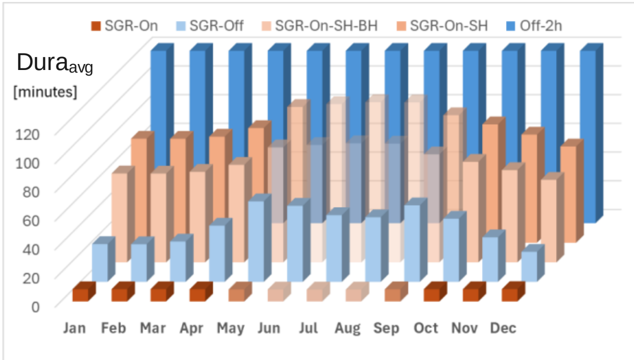


Figure 32 – Average duration of flexibility activation

Downward flexibility might be less relevant for grid flexibility, specifically during the winter period, except for its strategic use to prepone consumption to increase the upward potential for a subsequent period. Nevertheless, the downward power flexibility lies between 3.250 [kW] and 5.500 [kW] (October – April) and could reach up to 7.850 [kW], if the electrical back-up heater is activated as well ("SGR-On-SH-BH"). The shiftable energy can be largely increased by elevating the temperature set points of the space heating storage, as can be seen by the difference between the activation types "SGR-On" and "SGR-On-SH".

Obviously, the relationship between power flexibility and shiftable energy is related to the ***average duration*** of an activation of flexibility (Figure 32). Requesting downward flexibility by "SGR-On" results in a short rise in power of about 10 minutes, according to the model, and is independent of the temperature. While downward flexibility by increasing also the temperature set points provides flexibility for about 1 to 1,5 hours. Upward flexibility via "SGR-Off" varies with temperature and reaches from 20 minutes (cold period) to 55 minutes.

5.4.2. National level

Finally, aggregating the flexibility potential from residential heat pumps on national level for the scenario 2040, shows generally a similar characteristic as the communal level. The activation durations remain largely the same as in Figure 32 (details in

Table 20), while trends and seasonal variations of the flexibility potential, regarding power and energy, remain similar but obviously at increased numbers (Table 19):

Using ***upward flexibility*** ("Off-2h" & "SGR-Off, blue bars in Figure 33) seems more relevant during the winter period, but could also be used during evening peaks in autumn and spring. In the relevant period (Oct. - April) the total aggregated flexibility potential P_{mean} lies between -91 MW and -256 MW. The potential of shiftable energy E_{agg} and the duration of a flexibility activation differs largely between both options. Shiftable energy potential, if all heat pumps are blocked for 2 hours, could reach up to 460 MWh in the coldest period but might also sum up to 62 MWh in transition period (Sept.). Regarding the smart-grid ready solution “SGR-Off”, the duration largely depends on the outdoor temperature: average durations of about 50 minutes in Sept result in more than 62 MWh of shiftable energy for this scenario. On the other hand, when the durations of an average flexibility activation drop to about 20 - 27 min in the cold winter months, the shiftable energy sums up to 89 MWh on average, at a higher power flexibility.

The ***downward flexibility potential*** on national level (“SGR-On”, “SGR-On-SH”, “SGR-On-SH-BH”, red bars in Figure 33) might be appropriate to buffer wind power peaks, or solar power peaks during transition seasons. For previously mentioned reasons, downward flexibility will not be further considered outside the heating period. Using the “Smart-grid ready On” option and an increase of the set temperature in the buffer storage (“SGR-On-SH”) show similar behaviour and relatively stable power levels in the relevant period, about 225 to 345 [MW]. If using the back-up heater in addition (“SGR-On-SH-BH”) would even further increase the power to about 380-540 [MW]. The shiftable energy potential E_{agg} for the “SGR-On” option is comparably low and stable throughout the year, about 38 - 51 [MWh]. Energy shifting potential for both options, SGR-On-SH and SGR-On-SH-BH, shows a similar dynamic during the heating period, with about 256 - 420 [MWh] for SGR-On-SH and 370 - 640 [MWh] for SGR-On-SH-BH. It should be noticed, that the usage of the electrical back-up heater reduces drastically the efficiency of the whole system.

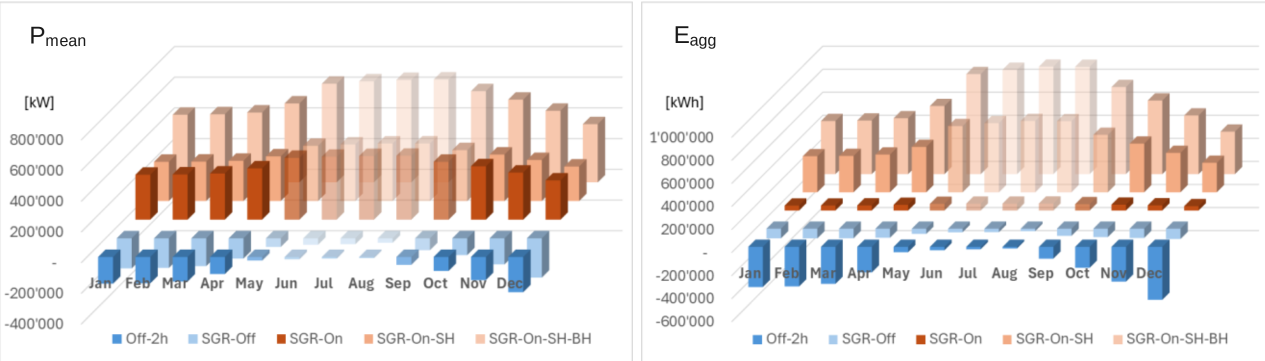


Figure 33 – Flexibility potential (P_{mean}-left) and shiftable energy (E_{agg}) on national level (scenario 2040)

Table 19 - Flexibility potential of residential heat pumps in 2040, characterized by upward- and downward-power flexibility (P_{mean}) as well as shiftable energy (E_{agg})

P_{mean} [kW]	*monthly averages of single hourly values*					*E_{agg} [kWh] monthly averages of single hourly values*				
	Off-2h	SGR-Off	SGR-On	SGR-On -SH	SGR-On -SH-BH	Off-2h	SGR-Off	SGR-On	SGR-On -SH	SGR-On -SH-BH
Jan	-174'183	-195'798	292'958	255'414	440'637	-348'365	-83'513	43'115	313'218	460'582
Feb	-171'522	-192'530	294'622	256'654	443'732	-343'045	-83'816	43'166	315'422	465'103
Mar	-160'371	-181'266	300'891	262'204	455'164	-320'742	-82'839	44'212	327'975	484'935
Apr	-110'974	-131'950	334'379	290'991	514'284	-221'948	-78'509	48'989	393'791	591'190
May	-23'254	-56'306	402'596	359'521	642'814	-46'508	-44'631	58'100	574'780	868'338
Jun	-14'767	-41'773	410'120	368'512	658'141	-29'533	-31'368	59'063	600'305	905'638
Jul	-10'546	-37'974	414'585	374'754	667'646	-21'093	-30'083	59'358	619'276	932'350
Aug	-7'239	-28'724	416'594	375'082	670'186	-14'478	-21'241	59'992	617'324	931'336
Sep	-51'352	-77'433	377'290	331'508	594'365	-102'704	-62'215	55'178	498'709	755'719
Oct	-90'750	-109'156	347'834	302'834	539'078	-181'500	-72'584	50'986	423'000	638'664
Nov	-150'540	-169'625	306'915	267'206	466'573	-301'079	-81'004	45'189	342'236	508'792
Dec	-229'681	-255'865	255'746	224'717	379'319	-459'362	-89'126	37'892	255'908	368'809

Table 20 – Average durations of flexibility provision of residential heat pumps in 2040, ($Dura_{avg}$)

$Dura_{avg}$ [min]	*monthly averages of single hourly values*				
	Off-2h	SGR-Off	SGR-On	SGR-On-SH	SGR-On-SH-BH

Jan	120	27	9	73	62
Feb	120	27	9	73	62
Mar	120	29	9	74	63
Apr	120	39	9	80	68
May	120	58	8	95	80
Jun	120	56	8	97	82
Jul	120	47	8	98	83
Aug	120	50	8	98	83
Sep	120	53	9	89	75
Oct	120	45	9	83	70
Nov	120	32	9	75	64
Dec	120	21	9	67	57

5.5. Results – technology penetration for today, 2030, 2040

Previous chapters described the flexibility potentials of residential heat pumps for divers activation signals and showcase the dependency on outdoor temperatures, the resulting seasonality, and characterize this flexibility by power, energy and duration, on communal and national level. Those figures can be understood as the maximum available flexibility, based on the underlying technology penetration scenario for 2040 (see 5.2), considering that 56% of the residential buildings are operated by heat pumps, resulting in 98.000 heat pumps systems on national scale.

As described in 5.2, the 2020 technology penetration scenario considered about 3.000 heat pumps in Luxemburg, representing about 2% of the residential heating systems, while the 2030 scenario foresees 48.000 heat pumps for 2030 (30% share of the future building stock). Previously documented results covered the 2040 scenarios for 56% of the future building stock of 174.000 residential buildings with 98.000 heat pump systems. As the amount of heat pumps in those scenarios only affect the magnitude of power flexibility and energy flexibility within our model, while the other parameter stay constant, the duration remains unchanged - Figure 34 outlines the flexibility characteristics for 2020, 2030 and 2040.

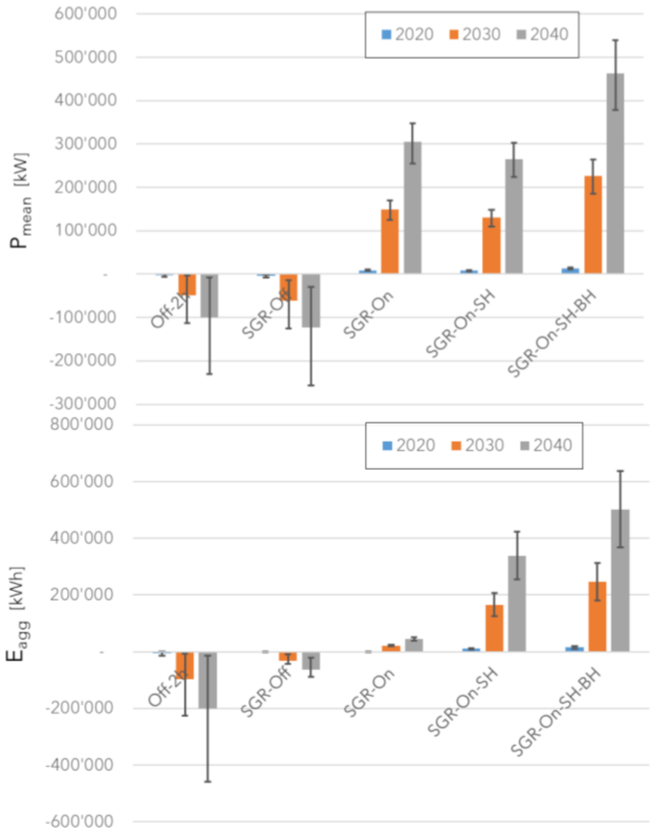


Figure 34 – Power flexibility (P_{mean}) and energy flexibility (E_{agg}) for three technology penetration scenarios (2020, 2030, 2040) - seasonal variability for the relevant periods indicated by the thin bars of each column

The broad bars depict the average of the power- (left graph) and energy (right) flexibility that could be provided according to the respective scenario and given activation signal. The lines on top of each bar mark the range given by the minimum and maximum of the monthly averages across the seasons. For downward flexibility, activating heat pumps, only the heating period is considered (Oct.- April.). Obviously, the power- and energy flexibility grows proportionally with the amount of heat pumps available to provide flexibility, as indicated in the upper graphics and by Table 21 – about 3.000 heat pumps systems for 2020, 48.000 heat pumps in the 2030 scenario and 98.000 in 2040.

Table 21 – Power- and energy flexibility and their duration for three technology penetration scenarios and 5 activation modes (min., max. and averages of the monthly averages)

		Off-2h	SGR-Off	SGR-On	SGR-On-SH	SGR-On-SH-BH
	[kW]	P_{mean}	P_{mean}	P_{mean}	P_{mean}	P_{mean}
2020	Avg.	- 2'988	- 3'696	9'144	7'972	13'882
	Min.	- 6'891	- 7'677	7'673	6'742	11'381
	Max.	- 217	- 862	10'436	9'086	16'174
2030	Avg.	-48'783	-60'343	149'273	130'148	226'622
	Min.	-112'497	-125'323	125'264	110'066	185'790
	Max.	-3'546	-14'069	170'369	148'328	264'040
2040	Avg.	-99'598	-123'200	304'764	265'717	462'684
	Min.	-229'681	-255'865	255'746	224'717	379'319
	Max.	-7'239	-28'724	347'834	302'834	539'078
	[kWh]	E_{agg}	E_{agg}	E_{agg}	E_{agg}	E_{agg}
2020	Avg.	-5'976	-1'903	1'344	10'165	15'079
	Min.	-13'782	-2'674	1'137	7'678	11'065
	Max.	-434	-637	1'530	12'691	19'162
2030	Avg.	-97'566	-31'058	21'939	165'940	246'164
	Min.	-224'995	-43'654	18'559	125'344	180'642
	Max.	-7'091	-10'404	24'973	207'185	312'817
2040	Avg.	-199'196	-63'411	44'793	338'793	502'582
	Min.	-459'362	-89'126	37'892	255'908	368'809
	Max.	-14'478	-21'241	50'986	423'000	638'664
	[min.]	$Dura_{avg}$	$Dura_{avg}$	$Dura_{avg}$	$Dura_{avg}$	$Dura_{avg}$
All scenarios	Avg.	120	40	9	75	64
	Min.	120	21	9	67	57
	Max.	120	58	9	83	70

5.6. Temperature sensitivity of the results

As the flexibility, characterized by power-, duration and resulting energy flexibility, is highly dependent on outdoor temperature, which is reflected by the seasonality and explained for each activation signal in chapter 5.3, the following graphs depict the flexibility over outdoor temperature, instead of months. The absolute numbers represent the 2020 technology penetration scenario, but those are less important in this context, which should rather stress the temperature dependency.

Upward flexibility, meaning switching off heat pumps via "SGR-Off" or a blocking signal ("Off-2h") is highly dependent on ambient temperature. As shown in Figure 35, the power flexibility is the highest at low temperatures, which has several reasons: more heat pumps are running simultaneously as the heating demand is obviously higher, but also since the heating water temperatures need to be increased, this results in low COPs, hence lower efficiency. The available power flexibility drops with higher temperature until the heating demand is considered minimal above 15°C. Both activation signal show similar values and behaviour, regarding potential power flexibility. Obviously, what distinguishes both activation signals, is the average duration for which the flexibility could be retained (Figure 36). Opposed to a fixed blocking signal for 2 hours, the duration of the SGR-Off flexibility depends on the heat demand during that period. Figure 36 shows that this duration could vary, specifically for SGR-Off, but those higher values should be interpreted cautiously: values for flexibility durations (for SGR-Off) higher than 80-100 minutes stem mainly from colder morning/night hours, during generally warmer periods – hence, where the heating demand during that period is rather low, although the momentary ambient temperature is below 15°C.

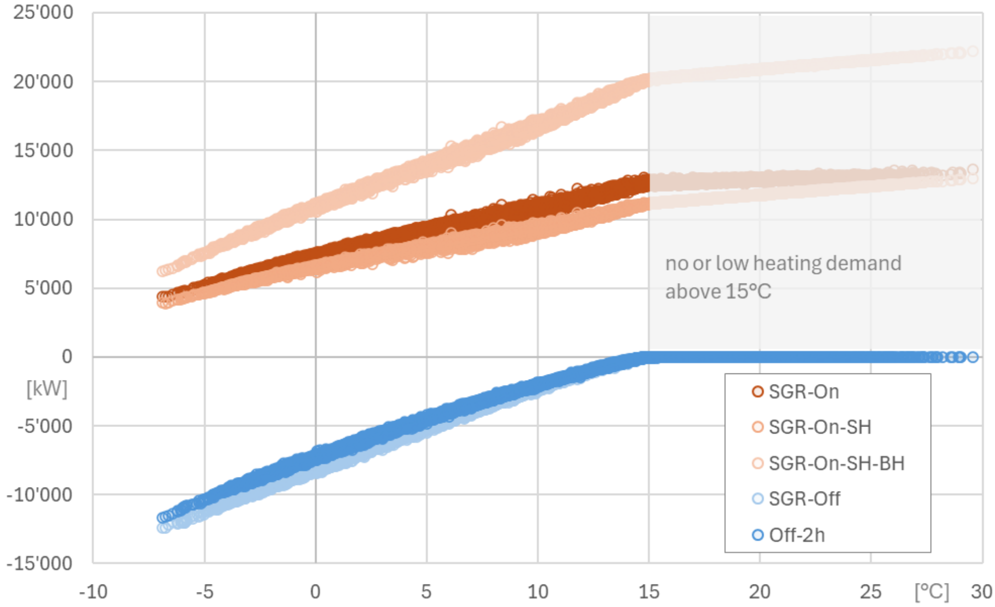


Figure 35 – power flexibility of heat pumps on national level over outdoor temperature (based on scenario 2020)

Providing **downward flexibility**, either via SGR-On or SGR-On-SH shows similar temperature dependency: at lower temperature, where more heat pumps are simultaneously running, less systems are available to ramp up power consumption (see Figure 35). With rising temperature, the potential increases until the heating demand is low / zero. Above 15°C the model doesn't consider heating demand anymore, hence switching on heat pumps to heat up the space heating storage is possible, but not reasonable anymore. Similarly, if the backup heater is used in addition to the heat pump to provide downward flexibility (SGR-On-SH-BH), the power level is generally higher and rises steeper until the heating demand is low. Expectedly, the additional purely electric heating power of the backup heater results in shorter durations, since the space heating storage reaches the increased temperature level earlier than in the SGR-On-SH option (see Figure 36). Generally, the duration of both options with increased space heating storage temperature is much higher than in the SGR-On scenario. For both the duration increases with rising temperatures, which is due to the spread between the necessary heating temperature and the fixed, increased heating storage temperature: since the heating curve defines the necessary heating water temperature entering the building in dependence on the ambient temperature, the difference to the fixed 60°C (for SGR-On-SH and SGR-On-SH-BH) increases with higher temperatures. The simple SGR-On activation signal has much shorter flexibility durations, due to a very tight hysteresis (5°C) of the temperature level in the storage, to allow for high efficiency. Also, the temperature dependency is hence less obvious and almost irrelevant. Only a slight drop of the duration can be recognized, due to higher efficiency of the HP at higher temperature (mainly for the air-sourced HPs).

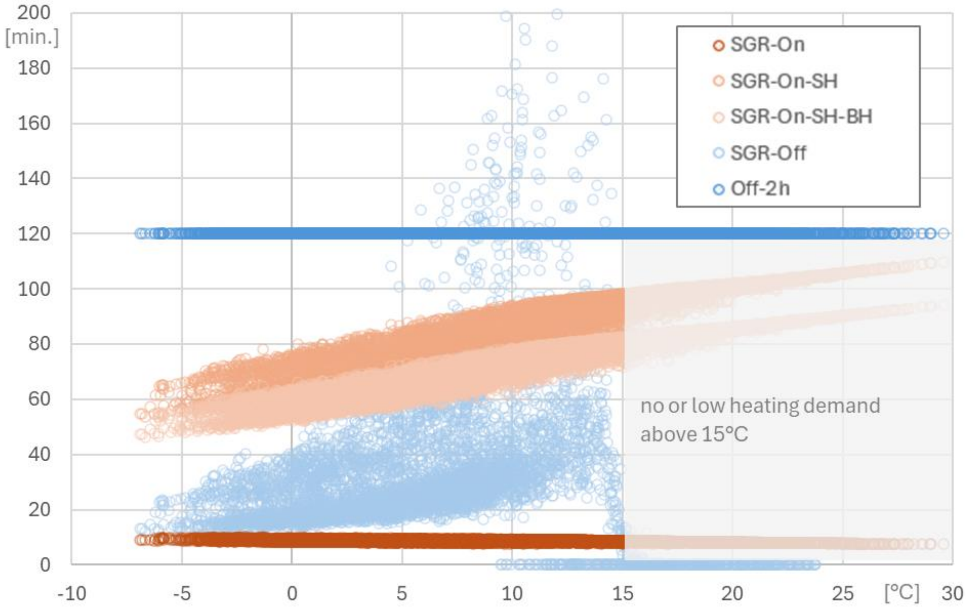


Figure 36 – flexibility duration of heat pumps on national level over outdoor temperature (based on scenario 2020)

5.7. Limitations of the model

The current model does not consider energy efficiency gains with rising building standards, which will decrease the energy demand and flexibility potential of heat pumps. Further, no climate change effect on rising ambient temperatures has been accounted for.

Further, the thermal inertia of the buildings is not considered for the actual flexibility provision, since the effect on the potential prolongation on SGR function is difficult to assess, if controlled by return temperature. Although, it is still expected to have a buffering effect, but the size is unknown. Thermal inertia is only considered in the estimation of heating demand.

To estimate the full technical potential, it has been assumed that all HP provide flexibility. As well as that the SGR functions as activation signal could be applied to all devices (whereas not all HP support this). Further, all HP have storage volume for SH and DHW.

6. Residential Sector – Electric Water Heaters

Electric water heaters (EWHs) with storage tanks represent a unique class of residential electrical loads with inherent flexibility potential. Unlike shiftable appliances, EWHs provide thermal storage, which allows decoupling between electricity consumption and end-use demand (i.e., hot water consumption). This flexibility makes them especially suitable for demand response applications, particularly downward flexibility (increased load) through preheating to absorb excess electricity during periods of low demand or high renewable generation.

More precisely, electric water heaters, as the ones considered within this chapter, mean larger scale water heaters as providing centralized domestic hot water supply. Such devices start from a storage volume of 50 Liters, hence have a significant size to be considered as storage devices.

6.1. Methodology for the electric water heater flexibility assessment

The flexibility assessment for residential electric water heaters follows a bottom-up simulation approach. It integrates both physical characteristics of the appliances and realistic usage patterns, enabling a dynamic analysis of load shifting potential under various control strategies. The key steps include:

- Creating a representative portfolio of devices and usage profiles.
- Modeling the electrical and thermal behavior of the devices using physical equations and constraints.
- Applying different flexibility control strategies to simulate their effect on power consumption.
- Aggregating results at the national and communal levels, scaled using household-level device ownership rates.

A schematic overview of the modeling and simulation process is shown in Figure 37.

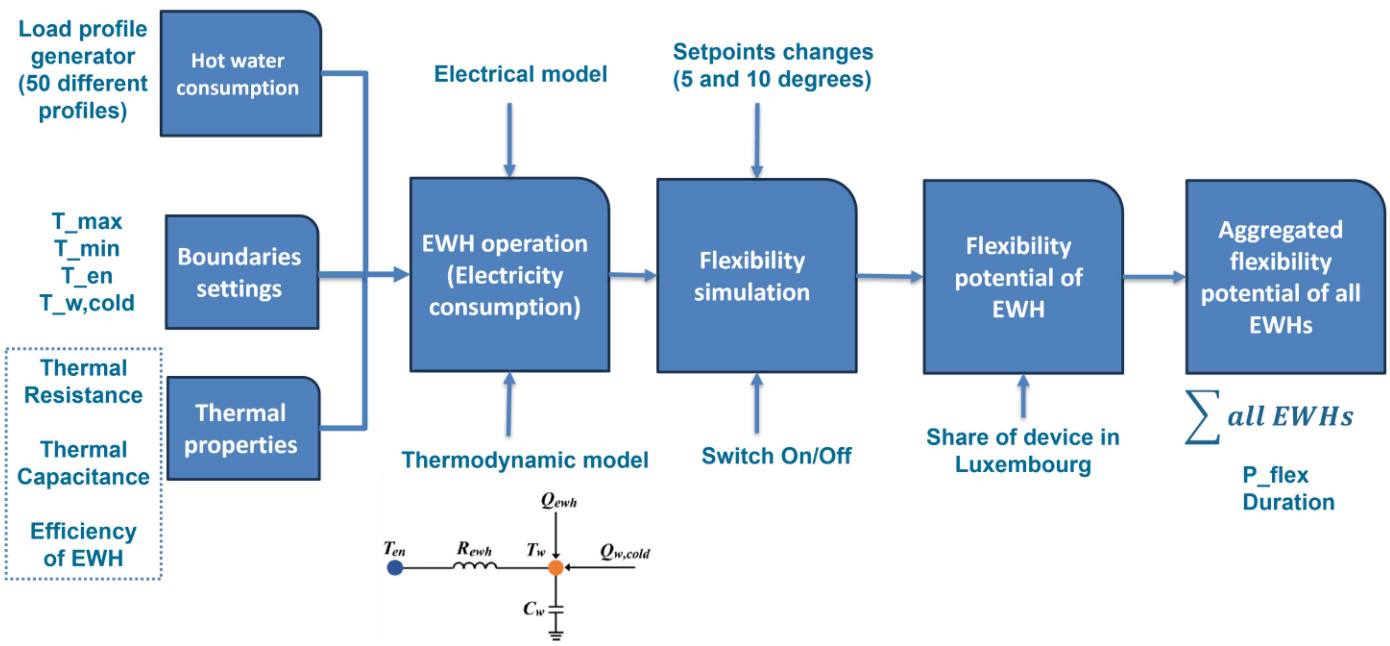


Figure 37 – Schematic overview of EWH modeling and simulation process

6.2. Defining a representative portfolio for electric water heater

To represent the variability in user behavior and device characteristics, a diverse portfolio of 50 households with electric EWHs was generated (Pflugradt et al., 2022). Each entry corresponds to a distinct household configuration, with its own hot water consumption pattern, tank size, thermal characteristics, and heating element specifications.

Input key parameters for each heater include:

- Tank volume (typically 50–150 litters),
- Heating element power (e.g., 3.5–4.5 kW),
- Thermal resistance of the insolation layer and capacitance of the storage,
- and initial setpoint temperatures (default set to 55°C)

To generate realistic variability in device characteristics, the key thermal and electrical parameters for each of the 50 electric water heaters were assigned using a stochastic randomization approach. The three main parameters: a) nominal power of the heating element (P_{rated}), b) thermal resistance (R_{ewh}), and c) thermal capacitance (C_w); were randomly sampled for each device based on a ±10% deviation around the following base values:

- $P_{rated}[W]$= 4000
- $R_{ewh}[K/W]$= 1.9
- $C_w[J/K]$ = 633,000 (for a typical 120 litters tank)

This ensured that, while all devices shared similar operating logic, their thermal response and energy consumption behavior reflected a natural diversity across households.

Temperature boundaries were fixed across all devices, with T_{min}= 50 °C and T_{max}= 60 °C. A fixed random seed was used to ensure reproducibility of the parameter generation process. This approach enabled the creation of a statistically varied but physically consistent population of electric water heaters for flexibility simulations.

6.3. Electric water heater operation simulation

The operational behavior of each EWH in the portfolio was simulated at a one-minute resolution over a full year, under different scenarios. The model incorporates both user-driven and thermally driven processes.

6.3.1. Hot water consumption

Hot water consumption is the primary user-driven input that governs the operation of electric water heaters. In this study, 50 individual hot water consumption profiles were generated to reflect diverse residential behaviors. These profiles define the volume of hot water drawn per minute, simulating activities such as showering, washing, or cooking. Each profile was constructed to represent realistic daily and weekly usage patterns, with randomized event timing and duration based on typical household routines. The goal was to capture both inter-day variability and intra-day peaks in demand.

Figure 38 presents an example of one such profile, showing the minutely hot water consumption pattern of a single household over the month of March. Peaks correspond to usage events, and the profile illustrates how demand varies across days and weeks. This variability directly affects the timing and magnitude of EWH operation, making it essential to accurately model hot water consumption in the flexibility analysis.

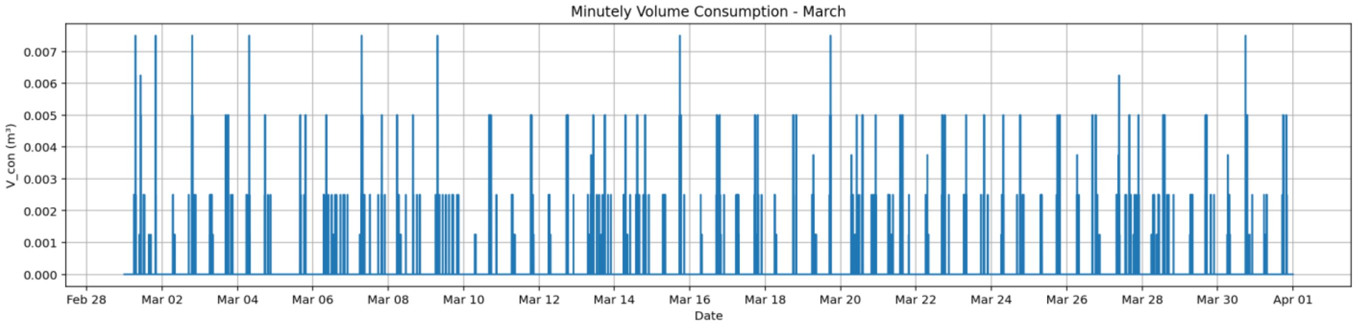


Figure 38 – Example of hot water consumption

6.3.2. Boundary settings and thermal properties

The model includes the following boundary temperature settings:

- ($T_{min} = 50\ °C$): Minimum allowed water temperature before heating is triggered
- ($T_{max} = 60\ °C$): Maximum water temperature (i.e., setpoint)
- ($T_{en} = 20\ °C$): environment temperature of the storage
- ($T_{cold} = 10\ °C$): Incoming cold-water temperature

These values are defined according to manufacturer specifications and typical residential usage expectations. The control logic ensures that the water temperature never falls below T_{min} and does not exceed T_{max} unless explicitly modified under flexibility strategies.

Each water heater was modelled with the following thermal parameters:

- C: Thermal capacitance of the tank (function of water volume and specific heat)
- R: Thermal resistance of the tank (determining heat loss rate)
- η: Efficiency of the heating element (typically assumed 100%)

These parameters define the rate of heat storage and loss, influencing how long preheating or shutoff strategies can be sustained.

6.3.3. Thermodynamic model

The thermodynamic behavior of each EWH was modelled based on an energy balance of the water tank. The temperature evolution of the water, $T_w(t)$, depends on the interaction between heat input from the electric heater, heat losses to the environment, and thermal disturbances caused by hot water withdrawals and cold-water inlets.

The model is described by the following set of discrete-time equations, adapted from established (Luo et al., 2024):

$$C_w \frac{dT_w}{dt} = \frac{T_{en}(t) - T_w(t)}{R_{ewh}} + Q_{ewh}(t) - Q_{w,cold}(t)$$

$$T_w(t+1) = aT_w(t) + (1-a)\{T_{en}(t) + [Q_{ewh}(t) - Q_{w,cold}(t)]R_{ewh}\}$$

Where:

- $T_w(t)$ is the current water temperature in the tank.
- $T_{en}(t)$ is the environmental or surrounding temperature (often ambient).
- R_{ewh} is the thermal resistance of the tank.
- C_w is the thermal capacitance of the tank.
- $a = \exp(^{-\Delta t}/_{R_{ewh} C_w})$ is a weighting factor resulting from discretization.

The heating power injected into the tank is modelled as:

$$Q_{ewh}(t) = P_{ewh,in}(t) \cdot \eta_{ewh}$$

Where:

- $P_{ewh,in}(t)$ is the electrical input power (usually P_{rated}).
- η_{ewh} is the efficiency of the heating element (typically assumed to be 1 for resistive heaters).

The heat loss due to water consumption is computed as:

$$Q_{w,in}(t) = C_{p,w}\rho_w V_{con}(t)\left[T_w(t) - T_{w,cold}\right]/\Delta t$$

Where:

- $V_{con}(t)$ is the hot water volume consumed at time t.
- $T_{w,cold}$ is the temperature of the incoming cold water.
- $C_{p,w}$ and ρ_w are the specific heat capacity and density of water, respectively.

The system is constrained by the following operational limits:

$$T_{min} \leq T_w(t) \leq T_{max}$$

These equations were implemented in the simulation to update tank temperature at each minute, providing the basis for computing electrical consumption and available flexibility under both normal and controlled conditions.

Figure 39 shows the equivalent thermal circuit representation and a schematic of the EWH model.

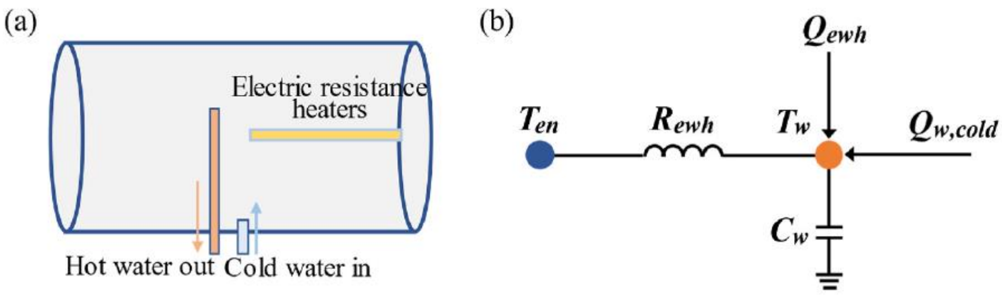


Figure 39 – Equivalent thermal circuit representation and a schematic of the EWH model

6.3.4. Electrical model

The electrical operation of the EWH is governed by a binary control logic based on the tank's internal water temperature and the state of the heating element. This logic determines when the heater should be turned on or off during each time step of the simulation.

Figure 40 presents the flowchart of the EWH electrical control logic implemented in the model.

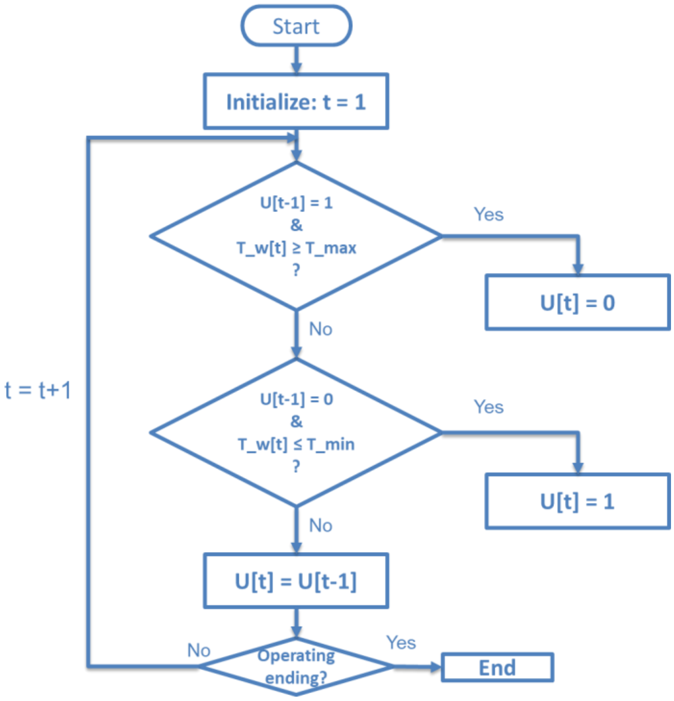


Figure 40 – Flowchart of the EWH electrical model

The key components of the logic are as follows:

- $U[t]$ represents the binary state of the heating element at time step t:
  - $U[t]$= 1 → heater is ON (consuming power)
  - $U[t]$= 0 → heater is OFF (no power consumption)
- $T_w(t)$ is the current water temperature in the tank.
- T_{min} and T_{max} are the lower and upper temperature thresholds.

Control Logic Description:

a) Initialization:
At simulation start, time step *t* is initialized to 1 and the initial heater state is set.

b) Switch-Off Condition:
If the heater was ON in the previous step ($U[t-1] = 1$) and the tank temperature has reached or exceeded T_{max}, the heating element is turned OFF ($U[t] = 0$).

c) Switch-On Condition:
If the heater was OFF in the previous step ($U[t-1] = 0$) and the tank temperature has fallen to or below T_{min}, the heater is turned ON ($U[t] = 1$).

d) Hysteresis Control:
If neither of the above conditions are met, the heater maintains its previous state ($U[t] = U[t-1]$). This avoids unnecessary toggling and stabilizes the system's thermal response.

e) Termination Check:
At the end of each iteration, the model checks whether the operating period has ended. If so, the simulation concludes.

This basic thermostat-based hysteresis control ensures that the EWH maintains the desired temperature range while minimizing switching frequency. The simplicity of this logic makes it robust and easy to integrate with additional flexibility strategies (e.g., forced ON/OFF, setpoint adjustments), which override or modify U[t] temporarily during demand response events.

Before applying any flexibility control strategies, the baseline behavior of each EWH was simulated under normal operating conditions. Figure 41 illustrates the baseline operation of one representative EWH over a five-day period. The three subplots show:

1. Hot Water Consumption (Top Panel):

   This plot displays the minutely volume of hot water consumed in litters. Clear peaks represent usage events such as showers, dishwashing, or general tap use. The daily pattern varies, highlighting both peak demand periods and days with minimal usage.

2. Tank Temperature Evolution (Middle Panel):

   The second panel shows the evolution of the tank's internal water temperature throughout the same period. The temperature oscillates between the defined lower and upper limits, 50°C and 60°C (highlighted with dashed lines). The heater turns ON when temperature falls to the lower limit, and OFF when it reaches the upper limit, ensuring continuous availability of hot water.

3. Electrical Power Consumption (Bottom Panel):

   The third panel shows the heater's power consumption over time. The ON/OFF cycling behavior is evident, with the heater operating at its rated power (4 kW) during active periods and consuming no power when idle. The heater activates only when necessary to restore the desired temperature range following water usage or heat loss.

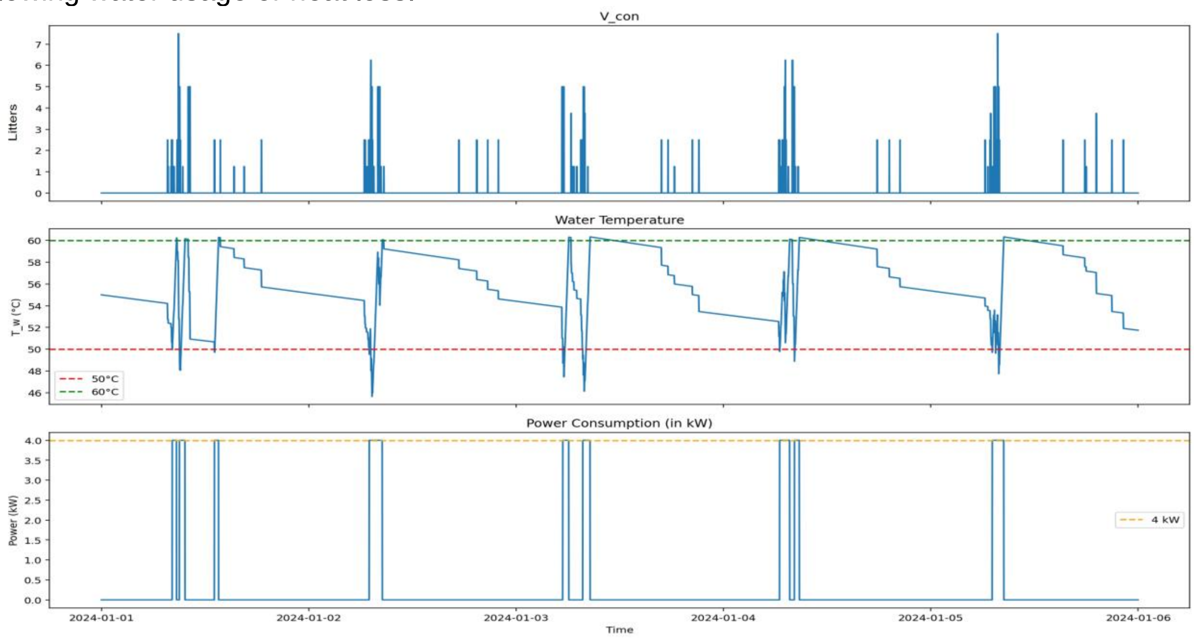


Figure 41 – Baseline operation of one representative EWH

6.4. Modeling of electric water heater flexibility

To evaluate the flexibility potential of EWHs, multiple control strategies were implemented in the simulation framework. These strategies influence the electrical behavior of the heater by modifying its control signal or operating conditions.

6.4.1. Switch On/Off

In this strategy, external ON/OFF signals are applied to interrupt or allow the operation of the heating element. However, unlike hard overrides, this method is implemented in a temperature-aware manner:

- If the water temperature reaches T_{max}, the heater will turn OFF even if the control signal allows it.
- If the water temperature drops to T_{min}, the heater will turn ON, regardless of the external OFF signal.

This approach provides flexibility while still ensuring comfort and hot water availability for the user.

6.4.2. Setpoint change

In this strategy, the ON/OFF signal is still applied as described above, but in addition the tank's temperature setpoints are temporarily shifted to modulate energy consumption, applied in four modes:

- +5°C Setpoint Increase
- +10°C Setpoint Increase
- −5°C Setpoint Decrease
- −10°C Setpoint Decrease

By raising the setpoint, the heater continues heating beyond its normal cutoff, allowing additional energy intake and creating downward flexibility (load increase). Conversely, lowering the setpoint causes the heater to start later and delay its next cycle, leading to upward flexibility (load reduction).

These setpoint adjustments are temporary and applied only during the defined flexibility event windows. After the event, the original setpoint is restored, and the heater resumes its standard operation. All strategies are evaluated under the same simulation conditions and applied across households to assess their aggregated flexibility potential.

6.5. Results at national level for electric water heater

To quantify the flexibility potential of residential EWHs at the national level, simulation results were scaled according to the number of households in Luxembourg and an estimated 15% EWH ownership rate (Gils, 2014). The simulations accounted for individual device dynamics and realistic water consumption profiles. For this aggregated assessment, it was assumed that all participating EWHs could be simultaneously activated or deactivated and would operate at full rated power from the start of a flexibility event.

Figure 42 shows the flexibility behaviour for "switch on/off" control strategy on national level. The top-left plot shows the average downward power flexibility and duration over time, highlighting the variable load increase capability throughout the day. The bottom-left plot presents the upward flexibility trends, showing average power reduction and corresponding durations. The top-right and bottom-right bar charts illustrate specific snapshots of flexibility potential at 8:00 AM as an example, displaying the distribution of available flexibility across different durations. These highlight the load that can be shed or added at a given moment and for how long it can be sustained.

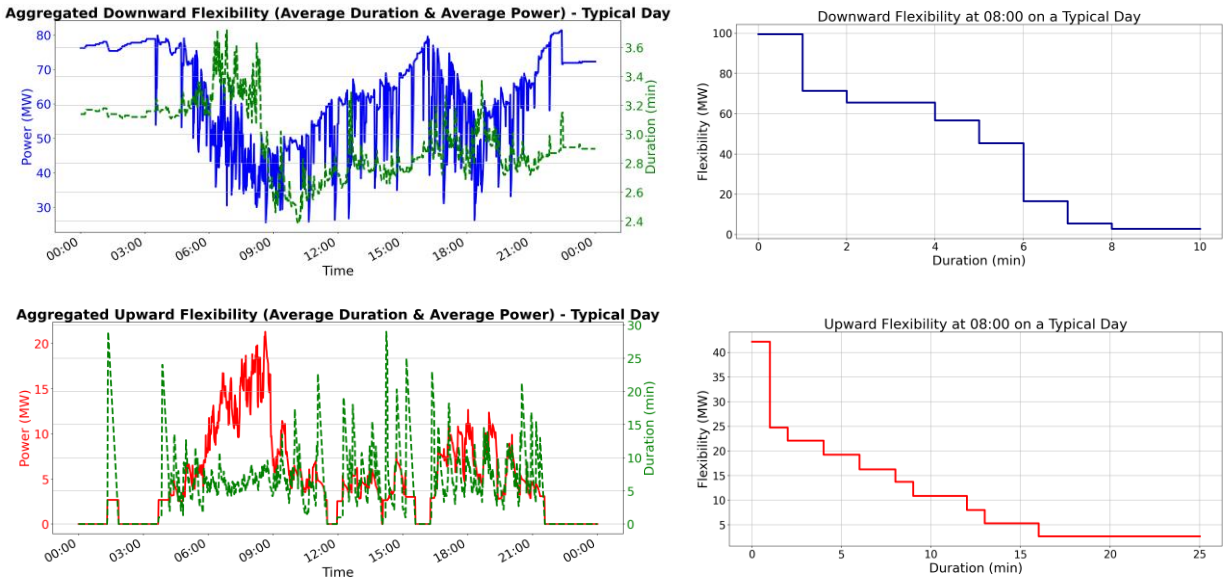


Figure 42 – National level - flexibility characteristics for "switch on/off" control strategy

Figure 43 and Figure 44 present a comparison of downward and upward flexibility of EWHs under three different strategies, respectively. This layout allows a separate visual inspection of the dynamic behaviour for each control strategy across the full day. The first plot compares power flexibility over time, and the second plot compares flexibility duration over time.

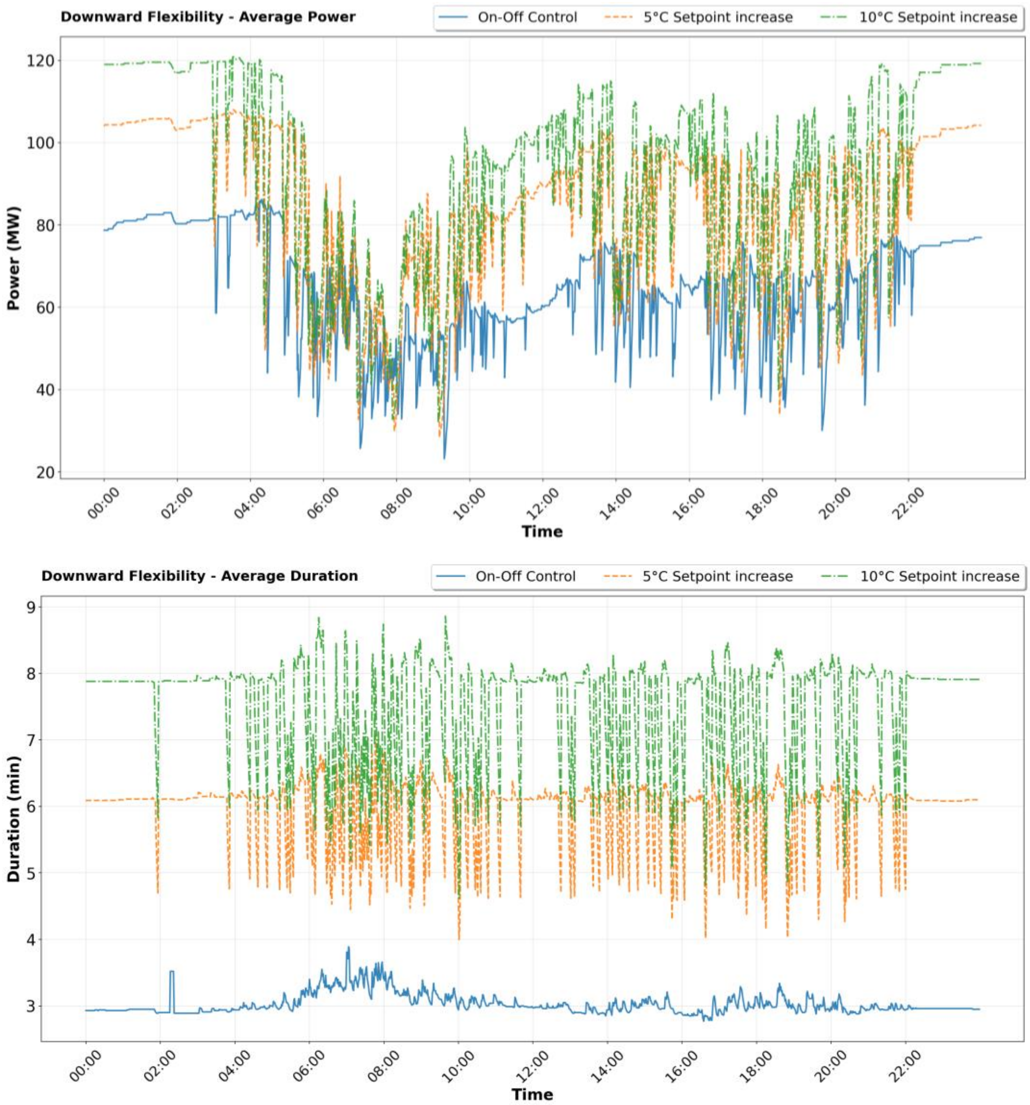
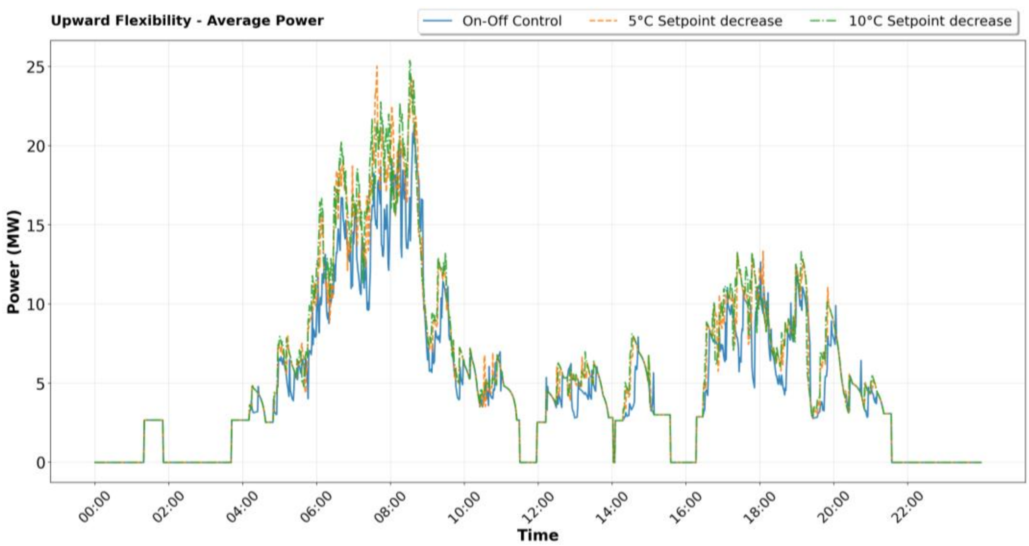


Figure 43 – Downward flexibility of EWHs under three different strategies – power (top), duration (bottom)



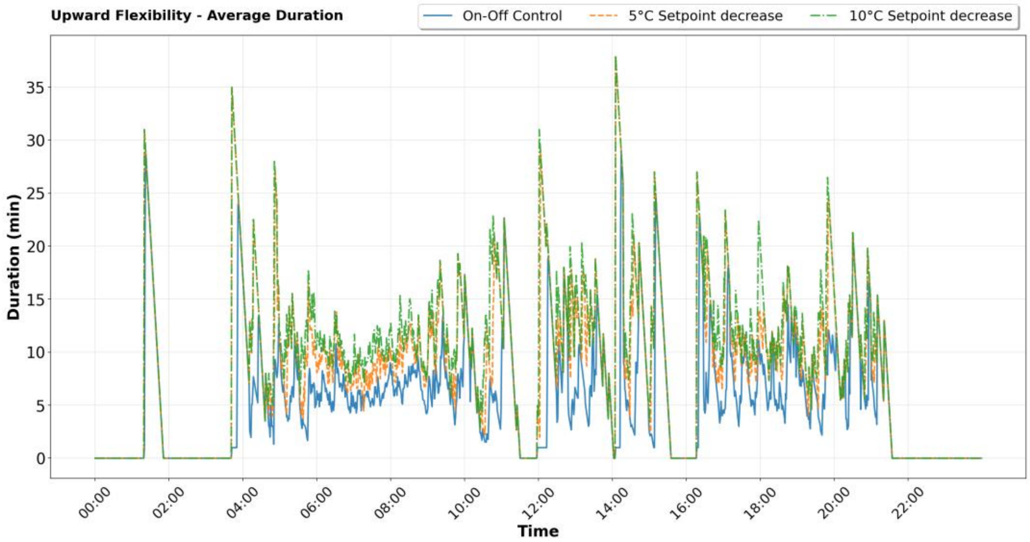
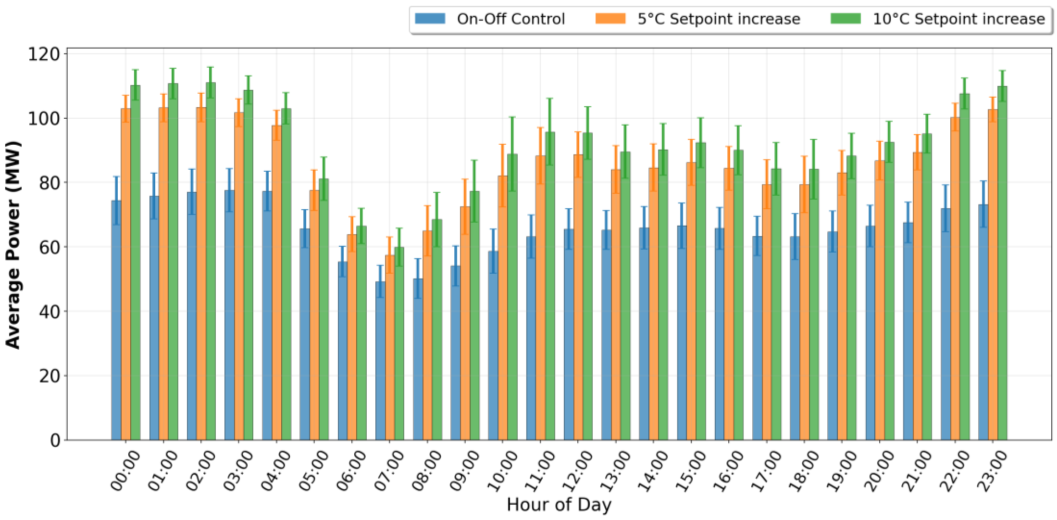


Figure 44 – Upward flexibility of EWHs under three different strategies– power (top), duration (bottom)

Figure 45 summarizes and compares the average downward flexibility potential of electric water heaters under three control strategies. The upper chart shows the hourly average power of downward flexibility throughout the day. All strategies exhibit higher flexibility potential during the night and early morning hours (00:00–04:00). Among the methods, the 10°C setpoint increase consistently results in the highest additional load, followed by the 5°C increase and then the On-Off control. This figure also displays the standard deviation error. The bottom plot compares the average duration of flexibility.



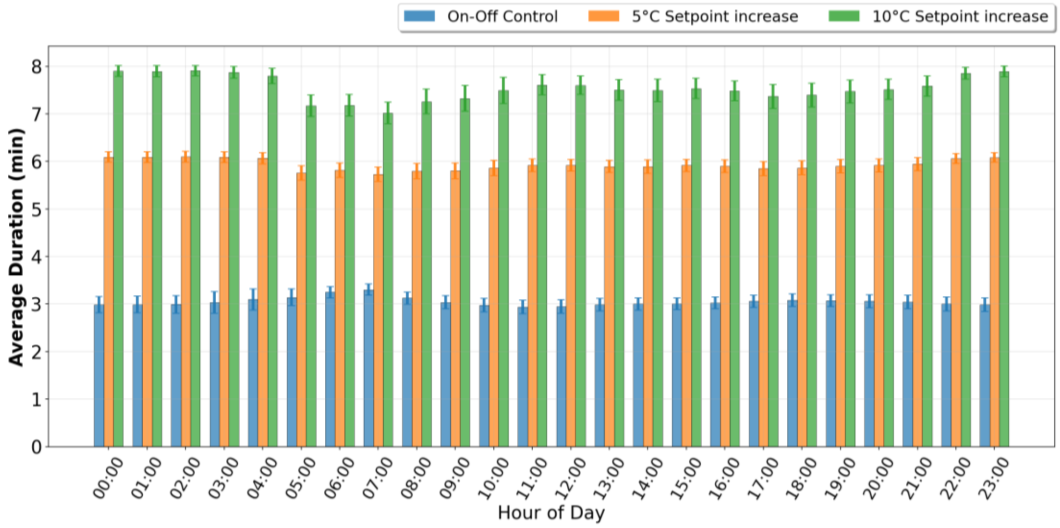
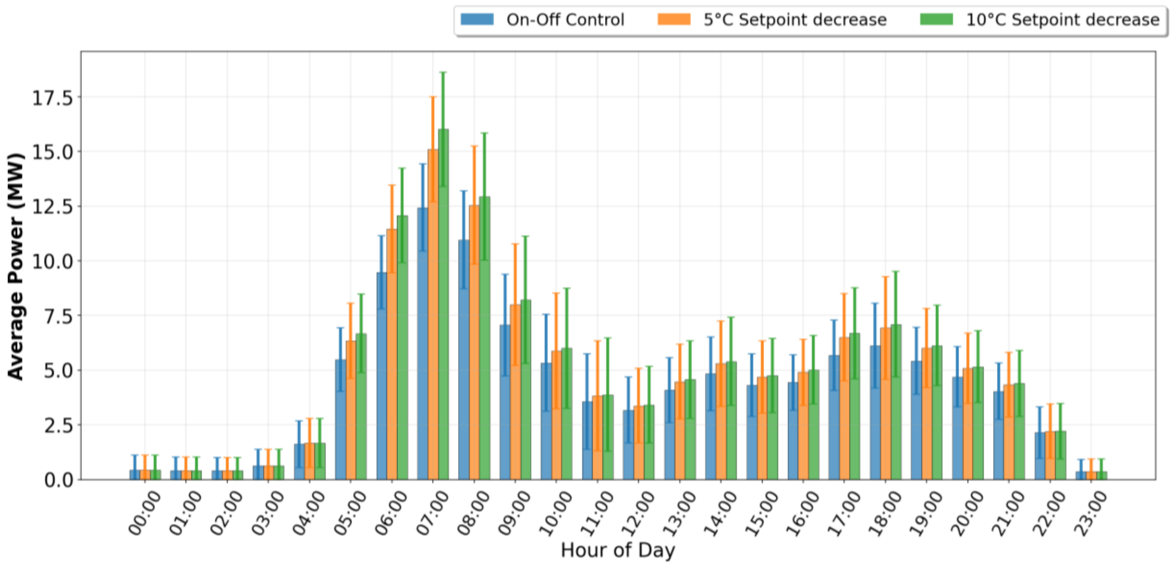


Figure 45 – Average downward flexibility potential of electric water heaters - power (top), duration (bottom)

Figure 46 summarizes and compares the average upward flexibility potential of electric water heaters under three different control strategies. The top chart shows the hourly average power of upward flexibility over a full day. All three methods demonstrate distinct time-of-day profiles, with peak flexibility potential observed between 06:00 and 09:00. Among the three methods, the 10°C setpoint reduction consistently provides the highest power reduction and longest duration, followed by the 5°C change and then the On-Off control. This figure also illustrates the standard deviation error. The bottom plot compares the average duration of flexibility.



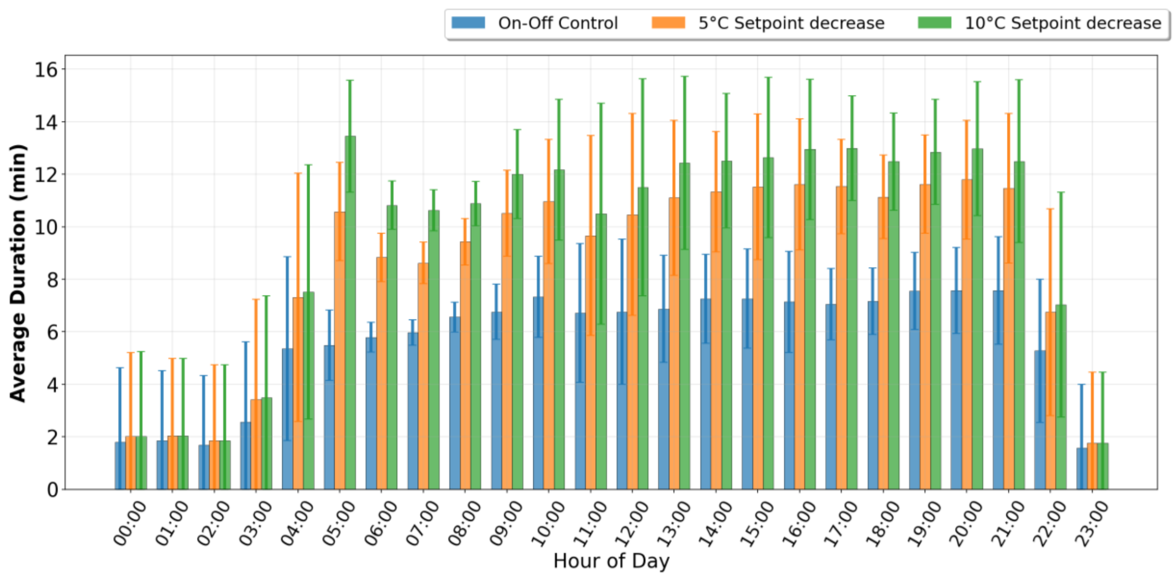


Figure 46 – Average upward flexibility potential of electric water heaters - power (top), duration (bottom)

Table 22 and Table 23 summarize the average downward (load increase) and upward (load reduction) flexibility potentials across different control strategies, respectively. These values reflect the average load shift and duration observed over a typical day.

Table 22 - Downward Flexibility Potential from Residential Electric Water Heaters

Flexibility Method	*Average flexibility potential (MW)*	*Average Duration (minutes)*
On/Off Control	**74.3**	**~3.6**
5°C Setpoint Increase	**90.0**	**~6.2**
10°C Setpoint Increase	**92.4**	**~7.7**

The results show that setpoint increase strategies provide higher downward flexibility than simple on/off control. A 10°C increase enables the largest average load increase, with flexibility reaching up to 92 MW for around 8 minutes. This is particularly effective during nighttime and early morning hours (00:00–04:00), when baseline reheating cycles are already active. Raising the setpoint during these periods allows more energy to be stored in the water tank, offering an efficient and controllable way to increase consumption.

Table 23 - Upward Flexibility Potential from Residential Electric Water Heaters

Flexibility Method	*Average Flexibility Potential (MW)*	*Average Duration (minutes)*
On/Off Control	**4.9**	**~5.6**
5°C Setpoint Decrease	**5.5**	**~8.4**
10°C Setpoint Decrease	**5.6**	**~9.3**

For upward flexibility — defined as a temporary load reduction — setpoint decrease strategies proved more effective than basic on/off control. A 10°C setpoint reduction resulted in the highest average load drop, offering up to 5.5 MW of flexibility for about 9 minutes, primarily by delaying heater activation. These reductions are most effective in the morning period, when consumption typically ramps up. This helps flatten the morning peak and reduce grid stress.

In summary, electric water heaters offer a significant controllable source of both upward and downward flexibility. The choice of control strategy directly influences the response magnitude and duration, making them more suitable for sustained demand shaping and grid support.

7. Residential Sector – White Wares

White wares in the residential sector refer to major household appliances traditionally associated with cooling, laundry and dishwashing activities. In the context of demand-side flexibility, the focus is on appliances that can be scheduled or shifted without significantly affecting user comfort. Accordingly, the appliances considered in this study are washing machines, tumble dryers, and dishwashers, as these are inherently shiftable loads due to their programmable operation cycles.

The analysis aims to quantify the flexibility potential of white wares across Luxembourg, accounting for probabilistic usage patterns, technical load profiles, and representative ownership rates. A stochastic modeling approach was adopted to simulate realistic daily operation patterns and explore the extent to which their start times can be shifted within acceptable time windows.

7.1. Methodology for whitewares flexibility assessment

The methodology follows a multi-step structured approach to evaluate the shiftable load flexibility potential:

- Derivation of probability of start times:

  The probability distribution of operation start times for each appliance was derived from representative sample data, reflecting residential usage patterns and capturing behavioural variations across households.

- Load cycle profile aggregation:

  Average electrical load profiles for a full operation cycle (aggregated across different program types or modes) were derived for each appliance type.

- Daily Load Pattern Simulation:

  By convoluting the probability of start times with the average cycle profiles, typical average daily demand patterns were generated.

- Flexibility Simulation:

  Applying different flexibility control strategies to simulate their effect on power consumption. Start times were probabilistically shifted within acceptable time windows to simulate demand response participation. Both weekdays and weekends were considered separately to capture behavioural differences.

- Scaling to National Level:

  Flexibility results were scaled using Luxembourg-specific device ownership rates (Gils, 2014):

  - Washing machines: 95%
  - Tumble dryers: 40%
  - Dishwashers: 50%

The usage patterns of these appliances are assumed to remain relatively stable throughout the year, given their limited sensitivity to seasonal changes.

A schematic overview of the whiteware flexibility modeling and simulation process is shown Figure 47.

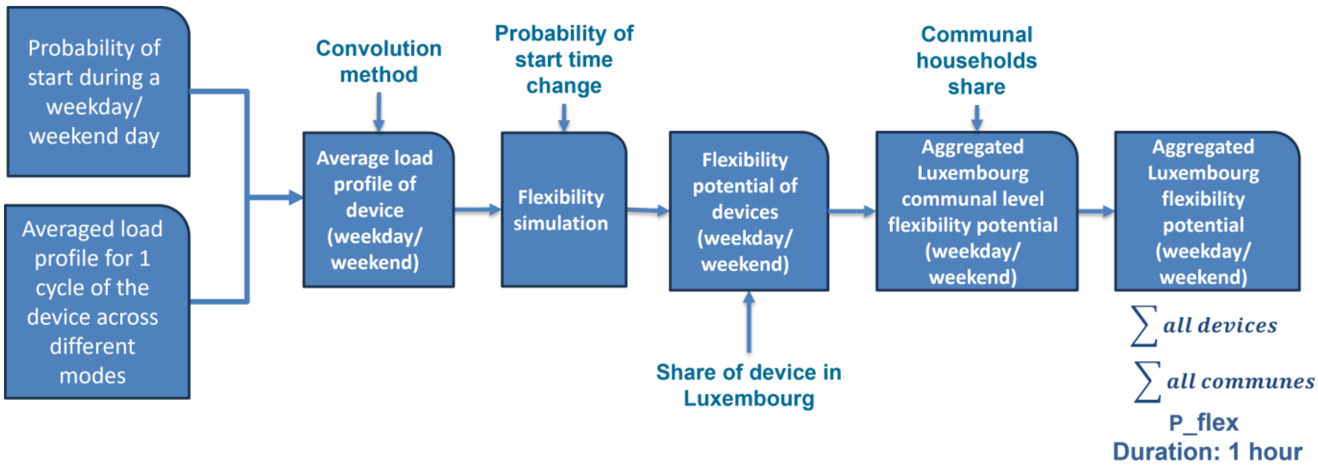


Figure 47 – Schematic overview of white ware modeling and simulation process

7.2. Defining a representative portfolio for whiteware

A representative portfolio was developed to reflect realistic operation of household whitewares. It comprises 100 simulated households, each with unique appliance usage patterns and stochastic variability. The portfolio ensures statistically meaningful diversity in operation behaviors across washing machines, dishwashers, and tumble dryers. This dataset serves as the input foundation for the subsequent operation and flexibility simulations.

7.3. Whitewares operation simulation

Using the representative portfolio, daily operation simulations were performed to capture realistic household-level consumption. Simulations reproduced daily electricity demand by combining probabilistic start-time behavior with representative appliance load profiles. This process generated baseline consumption patterns used later to quantify flexibility potential.

The simulation framework involved three main steps:

- Deriving the probability of start times to represent when appliances are typically used during the day.
- Assigning representative load profiles for complete operating cycles of each appliance.
- Combining these two components to generate daily average demand patterns for the 100-household portfolio.

7.3.1. Probability of start time

Start-time probabilities were derived for each appliance using the simulated household portfolio. This approach captures aggregate residential behavior rather than isolated single-device activity. Figure 48 illustrates how individual start-time probabilities from 100 simulated devices were aggregated. Minute-resolution profiles were averaged to hourly resolution, smoothing out random variations and highlighting general behavioural trends, typically in the evening peaks. The resulting hourly probability distribution was then used to generate representative daily load patterns for flexibility simulations.

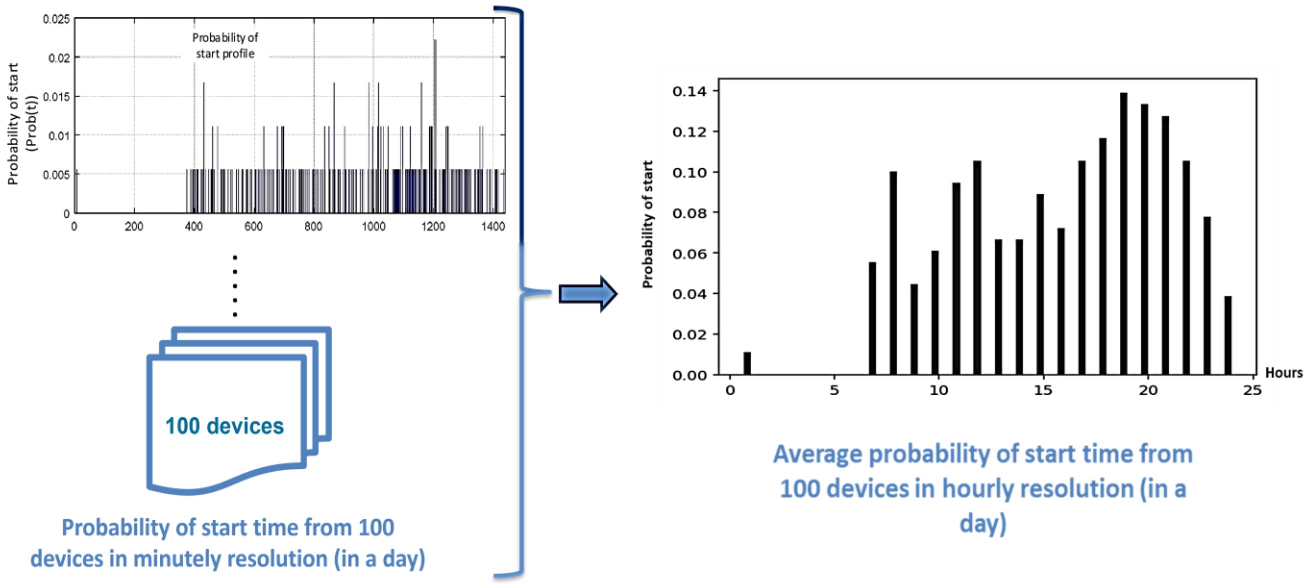
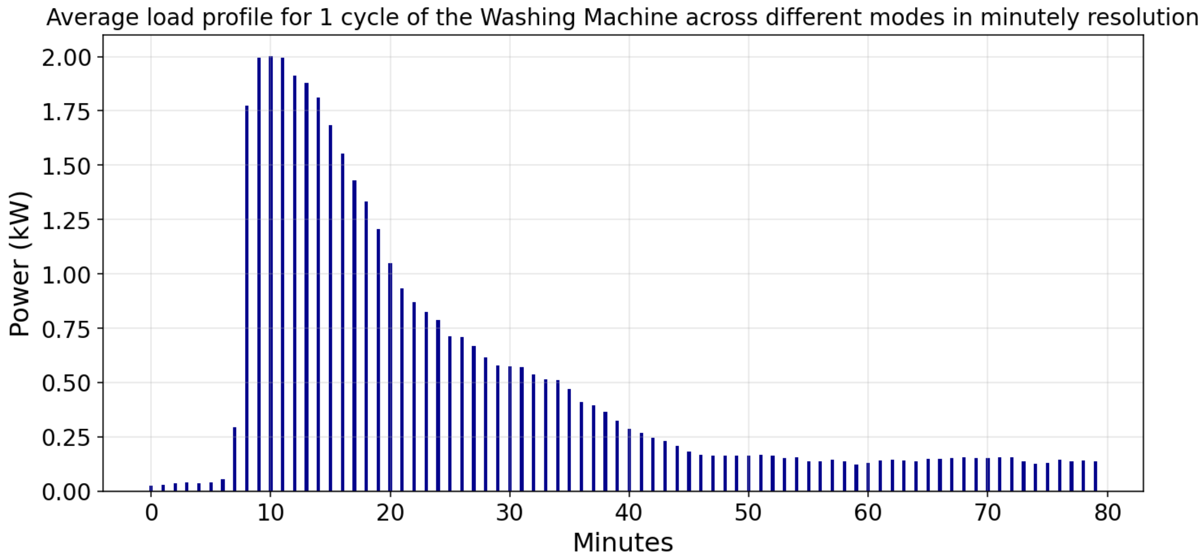


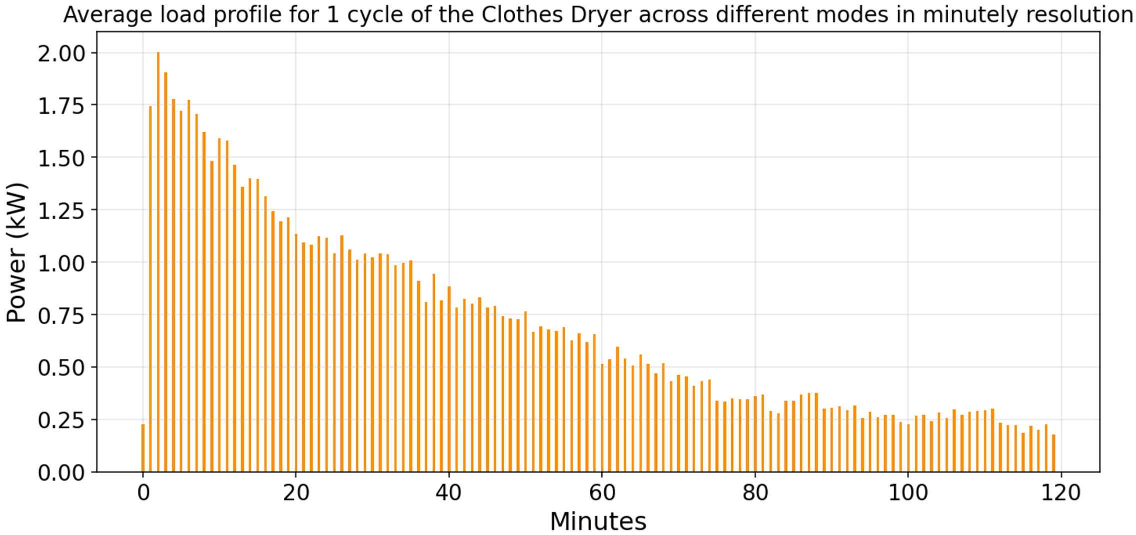
Figure 48 – Average probability of start time

7.3.2. Load profile for a single appliance operation cycle

The electrical consumption profiles for each appliance's full operating cycle were obtained from literature (Degefa et al., 2018). These profiles represent the average energy demand across different operational modes (e.g., eco, standard, intensive programs). Washing machines typically show pulsed heating and spinning phases, while dishwashers demonstrate multiple heating peaks, and tumble dryers are characterized by long, steady heating periods.

Figure 49 illustrates the load profiles of a washing machine, a dryer, and a dishwasher during a single operating cycle. These profiles show the characteristic pattern of each device.





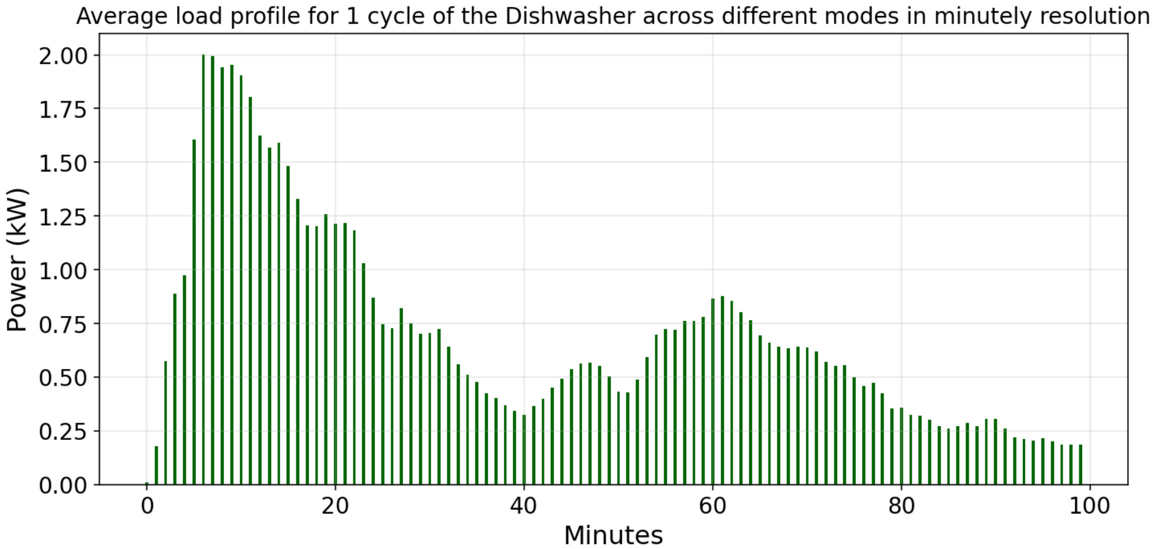


Figure 49 – Load profile of a a) washing machine, b) tumble dryer, and c) dishwasher during a single operating cycle (Degefa et al., 2018)

Taking as an example, the load profile of a washing machine aligns closely with the operational states and corresponding energy consumption summarized in Table 24. The cycle begins with a short water-filling phase lasting approximately 3 minutes, during which the power demand remains low, contributing only about 3 [Wh] to the total energy use. This is followed by the agitation and washing phases, which are the most energy-intensive parts of the cycle. Agitation, lasting around 10 minutes, and washing, which extends for 17 minutes, are primarily responsible for the sharp peak in the load profile, with a combined energy consumption exceeding 50 [Wh]. These phases correspond to the heating of water and mechanical drum movement, which together result in the observed peak of around 2 [kW] in the power profile.

Table 24 – Details of washing machine operating cycle

State	Cumulative time (minute)	Energy consumption (Wh)
Water fill	3	3.01
Agitation	10	53.9
Wash	17	
Drain	5	7.51
Spin	4	
Water fill	3	17.15
Rinse	5	
Drain	5	11.78
Spin	8	

7.3.3. Average load profile

The average load profile was derived by combining the probabilistic start-time distributions of the devices with their respective single-cycle load profiles. Figure 50 illustrates the process of deriving the average daily load profile for washing machines based on the combination of start-time probabilities and the averaged load profile for a single operating cycle. The top-left plot shows the average probability of start times for 100 devices, calculated in minutely resolution across a full day. This probability distribution captures realistic behavioural patterns of users, with higher probabilities observed during typical active household hours, such as late morning and evening periods.

The bottom-left plot displays the averaged load profile for one complete washing machine cycle in minutely resolution. The profile reflects the sequence of operational states, as already described in the cycle analysis.

The top-right plot demonstrates how these two elements are combined to create the average load profile over a day for 100 devices. By convolving the probability distribution of start times with the single-cycle load profile, the resulting curve captures how many devices are operating simultaneously at different times of the day, expressed in minutely resolution. Peaks in this curve directly correspond to periods with both high usage probability and high per-cycle energy demand.

Finally, the bottom-right plot presents the same information aggregated into hourly resolution, making it more suitable for system-level flexibility and demand-side analysis. This hourly profile highlights clear peaks during the late afternoon and evening hours, aligning with common residential appliance usage patterns, while maintaining lower consumption levels during the night and early morning hours.

This methodology ensures a realistic representation of aggregated daily demand by combining device-level technical characteristics with user behavioural patterns.

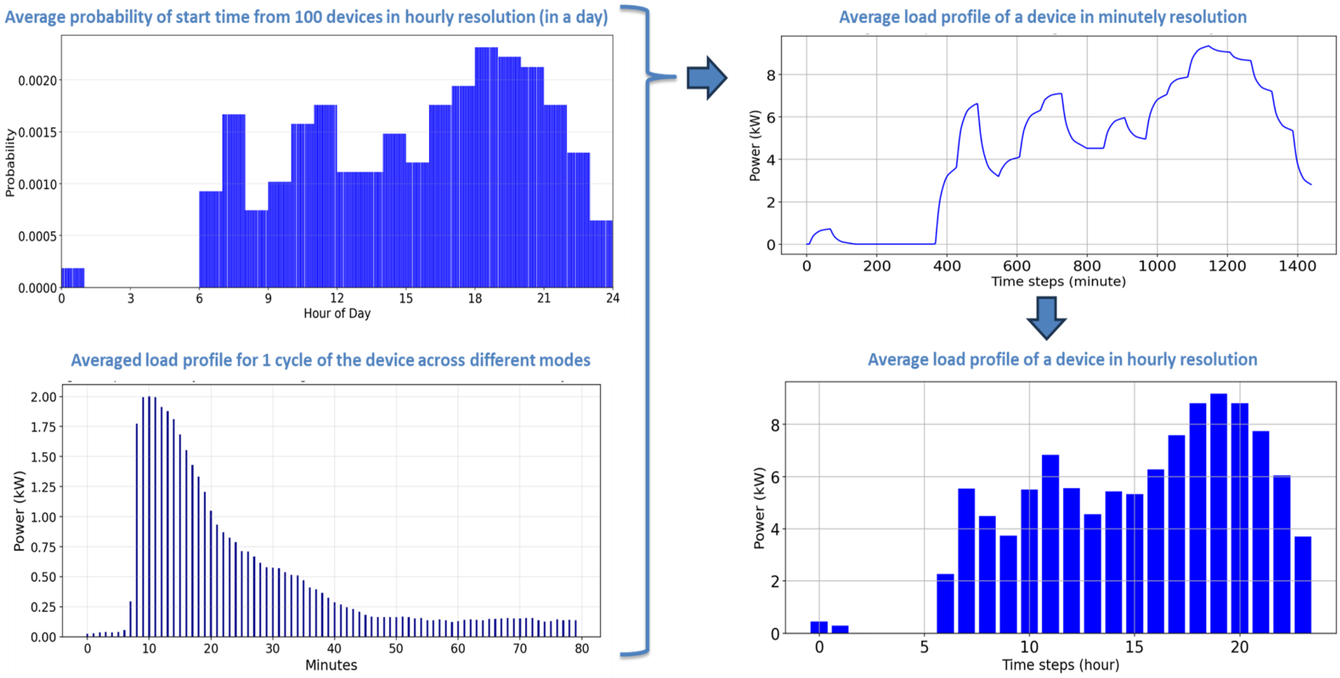


Figure 50 – Estimation of an average daily load profile for 100 devices (example - washing machine)

7.4. Modeling of whiteware flexibility

The flexibility modelling approach for whiteware appliances was designed to estimate a realistic demand response potential of these devices, while preserving user comfort and maintaining typical residential usage patterns. The approach is based on modifying the operation start times rather than altering the intrinsic load profiles, as the energy consumption of a washing machine, dishwasher, or dryer is strongly tied to its operational cycle and cannot be arbitrarily changed without affecting performance.

7.4.1. Probability of start time change

In this modeling framework, flexibility is introduced by allowing controlled shifts in the start times of appliances within user-acceptable limits. These time shifts represent the potential for demand response events, where the start of a washing or drying cycle can be postponed without significantly disrupting the household routine. The chosen shifting duration was set to one hour, based on several studies in the literature that identify this as a reasonable trade-off between grid flexibility needs and user acceptance (Degefa et al., 2018) (D'hulst et al., 2015) .

Figure 51 illustrates an example of the flexibility modeling approach applied to a whiteware device, specifically a washing machine, under a forward-shifting strategy for hour 13:00. The analysis demonstrates how shifting the probability of start times impacts the load profile and consequently reveals the flexibility potential. The figure is divided into three subplots, each focusing on a different aspect of the analysis: probability distributions, resulting load profiles, and flexibility potential.

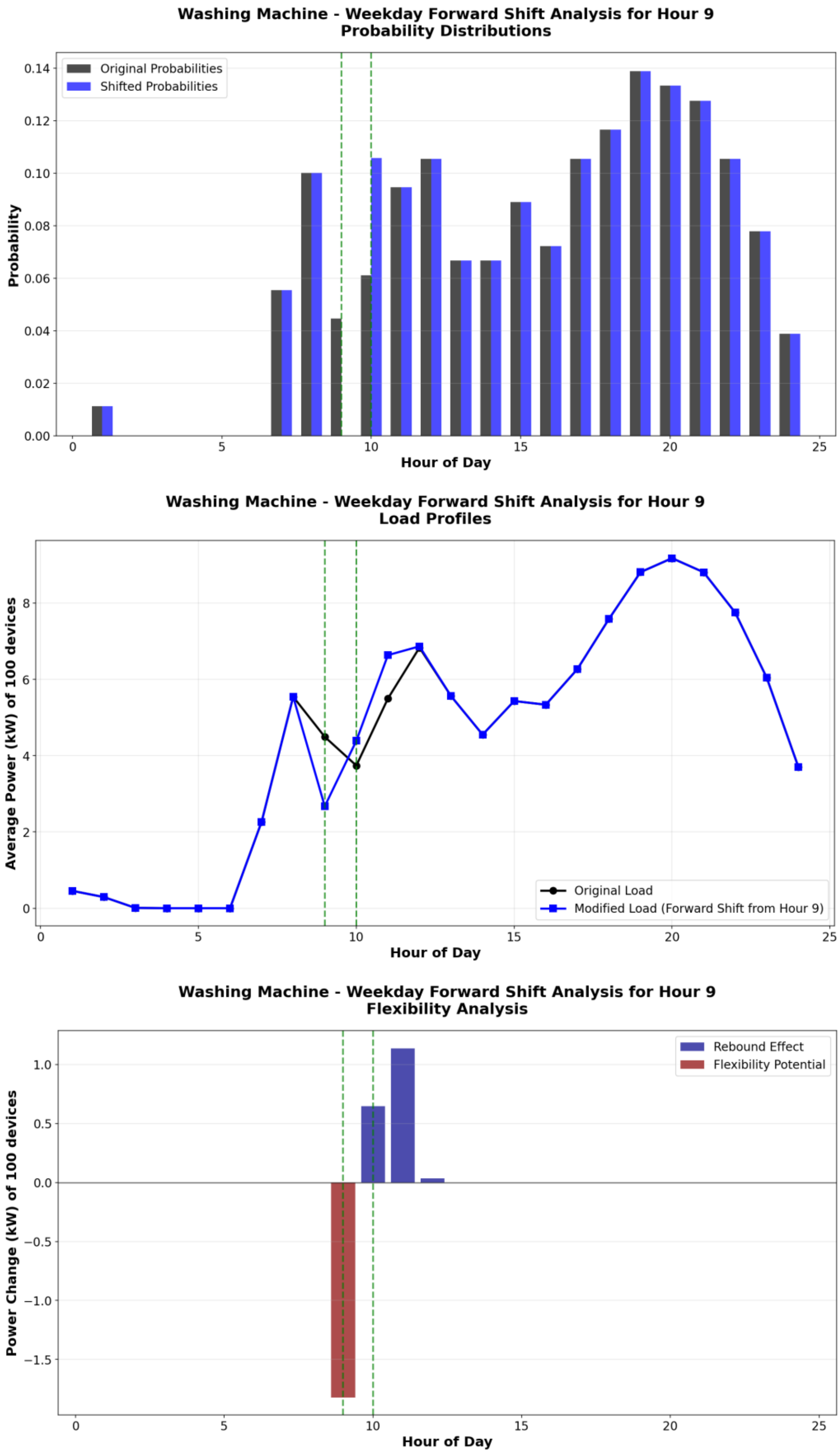


Figure 51 – Forward Shift Flexibility Analysis – a) probability distribution, b) average load profile, c) flexibility

The first subplot shows the original and shifted probability distributions of washing machine start times for a weekday scenario. The black bars represent the baseline probability distribution derived from the representative portfolio, while the blue bars indicate the modified probabilities after applying a forward shift by 1 hour up from 13:00. Thisshifting window was defined, based on realistic user comfort levels identified in the literature. As shown, the probability mass originally concentrated around 13:00 is moved to the next hour (green dashed lines indicate the boundaries of the shifting window). This modification simulates a demand response scenario where the washing machine's start time is slightly delayed while preserving the overall daily probability pattern.

The second subplot illustrates the impact of the shifted probabilities on the aggregated load profile of 100 washing machines. The black line corresponds to the original average power demand, while the blue line shows the modified load profile after the forward shift. A visible decrease in power demand is observed at 13:00 due to the reduced probability of starting cycles at that hour. On the other hand, the load increases slightly in subsequent hours, reflecting the redistribution of appliance activations.

The third subplot quantifies the flexibility potential and rebound effect resulting from this temporal adjustment. The brown bars represent the available flexibility potential, corresponding to the immediate reduction in load at 13:00 due to the forward shift. The blue bars show the rebound effect, representing the subsequent increase in power consumption in the hours following the shift, as the delayed cycles eventually start. The magnitude of the downward flexibility (brown bars) indicates the load that can be curtailed or postponed at a given time, while the rebound effect shows how and when this postponed load reappears. This balance between the two effects is crucial for aggregators or grid operators to understand the short-term demand reduction and the potential later increase in consumption.

7.4.2. Weekday / Weekend

The model differentiates between weekday and weekend usage patterns:

- Weekdays show concentrated evening peaks, mainly after work hours.
- Weekends have more distributed usage from late morning until late evening, offering higher flexibility potential during afternoon hours.

7.5. Results at national level for whitewares

The simulated results were scaled to national and communal levels based on the representative portfolio of whiteware devices, statistical ownership rates and Luxembourg's household numbers. Figure 52 illustrate the aggregated forward (upward) flexibility potential of residential whiteware appliances in Luxembourg at the national level, considering ownership rates for washing machines (95%), clothes dryers (40%), and dishwashers (50%). It shows appliance-specific flexibility profiles for a typical weekday. Washing machines exhibit the highest flexibility potential, peaking between 18:00 and 21:00, where over 10 MW of load can be shifted forward by one hour. This concentration reflects typical after-work operation patterns. Clothes dryers show a more dispersed flexibility profile with peaks in late evening hours, while dishwashers exhibit lower but more consistent flexibility, mainly between 18:00 and 22:00, coinciding with typical post-dinner operation. These patterns confirm the behavioural influence of ownership and usage habits, with washing machines being nearly universal in households, whereas clothes dryers and dishwashers are present in fewer homes, limiting their overall contribution.

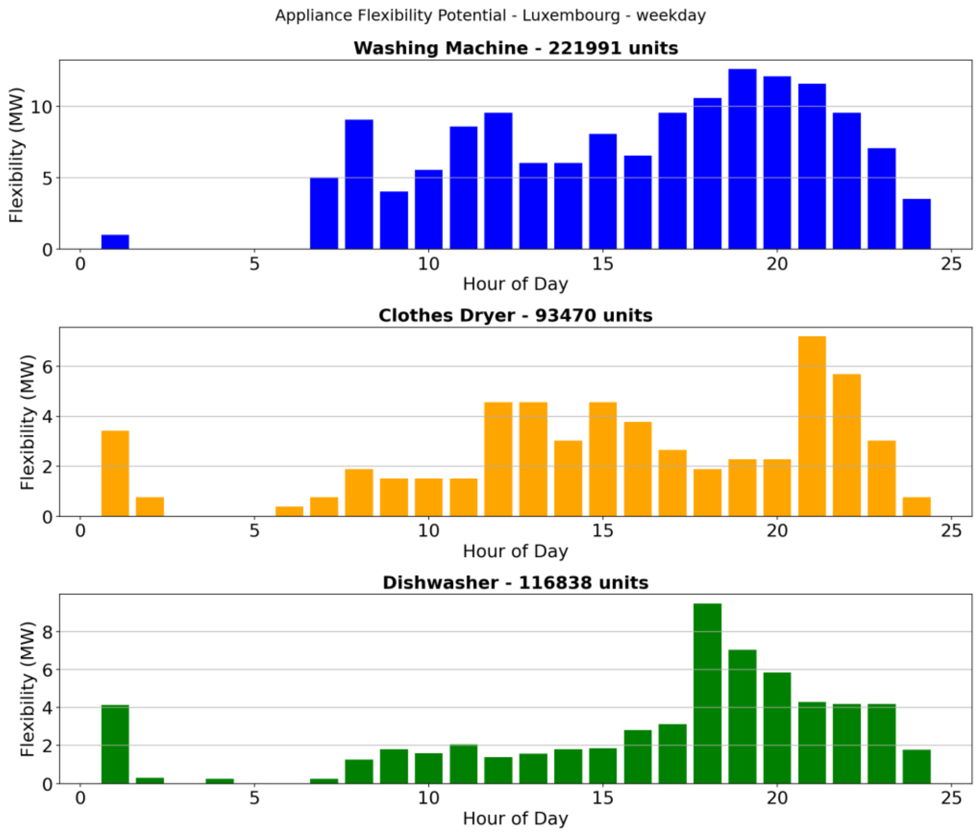


Figure 52 – Individual white ware flexibility (upward / forward flexibility)

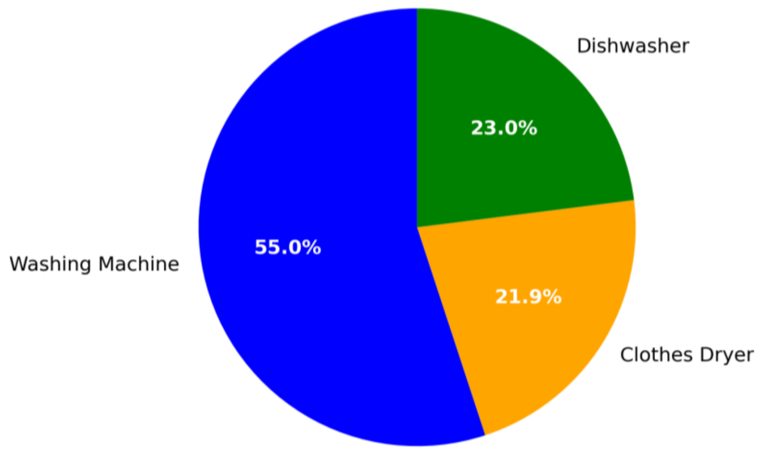


Figure 53 – White ware flexibility contribution by device

Figure 54 compares weekday and weekend aggregated flexibility potential. The stacked bar charts highlight that washing machines dominate the total flexibility, contributing approximately 55% of the national potential, followed by dishwashers (23%) and clothes dryers (21.9%), as shown in Figure 53. On weekdays, flexibility peaks occur in the evening, while on weekends, the peak shifts to the afternoon (around 14:00–18:00), indicating that weekend operation is less constrained by work schedules and more evenly distributed throughout the day.

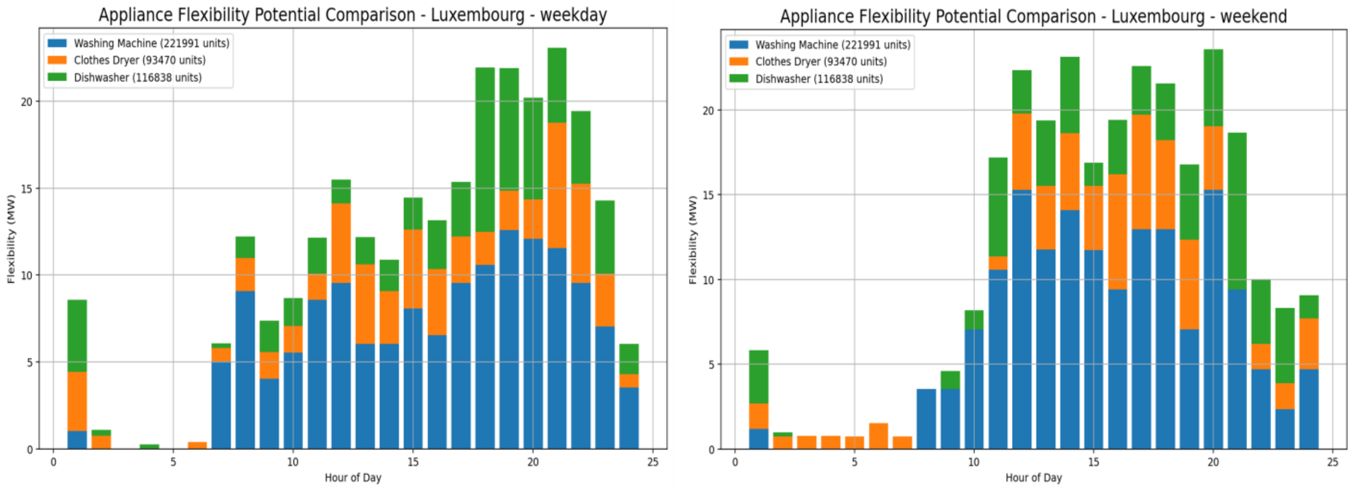


Figure 54 – Weekday and weekend aggregated flexibility potential

The analysis of the flexibility potentials results in the following hourly potentials, separately for weekdays and weekends. Table 25 summarizes the mean and peak values of the upward (forward shift) flexibility potential:

Table 25 – Aggregated demand response potential from residential whitewares

	Mean Flexibility Potential (MW)	*Maximum Flexibility Potential (MW)*	*Peak Hour*
Weekday	**11**	**22**	**Hour 21 to 22**
Weekend	**11,5**	**23**	**Hour 20 to 21**

8. Residential Sector – PV Battery Energy Storage

Battery energy storage systems for PV installations (PV BESS) are becoming increasingly popular and are in some EU countries, already today, the norm for residential PV systems. With the phaseout of pure feed-in schemes and focus on self-consumption mechanisms, the grid- and market integration of PV electricity should be incentivised. The objective of PV BESS is to increase the share of locally consumed electricity on the PV generated energy. Although the development of BESS in Luxembourg is not yet on the level of some leading EU countries, also here PV BESS are meanwhile being financially supported. Exact numbers of PV BESS in Luxembourg are not known, although the amount is expected to be rather small, but since end of 2022, about 820 batteries have been financially supported.

Besides the optimisation of self-consumption for the battery owner, the battery capacity could technically be used to provide flexibility. The potential for this flexibility has been estimated by a model considering representative PV- and battery systems for Luxembourg, typical household electricity consumption profiles and past meteorological data. In a last step, the potential is upscaled based on technology penetration scenarios for 2030 and 2040.

8.1. Methodology for assessment of PV BESS flexibility

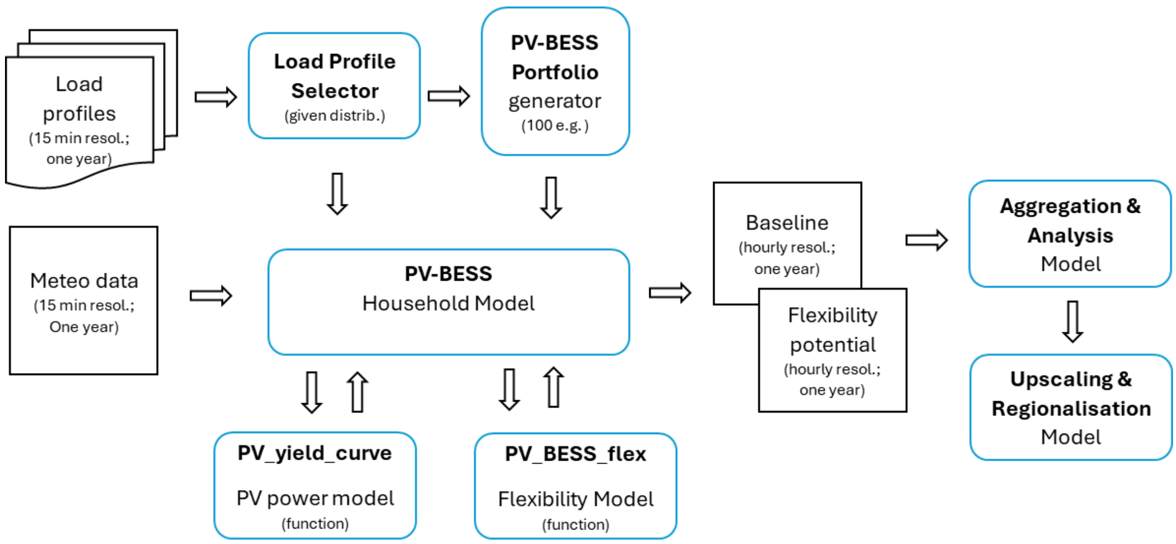


Figure 55 – Overview on the model to simulate PV BESS operation and estimate flexibility potentials

The estimation of flexibility potentials of PV BESS is based on the simulation of 100 statistically representative battery storage systems and connected PV systems, using past meteorological data and artificial electricity consumption profiles of residential houses. The calculated SoC (state of charge) allows at any time to estimate the power and duration for which the system could either be charged to store energy from the grid (downward flexibility) or to feed-in previously stored energy into the grid (upward flexibility). Those results for 100 representative PV BESS were then upscaled to the amount of known systems in Luxembourg today and at a later stage to the future technology penetration scenarios. Further, a statistical regionalisation allows for the allocation of flexibility potentials to communes.

8.1.1. Simulation of 100 representative PV battery storage systems

The simulation of the individual PV system is done via LISTs inhouse PV forecasting model – a physical model chain described in (Koster et al., 2014) and (Koster et al., 2022) – preformed for full year in quarter-hourly resolution. The rather detailed model considers reflection losses, temperature dependent conversion efficiency of the modules, ohmic losses in cabling (DC and AC), inverter efficiencies and many other factors.

The meteorological data required for the calculation is described in 2.2.1 and stems from the ECMWF[8] data base of historical weather data. For this part of the model, the global horizontal irradiance and ambient temperature is used.

The necessary electricity demand data for the simulated households originates from the artificial load profile generator developed by (Pflugradt et al., 2022) and is described in 2.2.3. Currently, 10 different household compositions are considered with the previously described probabilities to represent Luxembourgish households.

The state of charge of the battery system and feed-in to the grid is calculated as a simple energy balance, neglecting the batteries round-trip efficiencies, with the following prioritisation for the energy flow:

1) PV electricity is used to directly cover the household's current electricity demand.
   - If PV electricity is not sufficient to cover the demand,
     electricity is drawn from the battery storage system
   - If the SoC of the battery is 0%, electricity is drawn from the grid
2) Surplus PV production is fed into the battery storage system, if SoC < 100%
3) At SoC = 100%, production surplus is fed into the grid

This operation principle should represent the current purely self-supply focused operation of most PV BESS, without an energy management system influencing the own consumption (e.g. wall boxes) to optimise self-supply. The resulting baseline consumption- and feed-in curve is defined as the reference behaviour. Each deviation from this reference is seen as flexibility.

8.1.2. Flexibility potential estimation

The simulator gives detailed insights in the quarter-hourly PV production values, electricity consumption of the households, the resulting residual load, the batteries State-of-Charge (SoC) and the energy fed into the grid. Via this information, the model considers the possibility to provide flexibility in both directions:

Energy feed-in from battery to the grid (upward flexibility), respectively, feeding energy to the grid, instead of storing it.:
When SoC > 0, meaning whenever the battery is not empty, the BESS could be asked to feed energy to the grid with its maximum charging power for the duration until the battery is fully discharged. In addition, whenever there is a surplus PV production during that same period, this surplus could be fed into the grid as well. This results in an upward flexibility larger than the PV BESS discharge power.

Charging energy from the grid to the battery (downward flexibility):
When SoC < 1, meaning whenever the battery is not fully charged, the BESS could be asked to be charged from the grid, increasing the consumption of the household. Additionally, whenever there is a residual load of the household during the same period, this consumption would be covered from the grid, not the battery. PV-production is not curtailed in our model.

8.2. Scenarios – PV BESS penetration today, 2030, 2040

In the following, the current state of PV BESS in Luxembourg is documented, future scenarios are defined and justified and a representative PV BESS portfolio, including the most important technical characteristics, are developed.

[8] European centre for medium ranged weather forecasts

8.2.1. Residential PV battery energy storage systems - today

The exact number of PV battery energy storage systems (PV BESS) installed in Luxembourg is not known, but the amount is expected to be rather small. With the introduction of self-consumption schemes, and constant price drop for battery systems, the installation became more attractive. Since end of 2022 the installation is furthermore financially supported and about 820 batteries have been implemented since then (AEV[9]). During the period 08/2022 and 03/2025 the share of PV BESS on the total amount of supported PV systems was 21.6%. But this quota has increased during that period and reached up to about 35% in the most recent months.

For the spatial allocation of the flexibility potential to the individual communes it would be helpful to know their location, but this data is not publicly available. Hence, we try to approximate this by the available statistics on residential houses. Privately owned PV systems and PV BESS are predominantly situated on single-family homes. Multi-family homes and apartment house lag behind this development, due to a the more complicated ownership structure. Hence, it has been decided to upscale the absolute amount of flexibility by the technology penetration scenarios and allocate it to the communes proportional to the share of Single-family homes (SFH) on the national sum of SFH.

Hence, the baseline- and flexibility profiles simulated for 100 representative PV BESS are upscaled to the 821 known systems of today. This results in a share of 0.69 % of todays 118.371 SFHs being equipped with such systems. This factor is used to allocate the results to the communes, using the amount of SHFs of each commune, reported by STATEC[10] (Klein & Peltier, 2017).

8.2.2. Residential PV battery energy storage systems - 2030, 2040

Since no dedicated targets for residential PV Battery systems exist for Luxemburg, the FlexBeAn PV BESS scenarios are based on photovoltaic growth scenarios. The current growth rates of PV installations are rather high, in many countries of the EU as well as in Luxembourg. Political objectives for future photovoltaic growth exist on EU and national levels and are published and updated regularly as part of the National Energy and Climate Plans (NECP). But still, the real development of the individual RES growth, including PV, is difficult to forecast and the development is very individual for each technology and country. Versatile national photovoltaic scenarios are shown in Table 26, reaching from the initial version of the NECP with its reference and target-scenarios, as well as Fraunhofers scenario from the “Third Industrial Revolution” process, to the recent version of the NECP updated in 2024.

Table 26 – PV generation capacity scenarios, according to different sources

PV-Generation Capacity	NECP - Reference	NECP - Target	TIR / Fraunhofer	NECP – (Update 2024)
2030	608 MW	984 MW	318 MW	**1236 MW**
2040	857 MW	**1800 MW**	470 MW	

Most recent, official numbers for Luxembourg, reported by the ILR for end of 1st quarter 2025, stated an installed PV capacity of 590 [MW], which almost reached the initial NECP reference scenario for 2030 and surpassed by far the TIR scenario for 2030. In 2024 the NECP scenario for 2030 has been adapted and increased. Hence, our calculations for 2030 relate to the updated NECP and 2040 values relate to the initial NECP Target scenario.

These PV capacity scenarios are shown in Table 27 and further assumptions taken to reach to PV BESS scenarios: For each period (today until 2030 and 2030 until 2040) the amount of new installed PV systems

[9] Information from “Administration de l’environnement” via email (03/2025)
[10] Additional data received from STATEC, linked to publication: (Klein & Peltier, 2017)

is calculated and a share of residential PV systems on those system has been set to 37%[11]. While in the recent past, the share of BESS connected PV systems on the supported residential PV systems reached already 35%, we assume a share of 50% for the period “today – 2030” and 80% for “2030 – 2040”. Obviously, such assumptions underly large uncertainty.

This leads to newly installed PV nominal capacity connected to BESS of 177 MW until 2030 and additional 587 MW until 2040. The model applies these numbers to all SFHs in Luxembourg, using an average PV system size of 12 kWp. Set into relation to todays number of SFHs, this would correspond to a share of 13,2% of the SFH being equipped with a PV BESS in 2030, respectively 55% in 2040.

In addition to new installations, some the currently installed 590 MW of PV systems (end 1st quartal of 2025) could be upgraded with additional battery systems, which is meanwhile subsidised as well. The scenario foresees that until 2030 about 10% of this capacity would be upgraded with a battery storage, and additional 40% (reaching 50% share in total) of the existing capacity until 2040.

Table 27 – Development of PV BESS scenarios for 2030 and 2040

PV BESS-Scenarios	NECP – Target (PV)	new PV systems	Residential (37 %)	BESS share	new resid. PV BESS	BESS upgrade existing PV	Total growth PV BESS
2030	1236 MW	646 MW	239 MW	50 %	120 MW	59 MW	179 MW
2040	1800 MW	564 MW	209 MW	80 %	167 MW	236 MW	403 MW

[11] Value set after analysis of currently installed and authorized PV systems, according to CREOS data; PV systems up to 30 kWp have been considered residential

8.2.3. Building a representative PV-BESS set for simulation

As described previously, our model simulates the yearly operation of 100 representative PV BESS in hourly resolution. The representativeness of the technical characteristics of the systems is assured by reproducing statistical parameters. These parameters include PV nominal power, orientation and inclination of the PV system, battery capacity, charging- and discharging power etc..

Based on the data of supported PV BESS systems in Luxemburg, the graph below shows the histogram of PV nominal power of these systems, with an average nominal power of 12 kWp per system. The majority of system fall into the 8 – 10 kWp range.

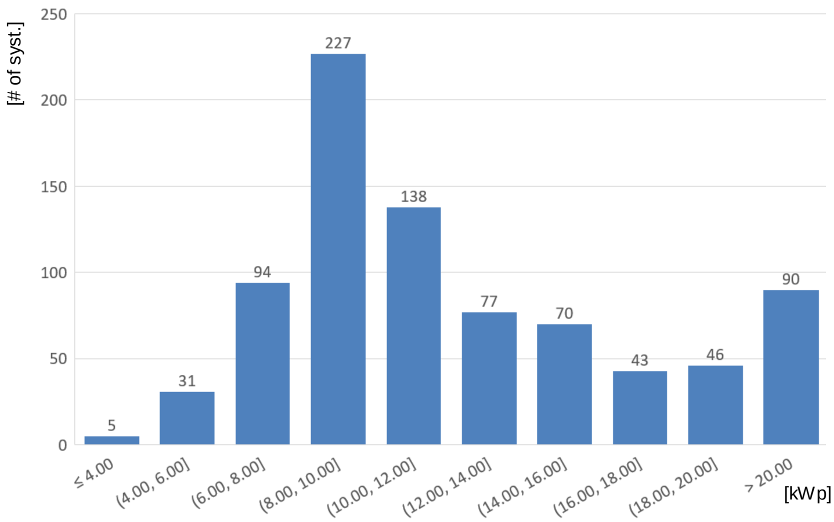


Figure 56 – Histogram of nominal power of residential PV systems connected to PV battery energy storage systems [data: AEV]

For our model, we considered PV systems ranging from 5 kWp to 19 kWp. The probability distribution from which the model randomly defines the 100 PV systems for the simulation is depicted in Table 28.

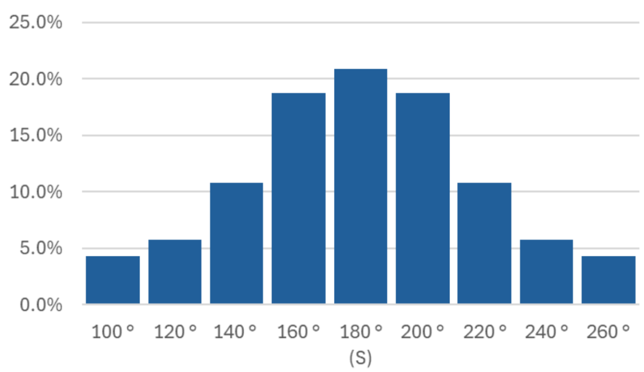
The orientation and inclination of the PV modules are influencing the yield of the PV system, but more importantly the daily production profile. This is decisive for the shape of the daily production curve, the schedule of the daily peak, timing of production start and end etc. Based on data from previous projects, the values in Figure 57 are used in the model.

The charging- and discharging power for the PV battery energy systems is not documented in the data source of subsidised systems in Luxembourg. The assumption used in this study, is that the charging and discharging power in kW equals the battery capacity in kWh. This might overestimate the charging power, specifically for the few larger systems which are often modular systems, but should not be far from reality for the majority of smaller scale systems:

Charging /discharging power [kW] = battery capacity [kWh]

Table 28 – PV nominal power distribution for PV BESS portfolio generation

Nominal power PV [kWp]	5	7	9	11	13	15	17	19
Share per nominal power	0.04	0.13	0.31	0.19	0.11	0.10	0.06	0.06



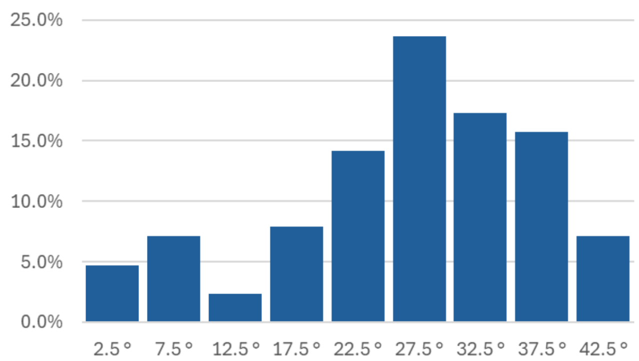


Figure 57 – Histogram of orientation (left) and inclination (right) of the simulated PV systems

The battery capacity of the supported PV BESS in Luxembourg is known and can be set into relation to the PV nominal power. Figure 58 plots the relation of “battery capacity / PV nominal power” in percent over the PV nominal power in the relevant range of supported PV systems and gives a trendline (orange). The trendline function is used in the model to derive battery capacity from the PV nominal power and randomly adds +/- 20% variability to the function to reproduce the real deviation from the trendline.

Finally, the average PV system’s nominal power of 12 kWp is corresponding to an average 9 kWh battery capacity.

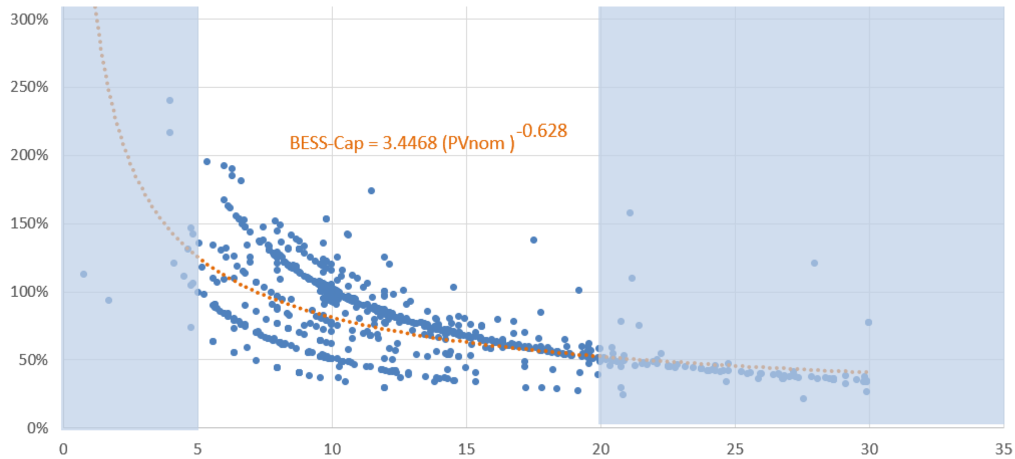


Figure 58 – Characteristics of common “battery capacity to nominal power-ratio”

8.3. Results for individual PV battery system - Example

Within this chapter, the results of the simulation for a single system are briefly illustrated as an example for the full 100 PV BESS set that's used for upscaling of the results.

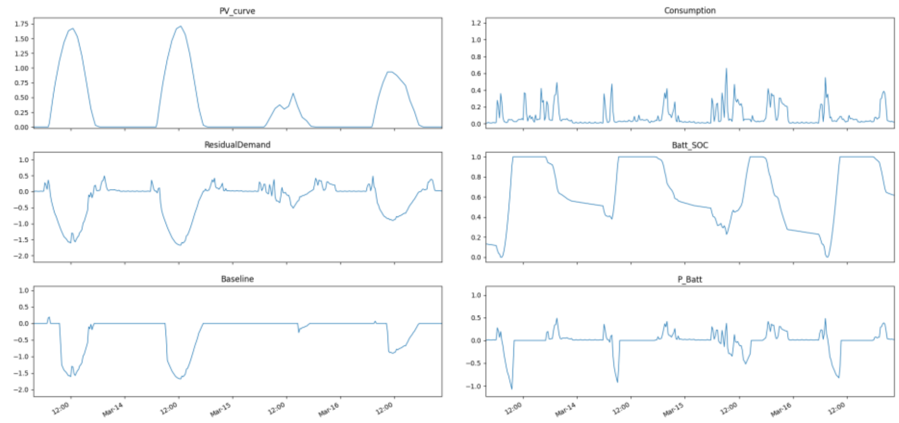


Figure 59 – Simulation results for 4-days baseline profile of a PV BESS

The example depicted in Figure 59 shows a 4-days profile for a 9 kWp PV system, connected to a 6.4 kWh battery system. Quarter-hourly PV production (top left) shows two clear-sky days, followed by 2 cloudy days. Considering the consumption profile of this household (top right), the resulting residual demand (mid-left) indicates already mainly surplus production of the PV system for the two first days.

This surplus is being stored to the BESS, results in a fully charged battery (SoC, mid-right chart) on all three days, even on the cloudy days 3 during afternoon, while during the other days the battery is already fully charged during the morning. Hence, the baseline profile of the household for those 4 days in March, measured at the electricity meter (bottom left), is mainly characterized by energy feed-in on days 1, 2 and 4. Consumption from the grid is hardly necessary. The charging and discharging power of the battery is depicted in the graph on bottom right.

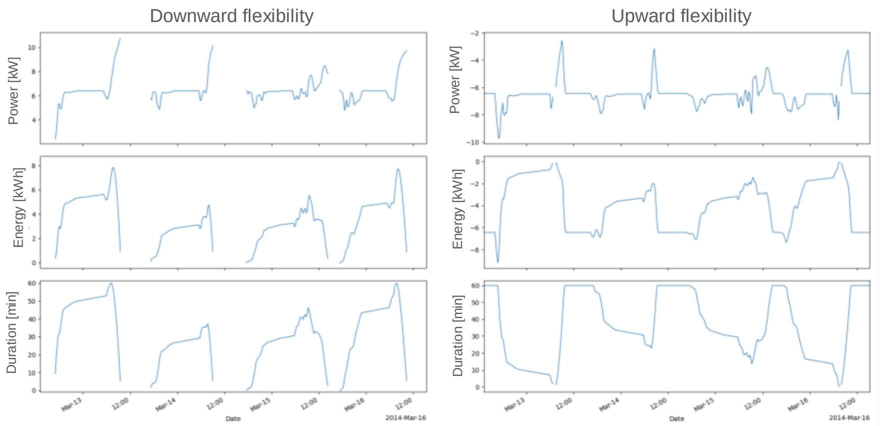


Figure 60 – Flexibility characteristics of a exemplary PV BESS

This baseline behaviour results in the flexibility characteristics shown in Figure 60: The battery could provide downward flexibility, absorbing energy from the grid, during nights and early mornings on these 4 days, whenever the battery has capacity available, shown in the left column graphs. The power fluctuates around the charging power of 6kW and the duration (hence also the energy) depends obviously strongly on the SoC. During noon, typically on these sunny days, the PV BESS could not provide downward flexibility since it's fully charged.

Upward flexibility, considering the feed-in of previously charged electricity, is (during these 4 days in March) possible almost anytime, as visualized in the right column of the graphics. The discharge power of about 6 kW could be provided for about 60 minutes, during noon and afternoon of days 1, 2 and 4, when the battery is fully charged, while the duration drops towards the night, reaching 30 to10 min. in this example.

While the example of these 4 days should only provide insights in the general logic behind the simulation and the model, the graphics in Figure 61 will give an impression of the seasonal availability of this flexibility from PV BESS: The PV production curve follows the typical seasonal variability as expected, with its main contributions between March and October. The consumption profile is rather stable throughout the year, with a dip during the summer holidays (which is considered relatively radical in the data used here).

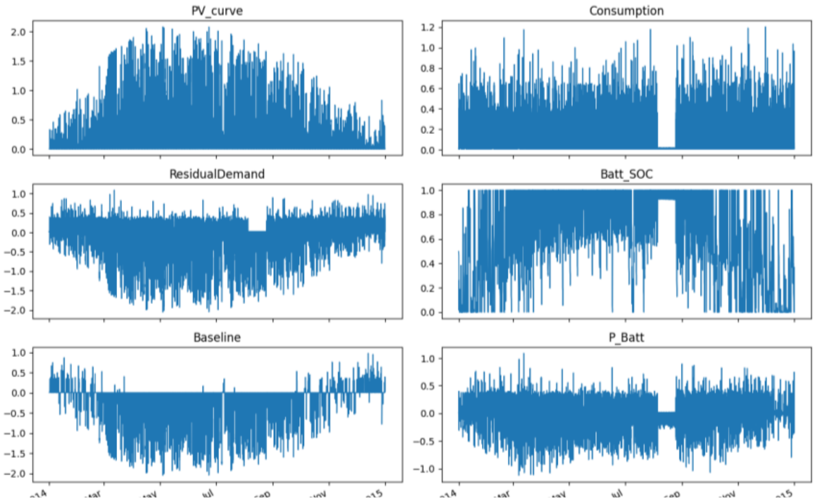


Figure 61 - Exemplary yearly baseline profile (quarter-hourly values)

During the spring and summer period, we observe that the SoC is alternating between 50 – 100% charge, normally.

Later during autumn and winter, the BEES is more and more often fully discharged and reaches only seldomly a fully charged status. This is also reflected by the baseline consumption / production of the household, which is from April to October self-sufficient and net-producer.

Analogue to these simulations results, the exemplary PV BESS system could potentially provide downward flexibility, for reasonable longer periods mainly during winter times. In the summer periods, the storage is often fully charged during the day and seldom discharged below a SoC of 50% during the nights, which results in 0 to max. 30 minutes downward power flexibility, of around 6-7 kW.

On the other hand, upward flexibility is available throughout the sunny periods (spring until early autumn) for 40 – 60 minutes, most of the time. While it is very limited (0 – 20 minutes) during winter months.

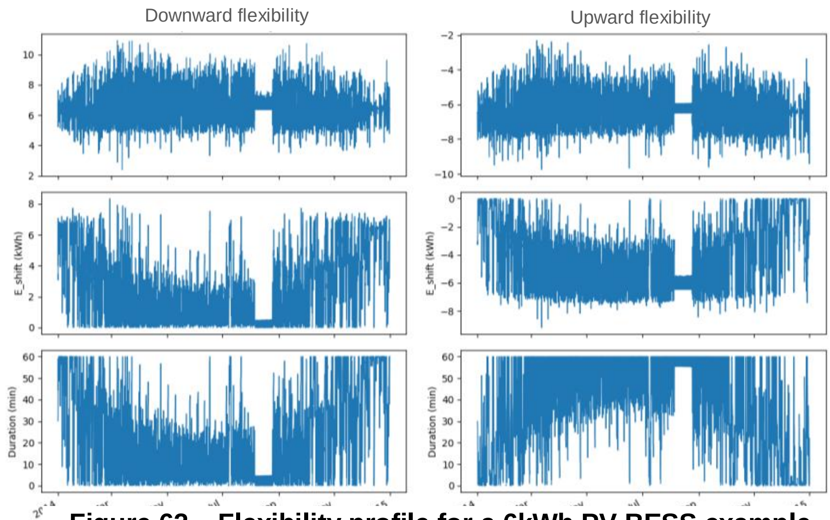


Figure 62 – Flexibility profile for a 6kWh PV BESS example

8.4. Results – example for a set of 100 PV battery system

The time series results for an aggregated set of 100 PV BESS, which are the basis for the analysis, the upscaling of results on national level and for the scenarios 2030 and 2040, are only briefly presented here.

The relative results, such as the daily and seasonal fluctuation of the availability of the flexibility, are similar to the single system results. The absolute size of the flexibility will be documented in the next chapter, after upscaling.

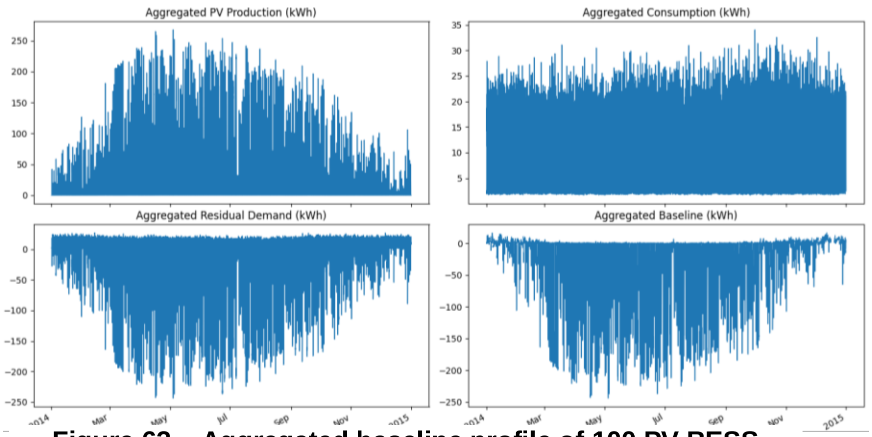


Figure 63 – Aggregated baseline profile of 100 PV BESS (quarter-hourly values)

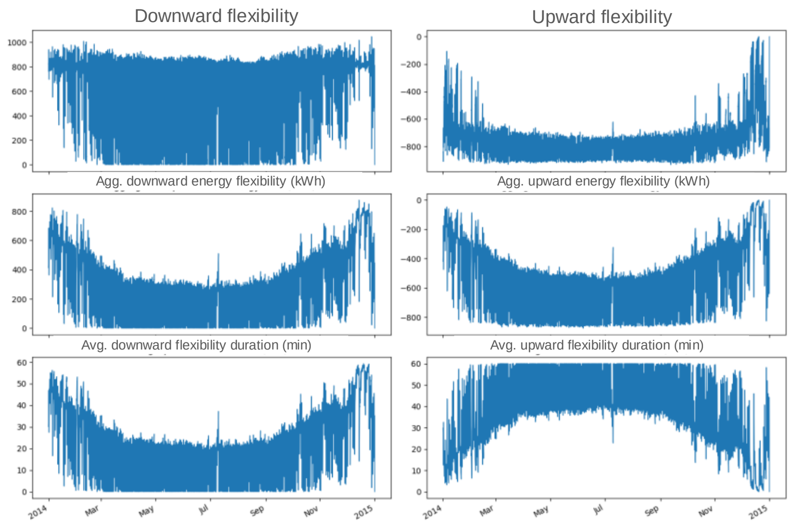


Figure 64 - Aggregated flexibility parameter of 100 PV BESS and averaged flexibility duration

Worth mentioning is the still large variability for some of the parameter, even on aggregated level. The simultaneity of PV production curves, in a relatively small area such as Luxembourg, is inherent to the nature of such systems. Also, the bandwidth of technical design parameter for residential PV BESS is relatively narrow. Hence, the resulting downward flexibility, during summer time, still ranges between 0 (when all batteries are fully charged) and 800 kW, with the daily cycle. Upward flexibility shows less variability, except for few winter days.

The quarter-hourly timeseries results, as depicted in the previous graphs, were analysed and summarized to typical daily flexibility profiles in hourly resolution. A first analysis step led to the conclusion, that it is not necessary to distinguish between weekdays and weekends. The only parameter that would justify to set up individual profiles would be a significantly different electricity consumption profile of the households. But, although there are differences in the consumption profiles, these are not substantial enough to lead to significantly different results. Hence, the daily profiles enable to identify the expected large fluctuations in the diurnal cycle, while individual season profiles allow to distinguish summer, winter and transition period.

In the following, the results for summer and winter period are being presented (transition period charts can be found in the annex):

Summer period

In Figure 65 the main characteristics for 100 PV BESS system, during a typical day in the summer period are depicted. As the PV production during this period is high, the systems show a net feed-in baseline, as expected. This generally results in a high upward flexibility potential (additional feed-in from the battery) and a low downward potential (storing energy from the grid) during the day.

The max power flexibility, be it for upward or downward flexibility, is obviously defined by the nominal charging and discharging power of the aggregated BESS and is hence rather independent of the season. In our case for 100 PV BESS, this lies around 750 kW. This hold true for all the seasons, but it is very different for how long this flexibility would be available: over the day as well as over the seasons, since it depends on the SoC of the aggregated storage.

During the summer period, the battery systems are quickly filling up during the morning periods and show a very low downward flexibility potential already up from 10:00 o'clock (left column). This is also reflected in the low flexibility duration, falling towards zero quickly. Even during nights, on average the duration reached max 20 minutes. Regarding upward flexibility, with average SoC's of the batteries ranging between 65 and 100 % during the day, the average flexibility duration is about 40 minutes during nights, up to one hour during the day.

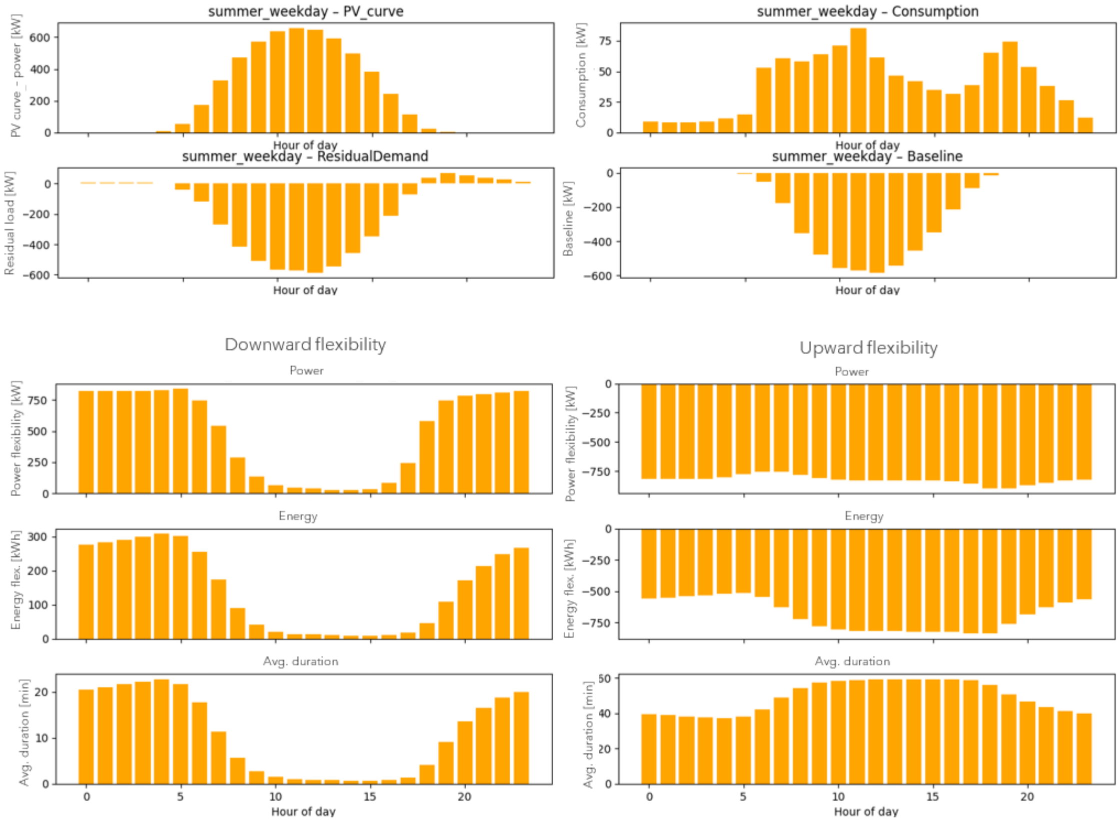


Figure 65 – PV BESS flexibility profile – summer (100 PV BESS)

Winter period

During the winter period, the much smaller PV production in combination to a slightly increased electricity demand, results in a much smaller surplus production. But still, the aggregated energy balance over the 100 PV BESS remains net positive, with the given technical characteristics (on average: 12 kWp PV systems connected to a 9 kWh battery.

Given the current purely self-consumption based operation mode, the batteries could potentially absorb electricity from the grid (provide downward flexibility) ranging between 40 minutes (during night towards early morning) and minimum 20 minutes during the afternoon, at the mentioned 500 - 750 kW charging power.

The upward flexibility profile, in terms of its duration, shows the inverted profile, reaching the minimum during early morning hours, when SoCs are low (with 20 minutes) towards an average of 40 minutes, maximum, during the afternoon.

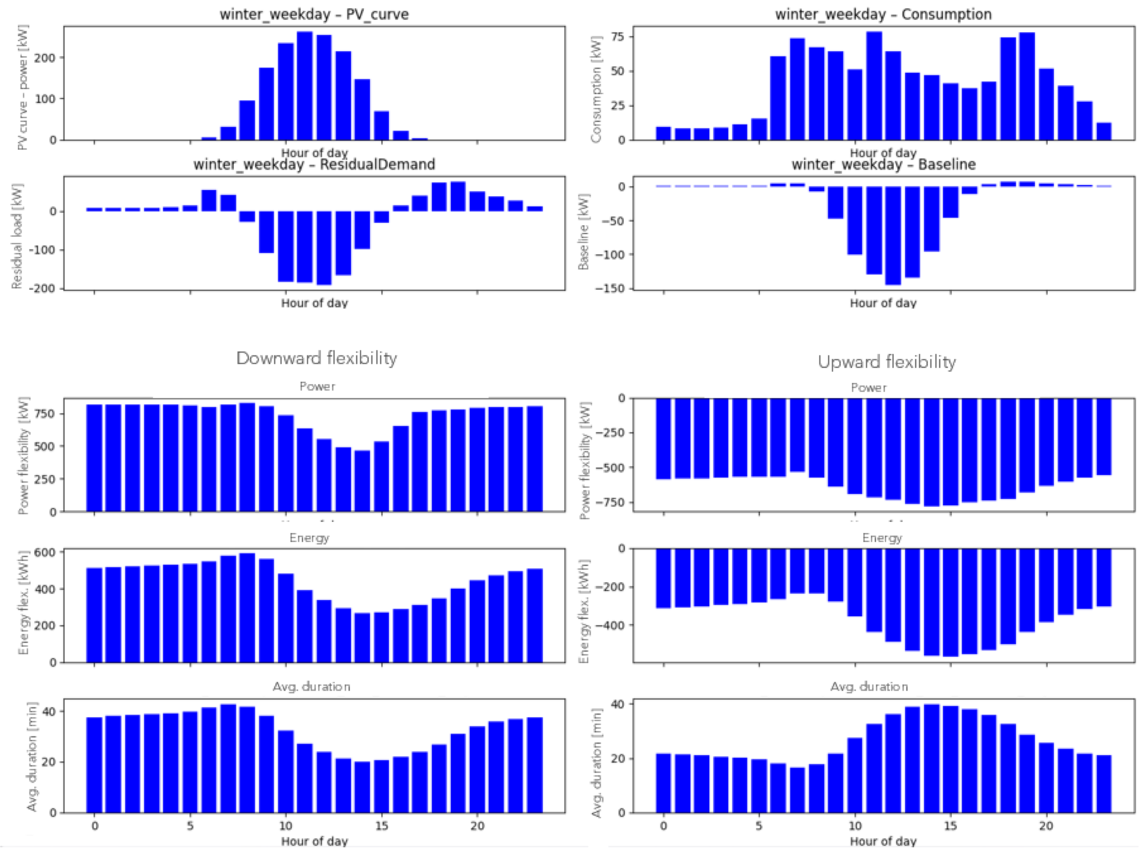


Figure 66 - PV BESS flexibility profile – summer (100 PV BESS)

8.5. Results – national and communal level – today, 2030 and 2040

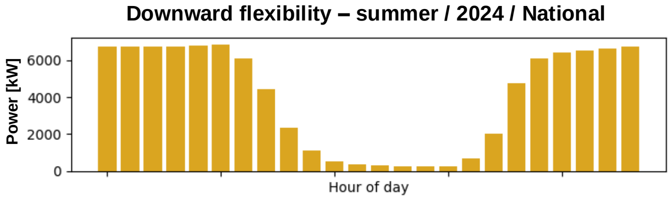
The simulation results for 100 representative PV battery energy storage systems are the basis for the upscaling on national level and the later allocation to the communes. Using the numbers of known PV BESS in Luxembourg today (8.2.1), the following results should represent the current potential for flexibility provision by these systems, under the current operation mode – optimisation of the individual self-consumption.

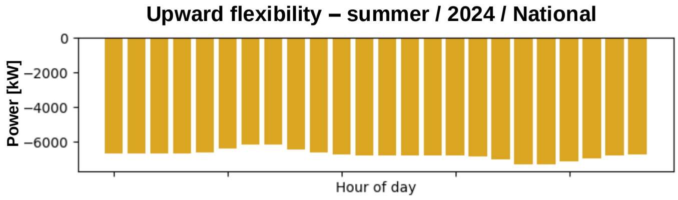
In a next step, the results are further extrapolated to the scenarios described in 8.2.2.

8.5.1. National level

Battery energy storage systems for PV installations are meanwhile being financially supported in Luxembourg with the objective to increase the share of locally consumed electricity on the PV generated energy. Until early 2025 about 820 batteries have been financially supported which we defined as todays technology penetration scenario.

Scaling the flexibility potential of the simulated 100 PV BESS up to the 821 battery systems known for today, leads to the power flexibility potential and average durations shown in Figure 67. The aggregated power flexibility to absorb electricity from the grid (downward) and to feed energy to the grid (upward flex.) has a maximum of slightly over 6’000 kW (in both direction).





Downward flexibility – winter / 2024 /

Upward flexibility – winter / 2024 / National

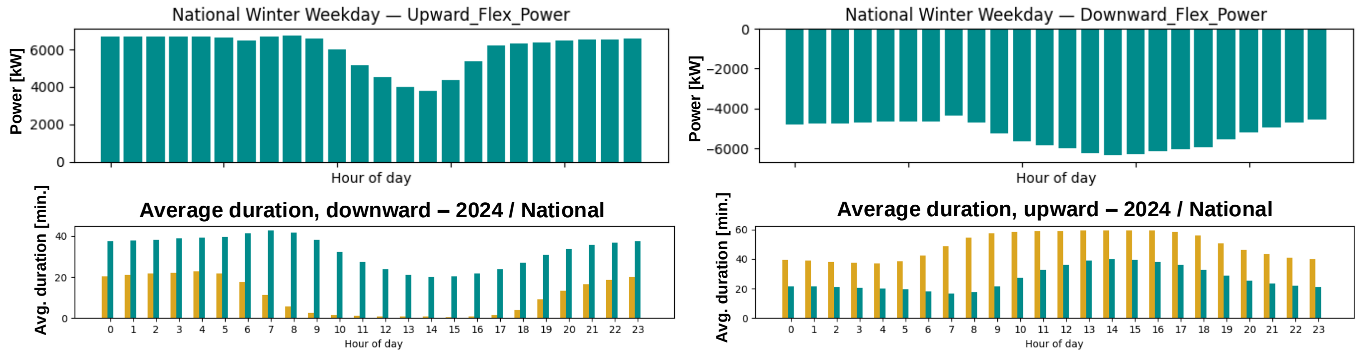


Figure 67 – Residential PV BESS flexibility potential – today (summer and winter)

The simulation results have been analysed to estimate the flexibility profile for a typical summer day, as well as a winter- and transition period profile:

As depicted above for winter and summer, with the amount of known PV BESS installations today, the ***flexible charging to store energy from the grid*** (downward flex., left graphs) has a clear diurnal profile. During summer (top, left), the batteries could take up energy from the grid until the early morning hours, when they start being charged by the PV systems. The power flexibility drops sharply during the morning, from initial 6'000 kW to almost negligible values – specifically when considering the average flexibility duration reaches a minimum already from 9:00 o'clock onwards (bottom, left graph). From noon until late afternoon, the power potential is almost zero, since the batteries tend to be fully charged. Even during nights, the average duration for which the systems could be charged during summer is rather short – up to 20 minutes, falling to almost zero quite early during the day.

During the winter period, the capacity to charge energy from the grid (downward) is permanently given (4'000 - 6'000 kW), although also here the capacity and duration (20-40 minutes) varies during the day.

The possibility to ***flexibly feed energy to the grid***, defined as upward flexibility, is rather stable during the diurnal cycle: During summer, the batteries almost never run empty, and could provide upward flexibility of about 6'000 kW for an average duration of 40 minutes during nights, and about one hour during the day.

In winter, the power during the day-light hours is about 20-30% higher than outside the sunny period of the day. The average duration a PV BESS could provide upward power flexibility varies now between 15 – 40 minutes during winter.

Huge growth expected – Results for scenarios 2030 and 2040

The most interesting aspect about the residential PV BESS potential are the large growth rates that can currently be observed: 35% of the recent requests for financial support for residential PV systems included a battery energy storage system. To project the number of PV BESS in 2030 and 2040, several assumptions need to be made, as laid out previously. Considering the past national and European developments of PV[12] and PV BESS installations, the PV growth scenarios described in the updated NECP (for 2030) and the "target scenario" in the initial NECP (for 2040) have been considered as a basis. Until 2030 we assume that 37% of the new PV installations are residential PV of which 50% would be built in combination with a battery system and that 10% of today's PV capacity will be equipped with a battery, resulting in 179 MW PV BESS capacity. From 2030 to 2040, again 37% of the new installations are considered residential systems, with a share of 80% BESS, and additional 40% of todays PV systems would be upgraded, meaning additional 403 MW of PV BESS capacity.

[12] The ILR reported a total of 590 MW photovoltaic installation at the end of the first quarter of 2025

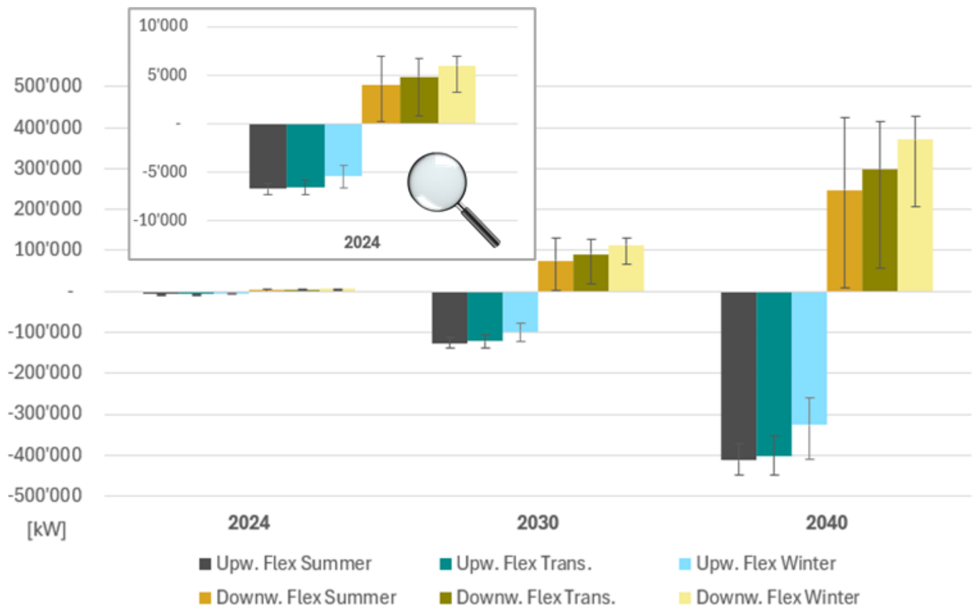


Figure 68 – Upscaled PV BESS power flexibility potential 2030 and 2040

Upscaling the simulation results with these numbers does not change the trends, schedules and duration, and so the findings documented before about seasonal and daily availability stay the same – as long as the operation mode remains unaltered. But the absolute numbers reach a tremendous size:

The daily average up- and downward flexibility for 2030, as depicted in Figure 68 and dominated by these huge growth rates, reach around 92 MW for downward and 121 MW for upward flexibility (transition period, gives a medium value). Until 2040, a further growth to 299 MW downward flexibility, respectively, 401 MW upward flexibility has been estimated. The bars show the average flexibility for each season and scenario year, while the daily variation of this power flexibility is expressed by the interval bars (thin black lines) for each bar.

Table 29 - average power flexibility of PV BESS across seasons and scenarios

	Season	Today (2024)	2030	2040
Average Upward Flexibility (feed-in mode)	Summer	6.7 [MW]	125 [MW]	413 [MW]
	Transition	6.6 [MW]	122 [MW]	401 [MW]
	Winter	5.4 [MW]	98 [MW]	327 [MW]
Average Downward Flexibility (storage mode)	Summer	4.0 [MW]	75 [MW]	248 [MW]
	Transition	4.8 [MW]	92 [MW]	299 [MW]
	Winter	6.0 [MW]	113 [MW]	370 [MW]

8.5.2. Communal level

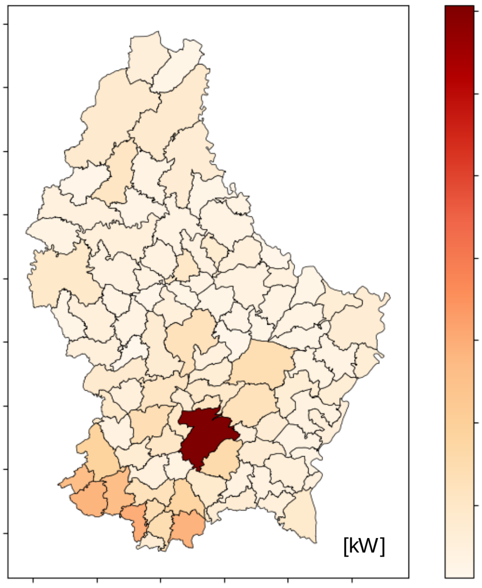


Figure 69 – Allocation of PV BESS flexibility of communes (summer, downward)

The allocation of the residential PV battery storage systems to the communes is done proportionally to the amount of single-family-houses in each commune (8.2). The map (Figure 69), showing the example of average downward flexibility during summer, should not provide absolute number, but rather give an impression on the spatial distribution of the systems, as considered by our model.

Obviously, with 8.8% of the national SFH, Luxembourg City has been allocated the largest share of the systems. The Following communes are Esch-sur-Alzette (3.7%), Dudelange and Differdange, both 3.6%, Sanem (3.3 %) and Petange (3.3%) .

The model furthermore provides graphs as depicted below (Figure 70), identifying the individual potential as well as depicting the known profiles across seasons and the diurnal fluctuation.

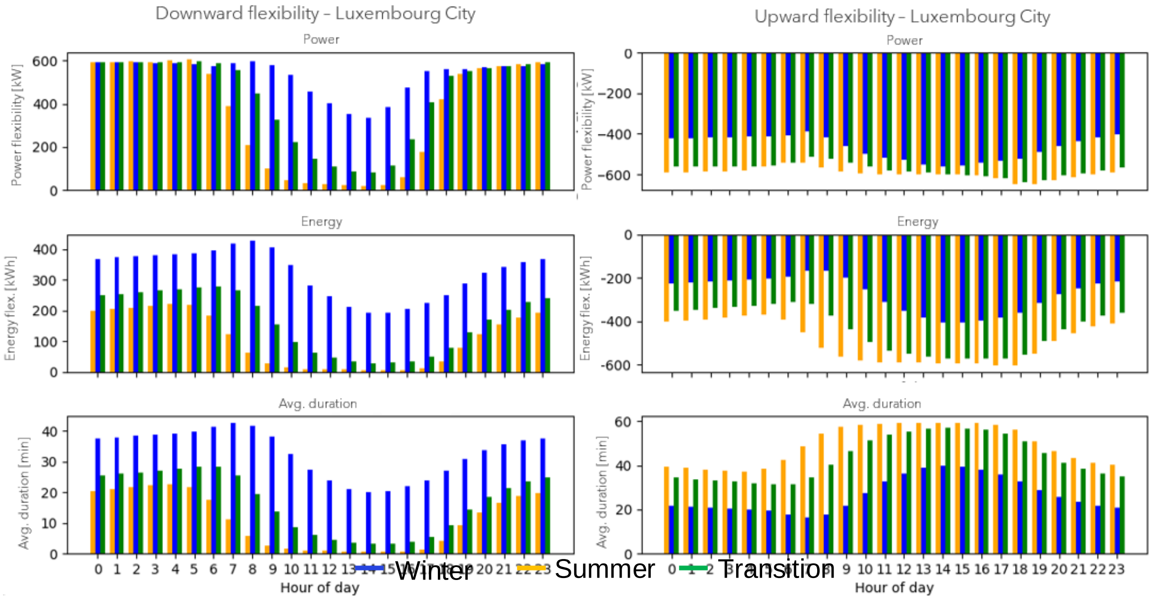


Figure 70 – PV BESS flexibility profile of Luxembourg City – today's technology penetration

8.6. Outlook and limitations of the model

All the above-described results assume a purely self-consumption based operation of the battery, not considering any intention to e.g. limit peak PV injection or other optimising control options. Since any surplus production is directly stored in the battery, the batteries are normally quickly fully charged and the feed-in to the grid around noon is not limited at all. Hence, the batteries have no grid-relieving effect, since the same grid capacity is required, as without batteries.

Although this has *not directly* been modelled, the results still indicate, that a forecast-based operation of the PV batteries would allow to use parts of the battery capacity available in the early morning hours, to mitigate the PV peak feed-in around noon, while still minimizing yield losses for the battery owners (depending on the quality of the forecast). Further, a smart and “grid-aware” operations would have the potential to mitigate evening peaks, even during winter periods, depending on the charging strategy.

A public support scheme for PV batteries should consider possibilities to mobilize this added value for the grid infrastructure and society.

Some of the assumptions and model principles should be mentioned as potential limitations:

- The charging and discharging power of the existing BESS is not know - the assumption to set charging/discharging power (in kW) equal to the battery capacity (in kWh) has direct influence on the duration of the flexibility provision. This is the reason why duration is limited to one hour, since the flexibility provision is furthermore considered to be performed at nominal power and not modulated.
- The mode of operation of the BESS could furthermore be following some smarter options (forecast-based etc.) which would lead to different results regarding timing and dynamics. Or consumption of some assets in the household could be adapted to the availability of PV electricity via an energy management system.

9. Electro-Mobility

Europe's as well as Luxemburg's climate change mitigation strategy is built upon several pillars, covering CO_2 emission reductions from buildings, industry and tertiary sectors, the energy sector and the important aspect of mobility. The major component of the clean mobility strategy is the shift towards full electric mobility concepts. Besides the arising challenges towards the charging infrastructure and potential effects on the distribution grid, this transition process comes also with opportunities for grid operators, regarding flexibility provision via "smart charging", or "vehicle-to-grid" concepts (V2G) in a later stage.

9.1. Methodology for the assessment of flexibility from e-mobility

The assessment of flexibility potentials from electric vehicles within this project covers flexibility provision via "smart charging" at three different charging locations: public charging stations, charging at home and at workplace. The methodology for the simulation of public charging processes deviates from the simulation of charging processes at home or at workplace, since the data availability is very different: While data on charging behaviour for the main public charging infrastructure is available to the project consortium (9.1.3), the charging behaviour of EV users for home charging and charging at workplace is unknown and has been simulated with the help of artificial mobility profiles (9.1.4).

9.1.1. Modelling of flexibility provision by EVs

The underlying model to describe the flexibility provision via "smart charging" is the same for all three charging locations. The basic principle is illustrated in Figure 71, showing the state of charge (SoC) of the EV battery over time of the charging process.

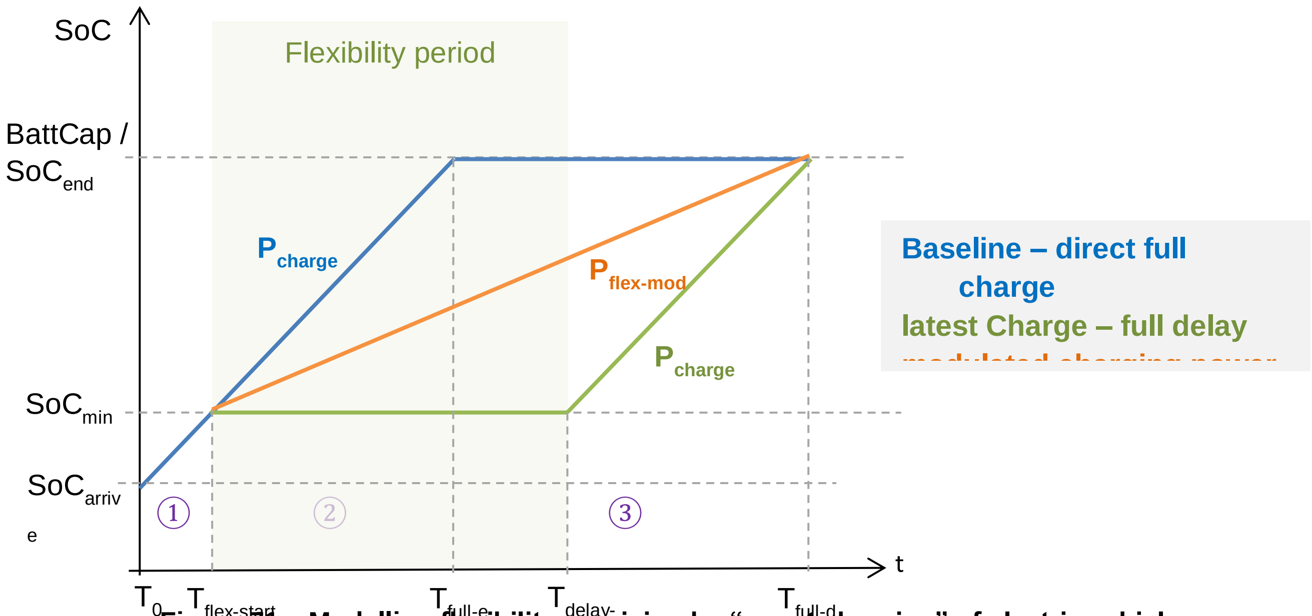


Figure 71 – Modelling flexibility provision by "smart charging" of electric vehicles

The EV starts a charging process with a given state of charge (SoC_{arrive}) and the user could define a minimum SoC (SoC_{min}) up from which he would allow to delay the charging process, as well as a presumable time when he is planning to leave. The rather conservative principle behind our model guarantees the user the charging up to SoC_{min} before any flexibility is delivered and the full charge at the planned time of departure, if the duration allows the full charge of the battery. When SoC_{min} is reached and the planned time of departure allows for a delay (until $T_{delay-max}$), the charging process could be postponed, giving flexibility to the system.

Although a user defined SoC_{min} is implemented in the model and it's impact on the results has been evaluated, it was decided to set this minimum state of charge to zero, by default, as reflected by the results presented in the following chapters.

The model calculates load profiles for,

Baseline behaviour – the charging curve when no flexibility is requested,
Latest charge – delaying the charging process until the latest moment in time that still allows for a full charge (if SoCmin is used, only once SoC_{min} is reached), and
modulated charging – reducing charging power to a minimum, guaranteeing full charge at departure.

Those resulting load profiles give rather static information about maximum flexibility and these results are simple to interpret. But the practical usability might be limited, which gets more clear in chapter 9.3. Hence, the introduction of **instantaneous flexibility** is considered more relevant:

Hourly instantaneous flexibility describes the amount of load reduction that could be acquired by activating flexibility *instantaneously* within a specific hour of the day. On the example of a single charging process, as indicated in Figure 71, instantaneous flexibility depends on the phase of the charging process:

① marks the period between arrival and $T_{flex\text{-}start}$, where SoC_{min} is not reached yet. If instantaneous flexibility is asked from this charging process, the flex is zero at this point in time.

② marks the period from $T_{flex\text{-}start}$ until $T_{full\text{-}e}$. During this period, if flex is requested suddenly, the EV could stop and delay it's charging process, instantaneously.

③ marks the period after $T_{full\text{-}e}$. If the EV would be requested to provide flex during that period, it would be already fully charged and can not provide flex anymore.

The graphics in chapter 9.3. (e.g. Figure 80 and following) depict instantaneous flexibility as shaded area below the baseline curve. The duration given for this flexibility corresponds to a mean duration of all charging processes providing flexibility during this hour.

After discussion and analysis of the results, and following an evaluation of the definition of "technical potential" for smart EV charging, it has been decided to set the default value for SoC_{min} to zero. This represents the full technical potential without a user-defined limitation via the minimal state-of-charge. The impact of setting SoC_{min} to higher values has been evaluated in a sensitivity analysis in 9.4.1.

9.1.2. Definition of EV fleet characteristics of the model

The fleet of vehicles in Luxembourg is being published monthly by the SNCA (Société Nationale de Circulation Automobile) via www.data.public.lu as part of Luxembourg's open data policy. The data set includes versatile parameter and allows to identify the type of drive train (e.g. full electric), as well as some information on the energy consumption per km (according to WLTP given by the manufacturer) and driving range with one charge, that enable to approximate the battery capacity.

The consumption data of electric vehicles [Wh/km] according to the registration statistics has been categorized to distinct ranges and the share of vehicles for each category has been estimated (Table 30). Similarly, the battery capacity data has been treated (Table 31), which was previously derived from the autonomy range.

Table 30 – Specific energy consumption [Wh/km] of EV fleet, according to WLTP in registration data

[Wh/km]	<= 120	120-150	150-180	180-210	210-240	>240	SUM
No. of EVs	66	5598	19401	2186	933	623	28807
Share	0.002	0.194	0.673	0.076	0.032	0.022	

Table 31 - Battery Capacity [kWh] of EV fleet, derived from registration data

[kWh]	<10	10-30	30-50	50-70	70-90	90-110	110-130	>130	SUM
No. of EVs	1083	751	4026	5890	11358	4887	594	218	28807

Share	0.038	0.026	0.14	0.20	0.39	0.17	0.020	0.008

Only those categories with a relevant share have been further considered – lower share categories are greyed out in above tables. The model generates an EV fleet portfolio representing the distributions given above, using an elasticity between both parameters, to avoid that EVs with high battery capacity and low consumption are generated and vis versa. The result is a randomized EV fleet with representative distributions of EV battery capacity and specific consumption, as depicted in Figure 72 for the example of 200 EVs.

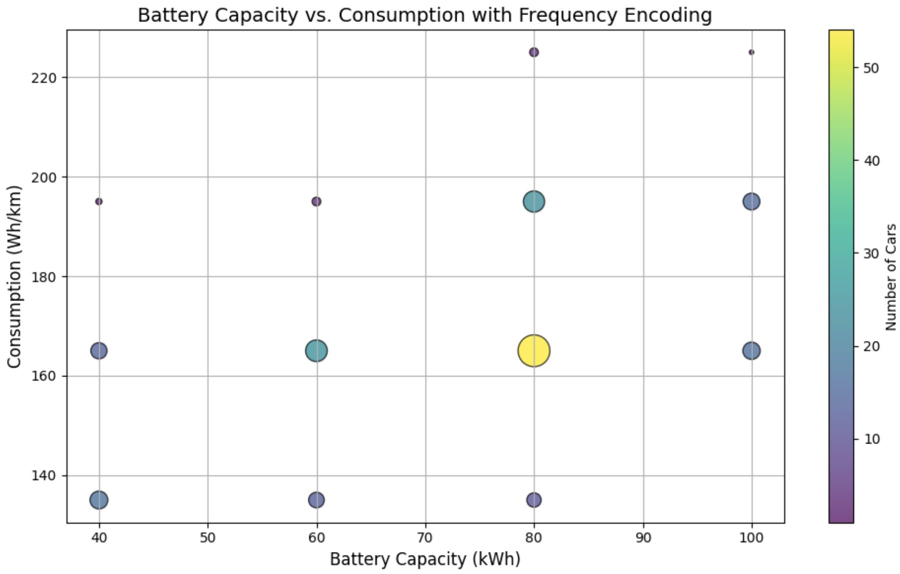


Figure 72 – Specific consumption and battery capacity of a representative EV fleet example for 200 EVs

As known from specialized driving tests under real-world condition, the real consumption of EVs is generally lower than the WLTP-based values given by the manufacturers. For example, the eco-tests of the German Automobile Club have shown a deviation of about +15% across all tested models[13]. Hence, we implemented a correction factor for this increased consumption of 15%.

Furthermore, the consumption is known to be dependent on the outdoor temperature. Tests identified higher consumption of 20 - 30%, in few cases even much higher, if the EV is operated at 0°C as compared to 20°C. Our model does not include additional temperature dependent losses, but applies a constant correction factor to account for this effect. Considering 4 colder months per year with increased consumption of up to 25%, the following constant correction factor of 8.3 % has been used:

*(4 / 12) * 25% = + 8.3%* *yearly correction factor for higher consumption in colder periods*

9.1.3. Methodology – Public EV Charging

The methodology to model EV charging and respective potential for smart charging flexibility is based on anonymized data from the public charging infrastructure “Chargy” operated by CREOS. The dataset contains basic data of about 740.000 charging processes in the time range from April 2023 until April 2024 – mainly start time, end time and the amount of energy charged. Hence, the following results of the analysis

[13] Website of the German Automobile Club ADAC, accessed Sept. 2025 (link)

of this data represent the “plug-in duration” and an estimated charging power, since it is unknown if the battery was already fully charged during this period.

Analysis of Chargy data

Those about 740.000 charging cycles stem from chargers of different types, including the more expensive fast chargers (Super Chargy), which have been excluded from the analysis since flexibility provision from those chargers is considered unlikely. Finally, 660.000 charging processes remained in the analysis – although some of those chargers might be limited in accessibility for the public.

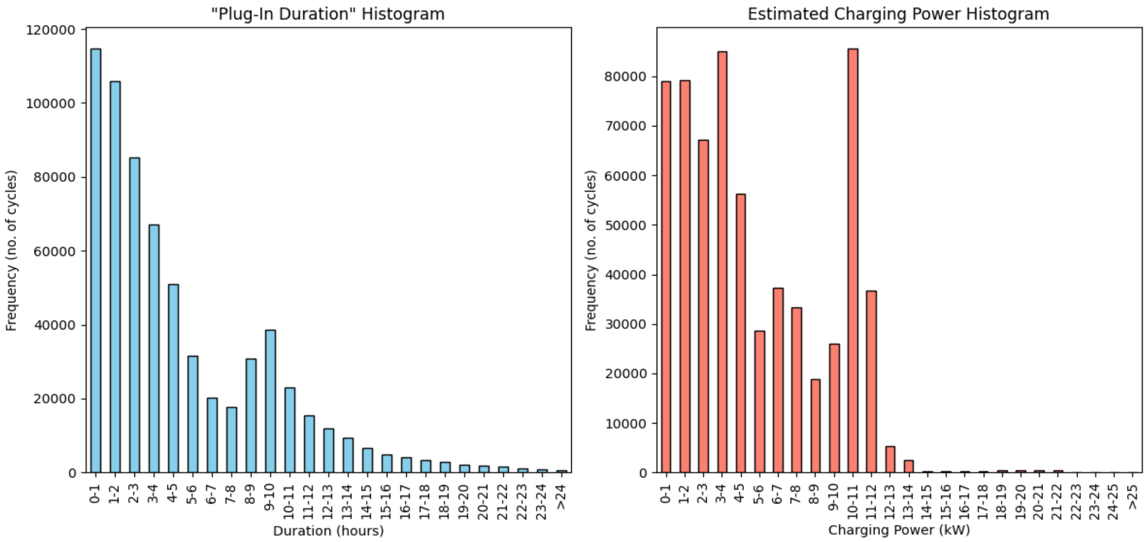


Figure 73 – Charging characteristics from public charging processes 04/2023 – 04/2024 (Chargy network)

Regarding the charging power, the effective power depends on several factors, but mostly on the charging power of the station as well as the EV itself. The analysis of plug-in times and charged energy leads to unprecise results for the charging power, but the categorisation of all charging processes reveals three peaks around the expected 3.6 kW, 7.4 kW and 11kW:

Table 32 – Occurrence of different charging powers in the data derived from public charging processes

Charging power	3.6 kW	7.4 kW	11 kW
share	29.2 %	18.1 %	52.7 %

Besides the technical parameter of the EV fleet and common charging power during public charging, the charging behaviour of the EV users is of utmost importance for the modelling: When do EV drivers charge where and for how long are they connected – insights that are also derived from this data set. In Figure 74 the average charging duration profiles for every weekday are plotted. This illustrates for each hour of the day the aggregated charging durations of all charging processes started in that hour – example: Monday 10:00, typically 560 hours of charging processes are started. The weekday curves show all a relatively similar shape, while the weekend day are distinctively different from the weekdays. Besides minor deviations from this statement for Friday and Saturday evenings. This leads to the conclusion, that our model will only differentiate for weekdays and weekends in the further modelling.

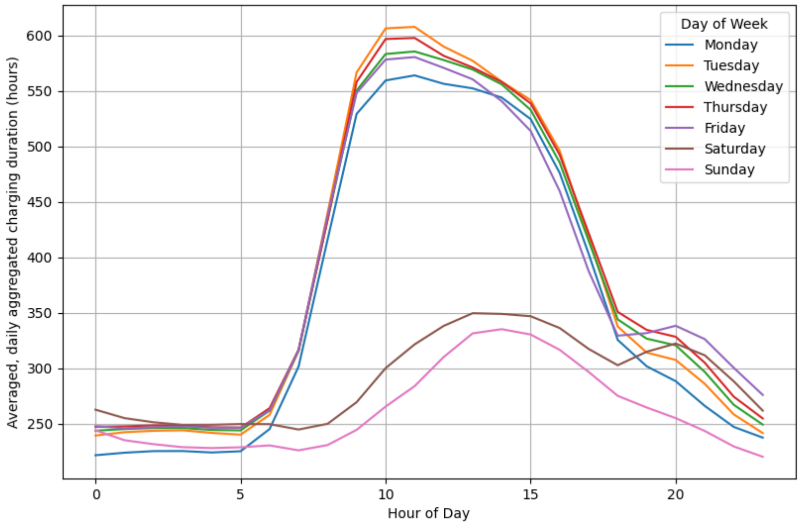


Figure 74 - Average charging duration profiles for each day of the week, by start time of the charging processes

In order to emulate the real charging behaviour for public charging in the model, a histogram of charging durations has been set up for each hour of a typical weekday and weekend day (Figure 75). The colours in the heat map indicate the amount of charging processes started during that hour, for a given duration. Based on this statistic, the model generates a representative set of charging cycles for each hour of the day during the simulation.

Since the data does not contain any information on the state of charge of the EVs the "SoC $_{arrive}$" need to be assumed.

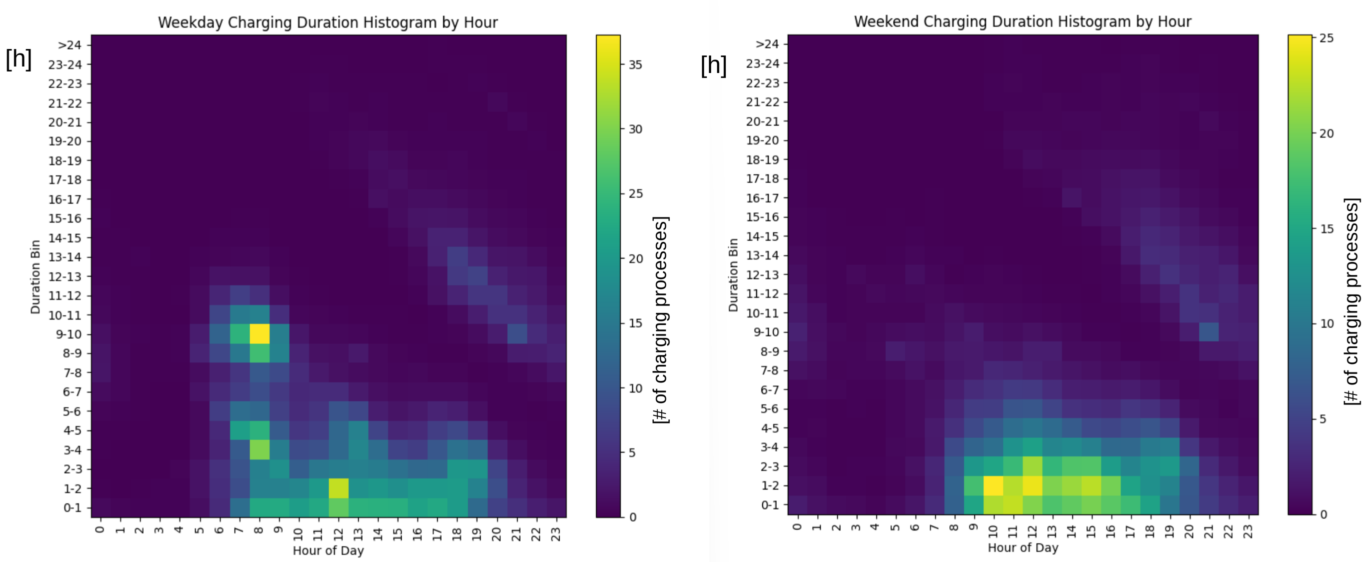


Figure 75 – Heat map plot of histograms of charging durations for each hour of the day (weekday – left; weekend – right)

9.1.4. Methodology – EV Charging at home and at workplace

For the charging behaviour of EV users at home and workplace, there is no data available to derive charging durations and schedules. The model to emulate the home charging behaviour, as well as the charging at workplace, is based on an openly available tool developed by *(Gaete-Morales et al., 2021)*, to create time series data for electric vehicles. The tool can be based on detailed mobility statistics, which are also not available for Luxembourg. So, the data for the German use case have been taken over, which comes with several major assumptions and characteristics:

- Model distinguishes workdays and Saturdays / Sundays
- Considers 62% of EV users as commuters and 38 % as non-commuter
- Commuters: 78% full-time / 22% part-time
- Yearly milage of 10.000 – 15.000 km

The model provides 200 yearly mobility profiles in quarter-hourly resolution – example for one week can be found in Figure 76:

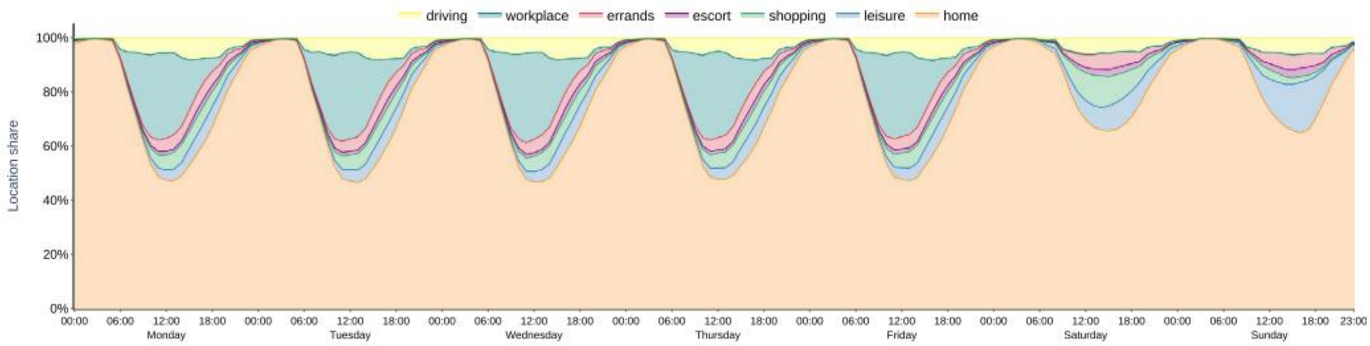


Figure 76 – Mobility profiles for 200 EVs, indicating their location over a full week *(Gaete-Morales et al., 2021)*

Model / Assumptions

These mobility profiles are used by the FlexBeAn model to simulate 200 EVs in hourly resolution over one year. For each "driving" time step, the consumption is calculated based on the EV characteristics (9.1.2) and driving distances and a new SoC is estimated. Flexibility could only be provided when the EV is plugged in and there is free capacity in the battery. One decisive parameter of the model is the assumption up from which SoC the user would plug-in his EV for charging, the "charging threshold". For the results presented in this report, a charging threshold of 50% has been considered – hence, once the user reaches a SoC below 50% and the car is either at home or at work, the model starts a charging process.

Charging condition: *(SoC < 50%)* *AND* *(location = home OR workplace)*

The sensitivity of the simulation results to the choice of the charging threshold has been analysed in a sensitivity analysis documented in 9.4.1.

Further, it is assumed that the EV remains connected to the wall box or charging station until the next "time of leave", according to the mobility data. During this period, flexibility could be provided until the latest possible start of the charging process that guarantee a full charge. If a minimum SoC, up from which the EV user agrees to provide flexibility is defined, the flexibility is only provided once this SoC is reached. As laid out previously, in this simulation SoC_{min} has been set to 0%.

Based on this model the baseline consumption of the 200 EVs is calculated and the potential flexibility, based on the same model as "public charging". In a next step, this baseline and flexibility potential is upscaled to national level and allocated to the communes.

9.1.5. Methodology – allocation to communal level

The baseline consumption from EV charging (public, home, workplace) as well as the flexibility potential is upscaled to the national level, using the absolute numbers of EVs and future scenarios, and is finally broken down and allocated to the communes. How this allocation is done depends on the charging type:

Public Charging

The data from public charging has been analysed and the charging stations allocated to communes. Based on these statistics, the hourly share for each commune on the public charging profile has been estimated for weekdays and weekends. This relative charging shares are used to allocate the upscaled baseline and flexibility results to each commune.

Home Charging

The SNCA registration data includes information on the communes where the EVs are registered and differentiates cars registered by private persons or companies. For the allocation of home charging activities, it can be considered that EVs, registered by private people, are charged in the respective commune. While companies cars are registered at the companies location. Hence, only the privately registered EVs have been considered to estimate the EV share per commune for home charging, and the upscaled numbers have been allocated using this statistics.

Workplace Charging

The allocation of workplace charging is done by figures estimate by STATEC and University of Luxembourg in (Ferro et al., 2024) covering the amount of jobs held by residents per commune. This breaks down to almost 77 % of the jobs being allocated in one of the 22 main communes clustered to 5 main agglomeration areas (Figure 77). The remaining 23.2% of jobs are distributed over 78 communes. The workplace charging baseline and flexibility has been accordingly allocated by these share of workplaces to the respective communes.

Towns in the cluster	Number of jobs held by residents	
	Workforce	Percentage
Luxembourg City	80 188	39.3%
Bertrange	5 116	2.5%
Niederanven	4 138	2.0%
Mamer	3 929	1.9%
Strassen	3 527	1.7%
Leudelange	3 387	1.7%
Hesperange	3 330	1.6%
Contern	2 862	1.4%
Sandweiler	2 754	1.3%
Total in the conurbation	109 231	53.5%
Esch-sur-Alzette	11 413	5.6%
Dudelange	4 052	2.0%
Differdange	3 983	1.9%
Sanem	3 247	1.6%
Pétange	3 206	1.6%
Bettembourg	2 773	1.4%
Käerjeng	2 303	1.1%
Total in the southern conurbation	30 977	15.2%
Ettelbruck	3 960	1.9%
Diekirch	3 919	1.9%
Colmar-Berg	2 083	1.0%
Erpeldange-sur-Sûre	1 165	0.6%
Total Nordstad	11 127	5.5%
Mersch	3 243	1.6%
Wiltz	2 147	1.1%
Total for the divisions	156 725	76.8%
Outside centres	47 368	23.2%
Total	204 093	100%

Source: STATEC RP 2021. Note: the numbers only include respondents to the question on the municipality of work

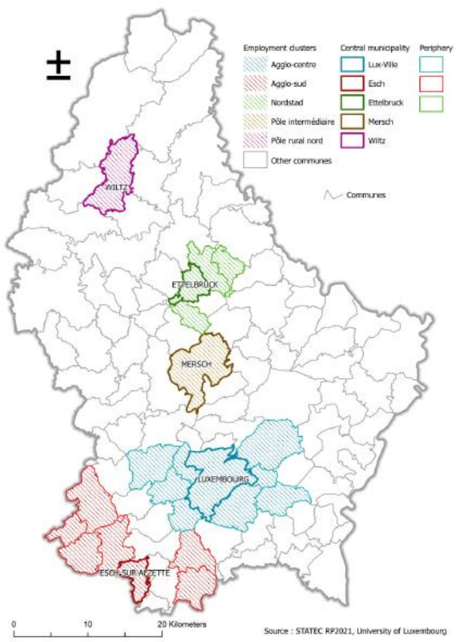


Figure 77 – Number of jobs held by residents, clustered to the main agglomeration areas (Ferro et al., 2024)

9.2. Scenarios for electric mobility

The SNCA, responsible for the registration of motor vehicles in Luxembourg, reports 34’819 full electric vehicles by the end of 2024 (excl. lorries / trucks), which is the number that is considered in the further assessment for “today”. Future growth rates are expected to be very high, as the shift towards electric mobility, driven by the national decarbonisation strategy, is a politically supported transition process. This is documented in the national energy and climate (MEA & MECD, 2018), as well as in its updated version (MEA & MECD, 2024), the “Third industrial revolution” strategy paper (The TIR Consulting Group, 2016) and has been taken up by CREOS in their scenario report (CREOS & Schroeder, 2024) although, the absolute numbers for the projected scenarios differ substantially (Table 33).

Table 33 – Versatile scenarios for EV growth from today towards 2030 & 2040

Scenario-Name	**Today** (2024)	**2030**	**2040**
NECP Ref.	34’819	113’750	182’000
NECP Target	34’819	287’804	472’000
TIR medium	34’819	98’046	248’000

The latest edition of the CREOS Scenario report 2040 (Version 2024) takes over projections by STATEC, which have been also chosen as a basis for this assessment for the years 2030 and 2040:

Table 34 - FlexBeAn EV Scenario, aligned with CREOS Scenario Report 2040, v2024

FlexBeAn EV Scenario	**Today** (2024)	**2030**	**2040**
No. of EVs	34’819	154’086	430’525

9.3. Results – Flexibility potential by EVs at public charging

This chapter describes the baseline consumption and flexibility by “smart charging” at public charging infrastructures for EVs, as resulting from the FlexBeAn model, based on anonymized “Chargy” data.

9.3.1. Maximum delayed charging and modulated charging power

The figure below shows the baseline consumption for public charging based on our analysis of the “chargy” data for a typical weekday as a solid blue line (Figure 78). After very low charging activities during early morning hours, the profile rises steeply up from 6:00 in the morning until it reaches a peak of about 4.000 [kW] at 9:00. After this peak, the profile drops constantly, reaching a minimum at about 17:00 o’clock, and rises toward a much smaller peak of about 2.000 [kW] at 19:00, followed by another drop until midnight. Since specifically the EV users arriving during the morning hours at the charging stations, typically stay connected for a rather long time (4h – 9h), there is a certain potential to shift parts of their charging activities towards the afternoon. This is illustrated by the profile “max delay”, which (as described in 9.1.1) considers the full delay until the latest possible charging start time, to still guarantee a full charge. As depicted in the graph, by this “max. delay strategy”, the overall peak would be reduced to about 3.650 [kW] and shifted towards the afternoon (14:00), the much smaller “evening peak” would be reduced and consumption spread over night into the early morning hours.

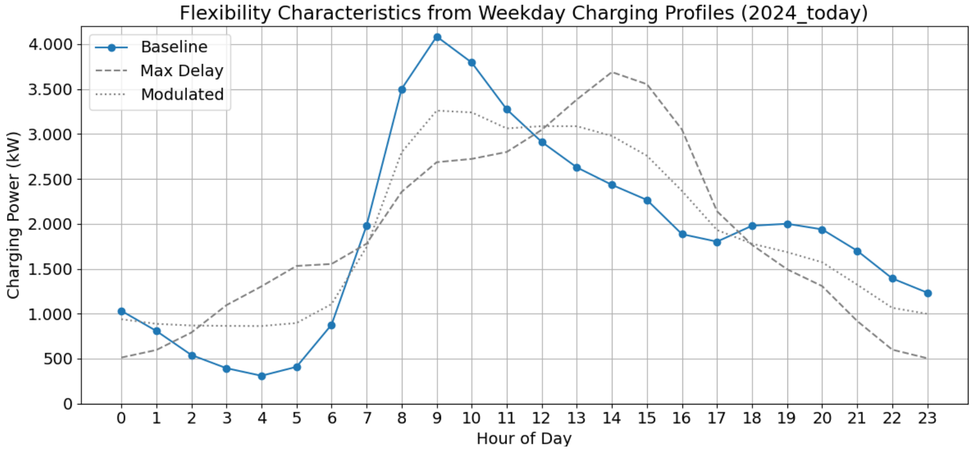


Figure 78 – Baseline and flexibility from public EV charging on weekdays - today

Similarly, the "modulated power" option could result in a smoother, reduced charging profile, as compared to the baseline, but the overall schedule would be maintained. This option shows minimas and maximas during the same hours as the baseline profile, but with smaller amplitudes, reducing the 9:00 o'clock peak from 4.000 [kW] to 3.250 [kW] and smoothening the early morning dip, representing overall a much more balanced charging profile.

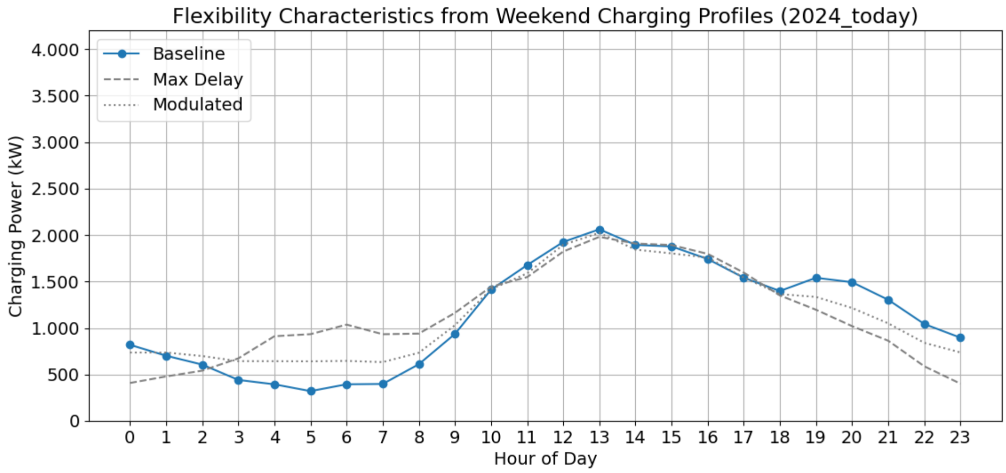


Figure 79 - Baseline and flexibility from public EV charging on weekends – today

The typical weekend day is characterized by a generally much lower charging baseline profile, reaching a peak of slightly over 2.000 [kW] at 11:00 which is relatively stable until 15:00 (see Figure 79). Since the average charging duration at the public charging stations during weekends is substantially shortened, the flexibility potential is largely reduced, as compared to weekdays. Both flexibility strategies ("max. delay" and "modulated charging power") show a small smoothing effect during morning and evening hours, at generally low consumption levels, but would hardly influence the peak consumption.

9.3.2. Instantaneous flexibility – public charging

While the results of the previous sub-chapter represent rather constantly applied smart charging strategies in order to smoothen the profile, the concept behind "instantaneous flexibility" is the demand driven instant reduction of the load via a signal. This means that the grey shaded area underneath the baseline profile of a weekday in Figure 80, represents the flexibility potential ***for each specific hour*** : e.g. the baseline shows a peak of 4.000 [kW] at 9:00, which could be potentially reduced to under 1.600 [kW], if all ongoing and started charging processes of this hour are asked to delay their charge, if possible (see 9.1.1). The concerned charging processes at 9:00 (ongoing or started during that hour) have different durations for their delay, while some could not be delayed at all, but on average they could provide this flexibility for 4 hours, as shown by the blue bar referenced to the right axis.

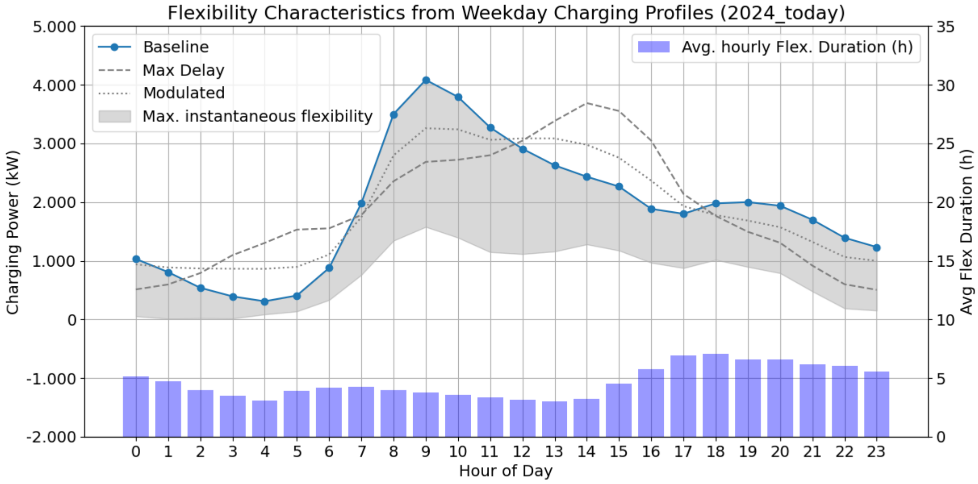


Figure 80 – Instantaneous flexibility during weekdays by public charging – today

The same logic applies to the weekend profile in Figure 81, just at much reduced amplitudes. During the peak plateau between 11:00 and 15:00, the charging power could be reduced instantly (during a specific hour) by about 800 [kW], almost half of the load, while the average duration is 2,5 h - 4h, during that period.

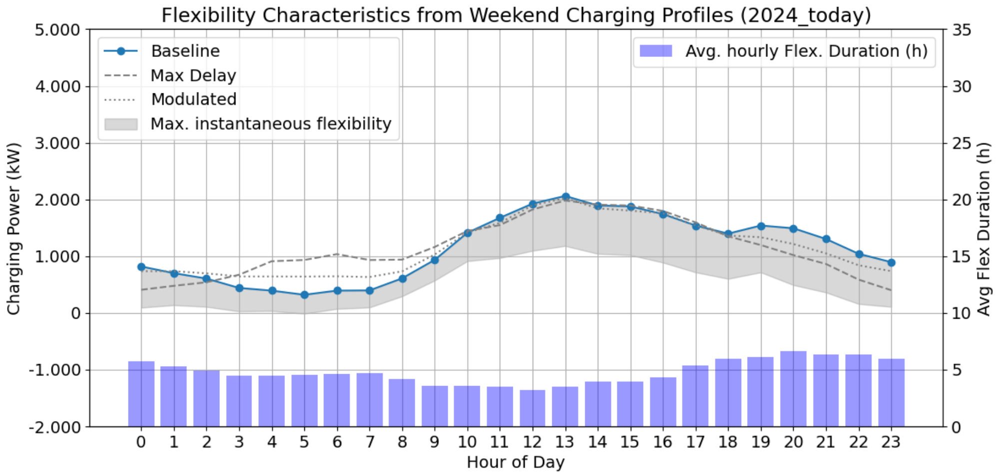


Figure 81 - Instantaneous flexibility during weekends by public charging – today

The main results are included in the Table 35, giving the hourly values for the baseline charging profile of public charging, as well as the instantaneous flexibility values and the respective average duration, at each hour of the day.

Table 35 – Baseline- and instantaneous flexibility-profile of public charging today

	Public – weekday			Public – weekend		
Hour of day	Baseline [kW]	Instant. Flex.[kW]	Duration [h]	Baseline [kW]	Instant. Flex.[kW]	Duration [h]
00:00	847	835	5.5	735	730	6.3
01:00	737	658	4.8	669	575	5.7
02:00	576	508	4.2	559	484	5.7
03:00	477	384	3.8	464	418	5.2
04:00	386	322	3.5	357	293	4.6
05:00	441	307	3.9	358	267	4.4
06:00	852	660	4.1	343	297	4.0
07:00	1946	1236	4.1	431	286	4.3
08:00	3404	2179	3.9	651	414	3.4
09:00	4012	2546	3.9	1014	521	3.4
10:00	3718	2367	3.8	1458	579	3.3
11:00	3345	2162	3.5	1773	715	4.6
12:00	2973	1817	3.3	2033	866	4.5
13:00	2606	1365	3.2	2150	998	4.5
14:00	2341	984	3.7	2184	946	4.3
15:00	2041	777	4.2	2051	906	4.3
16:00	1972	741	5.0	1688	704	4.5
17:00	1801	767	6.5	1421	708	5.3
18:00	1967	942	6.9	1618	781	6.0
19:00	2095	1026	6.6	1680	975	6.3
20:00	1874	1052	6.4	1560	1019	6.6
21:00	1485	1095	6.2	1417	1038	6.4
22:00	1357	1124	6.3	1062	898	6.6
23:00	1104	934	6.0	970	781	6.5

9.3.3. Results for public charging – communal level

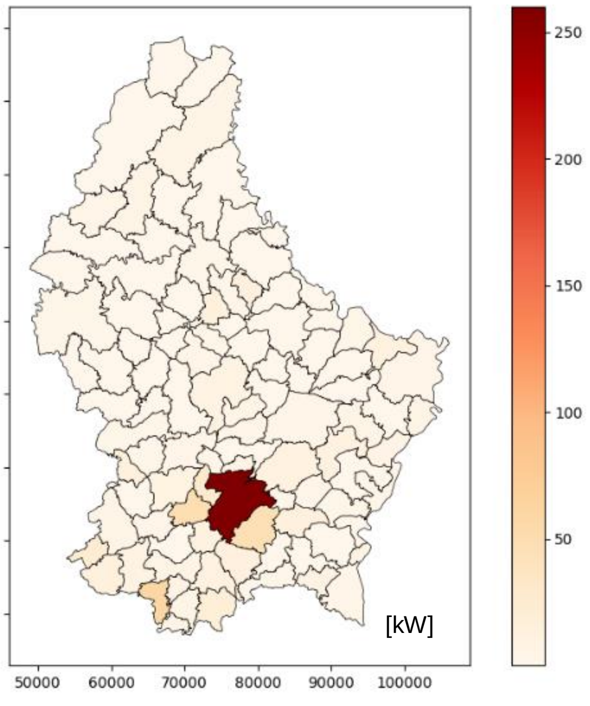


Figure 82 – Communal distribution of average instantaneous flexibility from public charging

The estimated instantaneous flexibility is being distributed over the communes, based on the hourly share of the public charging stations within a commune on the public charging load profile.

Instead of giving the absolute numbers for the 100 communes (*find table in the Annex)* a qualitative impression of the distribution of public charging activities and related flexibility can be gained from Figure 82. The focus of public charging infrastructure and demand on the City of Luxembourg is obvious, reaching 31.6 % of the total potential. The next six communes with highest shares are Esch-sur-Alzette (7.2%), Bertrange (5.9%), Hesperange (5.5%), Strassen (3.4%), Pétange (2.7%) and Dudelange (2.3%) – summing up to almost 60% of the national potential from public charging for these seven communes.

9.4. Results – Flexibility potential by EVs while charging at home and workplace

In the following chapter, the baseline consumption and flexibility by “smart charging” at home charging and charging at workplace are presented. Those values stem from a simulation of 200 artificial mobility profiles for EVs, as incorporated in the FlexBeAn model. The charging threshold has been set to 50%, which means that EV owners would plug-in their EV (either at home or at workplace) whenever this threshold is surpassed. Further, it is assumed that the EV remains plugged-in until the next leave.

9.4.1. Simulation results - 200 EVs charging at home or workplace

The model used within this project to estimate baseline consumption and flexibility potential from home- and workplace charging simulates artificial mobility profiles of 200 EVs in hourly resolution over one year, estimating their energy consumption for typical mobility behaviour and assesses charging periods. The simulation results for 200 EV are upscaled in a following step to the national level and future scenarios. This means, that the profiles for 200 EVs, presented in this chapter, give already all the insights in the schedules and dynamics of the charging profiles on national level, but the absolute numbers will be presented in the later chapter (9.4.2).

The general tendency for **home charging**, approving our expectations, is that the EV users charge at home mainly towards the evening hours and overnight. Obviously, the model also reproduces charging behaviour at workplace during the working hours, with a focus on the morning period. With a typical yearly milage between 10.000 – 15.000 km per year, the model resulted in 3 - 5 charging periods per month for the average EV, resulting in only few periods where the EV would be connected to the grid and could potentially provide flexibility. Some other studies assume that EVs might be plugged in whenever parked at home, for example, which would result in drastically higher “grid availability”, although this would only be reasonable in case of V2G-scenarios. The “smart charging” scenario would not be largely affected by this assumption since the free capacity in the battery would be very limited, if plugged in after each short trip.

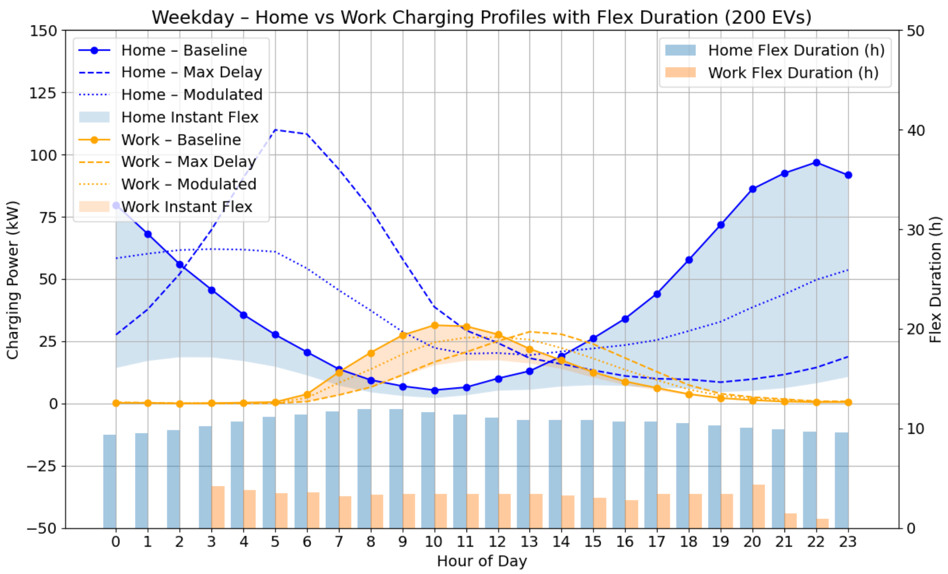


Figure 83 – Baseline- and flexibility- profile for home- and workplace- charging, as simulation result for 200 EVs during a typical weekday

Analysing the simulation results and deriving a profile for a typical weekday, results in baseline consumption as depicted in Figure 83. For home charging (blue solid line), from midnight to early morning hours, the charging power gradually drops, since EVs reach their full charge. After a very low charging power during the morning, the profile gradually rises over afternoon and reaches its peak between 19:00 and 23:00. A permanent “max delay” smart charging strategy (blue dashed line) would shift nighttime charging towards the morning and could reduce the evening peak even by up to 80%, since the long charging periods in the evening allow to shift almost all the ongoing charging cycles. A more moderate smart charging strategy with modulated charging power would smooth the charging profile, reduce the evening peak by about 50%, but would generally have less impact on the consumption schedule.

The hourly, instantaneous flexibility potential (blue shaded area underneath the baseline) indicates the signal based, instantly reduction of the charging power and can be approximated to be even up to 80-90% during the periods of highest charging power (from 21:00 up to the early morning hours). During the day, this flexibility potential is rather low. The average duration a EV fleet could provide this hourly, instant flexibility is about 8-9 hours during the evening and night times, when the potential is high, and about 10-12 hours during the day, at a low absolute potential.

Baseline consumption for **EV charging at workplace** (solid orange line) is generally estimated to be much smaller than for home charging, and the schedule is almost the inverted profile. The instant flexibility potential (orange shaded area) is only relevant during a period from 6:00 to 14:00 and could reduce the consumption by about 50-70% of the baseline profile in the morning hours, with an average duration of 2 - 4,5 hours, but is very low after noon.

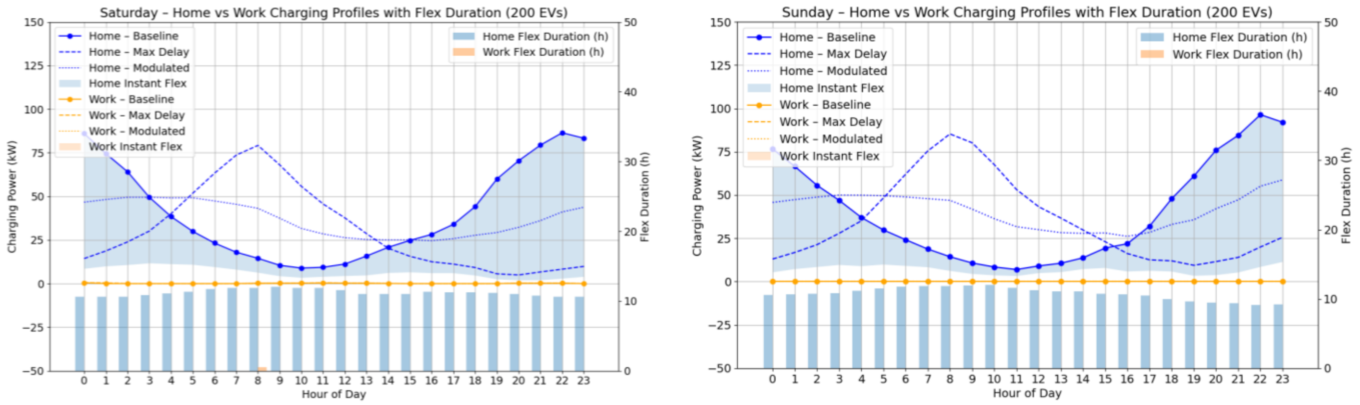


Figure 84 - Baseline- and flexibility- profile for home- and workplace- charging, during weekends (200 EVs)

While analysing the simulation results, similarly to weekdays, the typical baseline- and flexibility profiles for Saturdays and Sundays have been derived from the data. Both weekend days show similarly shapes for all estimated metrics: baseline consumption, max delay flexibility, modulated power flexibility, as well as instantaneous hourly flexibility. As compared to weekdays both week end days show only slightly lower baseline profiles, at comparable schedules and dynamics. Only Saturday night seems to deviate a bit more from the other days, with a lower general consumption level. Instantaneous flexibility and the related duration remains at comparable levels.

Sensitivity analysis – minimum State of Charge, before flexibility provision - (SoC_{min})

The idea behind the minimum state of charge, which is supposed to be defined by the EV user when starting a charging process, is to enable the user to assure that he/she has, as soon as possible, a minimum range of mobility for unforeseen rides. Obviously, setting a high SoC_{min} could be rather limiting to the flexibility potential, and the definition of that value is certainly very subjective, depending on user behaviour and other circumstances. It could further be argued if the SoC_{min} should be set at all, when estimating the “technical” flexibility potential. Hence, in the following we are assessing the effect of SoC min on the overall result.

Varying SoC_{min} from 0% to 75%:

The upper graph visualizes, that for ***Public charging***, SOC_{min} plays a big role: The graph depicts the baseline charging curve and the level to which the charging could be reduced by instant flexibility for different SOC_{min}. During the peak hour, where also the residence time of EVs in public charging is the longest, the sensitivity is the highest. At times where fluctuation of EVs (arrival & departures) is lower, e.g. nights, the sensitivity is much less.

Regarding ***home and workplace charging***, the impact of SOC_{min} is particularly high for home charging, where the residence times are long. The flexibility at 75% SOC_{min}, e.g. in the important evening hours where many EVs arrive at home, is quite limited. The change towards 50% has huge impact, further decrease to 25% as well, while setting to 0 does affect the result rather marginal. At workplace, sensitivity is specifically given in the morning hours, before 11:00, but the impact is comparably limited.

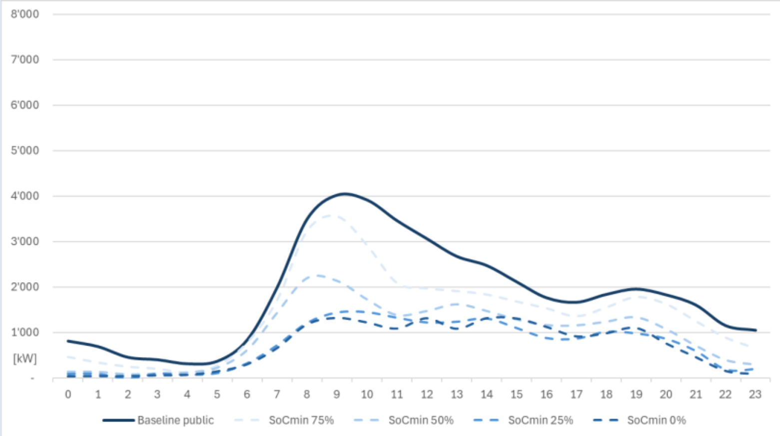


Figure 85 – sensitivity of public charging flexibility on SOC_{min}

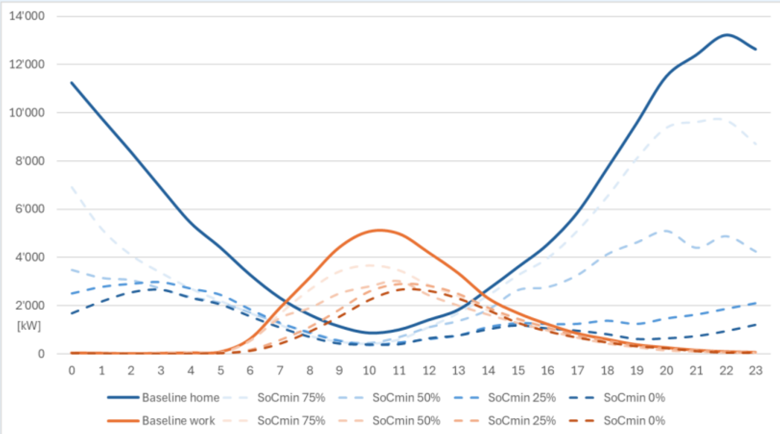


Figure 86 – sensitivity, home & work charging flex-to SOC_{min}

Generally, considering a minimal state of charge (SOC_{min}) is found to have strong impact on the resulting flexibility, specifically important during the typical arrival times. Defining a SOC_{min} of 75% restricts the instant flexibility fundamentally. A value of 50% and 25% increases the amount of flexibility to a large extend, could even reach 200-300% during peak times as compared to a SOC_{min} of 75%, while a further decrease towards 0% results in only minor additional flexibility, according to our model.

Impact on overall flexibility potential

Averaging the fluctuating instant flexibility over the diurnal profile and comparing the results for different SOC_{min} and charging locations lead to the results shown in Figure 87. SOC_{min} sensitivity is particularly high for the home charging result and less impacting for the other two locations. The overall results confirm the impression of a very restrictive impact of a high SOC_{min} on the flexibility potential.

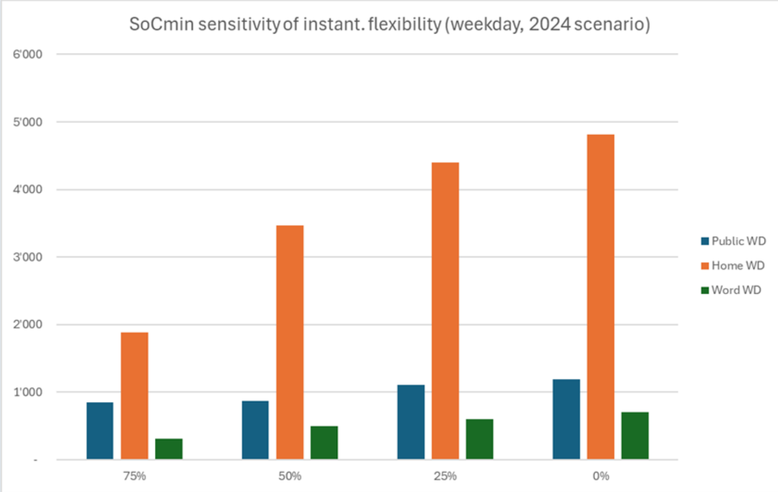


Figure 87 – overall sensitivity of results on SOC_{min}

The aggregation of the daily averaged instant flexibility potential, acoss charging locations, results in a 121% higher flexibility for 0% SOC_{min} as compared to 75%, as indicated in Table 36.

Table 36 – sensitivity of instant flexibility on SoC_{min} definition (weekday, 2024)

SoC min	75 %	50 %	25 %	0 %
agg. avg. flexibility	3’036 kW	4’826 kW	6’110 kW	6’702 kW
Rise in instant. Flex.	-	+ 59 %	+ 101 %	+ 121 %

Conclusion: Based on the results of the sensitivity analysis, showing particularly high sensitivity of the flexibility to SoC_{min} , and the purpose of this study to estimate the full technical flexibility potential of this technology, it has been decided to present by default the results of the model for an SoC_{min} = 0. Previous and following chapters are therefore modelling results without a set minimum of State of Charge (SoC_{min} = 0).

Sensitivity analysis - Charging Threshold

The state of charge of the battery, up from which an EV user decides to plug-in the car for charging might be a very subjective value or might even depend on random factors. But the choice of this parameter is decisive for the grid availability of the EV. To compare and estimate the effect of the parameter choice on the simulation results, two extreme values of 20% and 80% were chosen and the resulting graphs are depicted below. The main results in previous and following chapters have been estimated using a charging threshold of 50%.

Charge Threshold: 80%

Assuming that users regularly charge the EV once the SoC drops below 80% increases the peaks of home- and work-charging baselines and shifts these to earlier times. It further reduces the morning baseline of home charging, since the average charging duration drops largely. It has only marginal impact on the instant flexibility per hour, with an SoC_{min} of 0%.

Anyhow, this value seems unlikely without incentivising this behaviour.

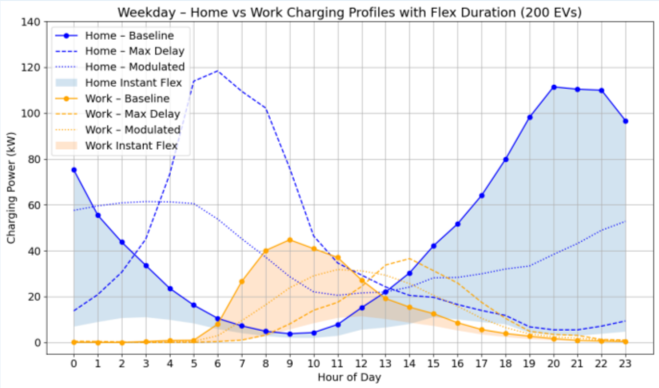


Figure 88 – Charging threshold 80%, for home and workplace charging

Charge Threshold: 20%

A charging threshold of 20% seems rather low, specifically for home charging. It reduces the evening peak of the simulation results and increases the charging power during the morning hours for home charging. It reduces and shifts the baseline of workplace charging to later hours. Generally, the instant flex. is reduced, since the average required charging duration for a full charge is largely prolonged. Those longer charging durations and lower grid availability of EVs reduce the share of the stationary duration that is usable for flexibility provision.

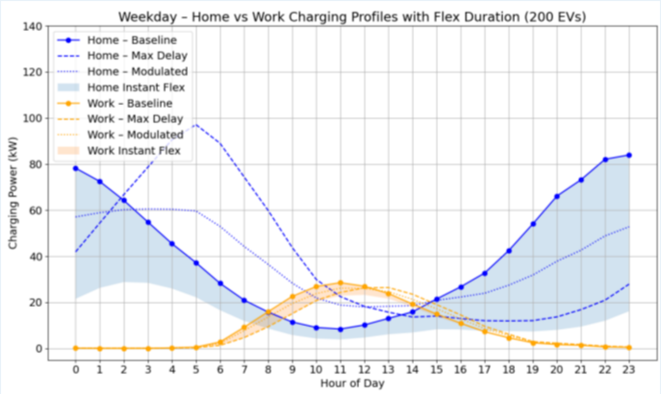


Figure 89 – Charging threshold 20%, for home and workplace charging

9.4.2. National level & Communal level - today

As described earlier, the simulation results of the 200 EV mobility profiles have been upscaled to the number of EVs registered in Luxembourg today. This means, that all dynamics and schedules regarding the daily and weekly charging baseline as well as the flexibility profiles remain unchanged, as presented under 9.4.1, but the absolute values are upscaled.

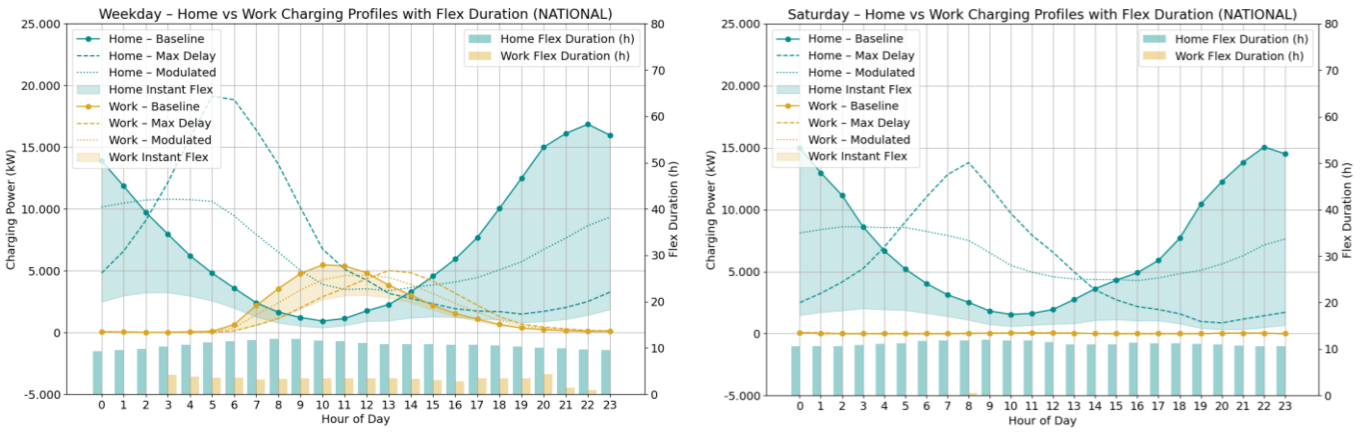


Figure 90 – Baseline- and flexibility profile for home charging and at workplace (left axis), incl. average duration (right axis) at todays EV penetration; left graph: weekday; right graph Saturday, exemplary for weekends

As shown in Figure 90 for a typical weekday, the baseline consumption for home charging at night comes from a high level of 13.9 [MW] that could be reduced by about 11.4 [MW] instant. flexibility. The baseline profile falls under 1 [MW] during the morning at low flexibility. The baseline profile peaks at 22:00 at about 16.8 [MW] with the highest flexibility around 22:00 at 15.4 [MW]. The average duration remains unchanged as compared to the unscaled results, in between 9 and almost 12 hours. The weekend profile for home charging is similar to the weekday, at slightly reduced absolute values for the baseline, a lower evening peak and slightly increased flexibility and durations, due to longer idle times. See Table 37 for absolute values.

Table 37 – Baseline- and instantaneous flexibility for home- and workplace charging

	Home – Week day			Home – Saturday			Home – Sunday			Work – Week day		
Hour of day	Baseline [kW]	Instant. Flex.[kW]	Duration [h]	Baseline [kW]	Instant. Flex.[kW]	Duration [h]	Baseline [kW]	Instant. Flex.[kW]	Duration [h]	Baseline [kW]	Instant. Flex.[kW]	Duration [h]
00:00	13898	11413	9.3	14980	13500	10.6	13344	12414	10.6	46	0	0.0
01:00	11857	8877	9.5	12977	11254	10.6	11586	10325	10.6	39	0	0.0
02:00	9740	6505	9.9	11159	9301	10.6	9683	8215	10.7	10	0	0.0
03:00	7966	4738	10.3	8620	6590	10.9	8172	6496	10.9	24	22	4.2
04:00	6224	3256	10.7	6693	4748	11.1	6452	4900	11.2	61	59	3.8
05:00	4816	2241	11.1	5209	3326	11.3	5189	3477	11.5	98	81	3.5
06:00	3599	1625	11.4	4047	2396	11.7	4209	2630	11.8	652	519	3.5
07:00	2405	1145	11.7	3130	1735	11.9	3267	1823	11.8	2188	1603	3.2
08:00	1645	862	11.9	2520	1429	11.9	2496	1420	11.9	3558	2443	3.3
09:00	1217	690	11.9	1826	1087	12.0	1866	1092	11.9	4773	2871	3.4
10:00	935	547	11.6	1550	968	11.8	1467	838	12.0	5473	2809	3.4
11:00	1136	566	11.4	1629	945	11.9	1214	656	11.6	5403	2415	3.4
12:00	1753	852	11.0	1951	1194	11.5	1573	718	11.3	4833	1808	3.4
13:00	2272	1311	10.8	2751	1932	11.0	1844	891	11.1	3823	1020	3.4
14:00	3305	2114	10.8	3626	2560	11.0	2387	1126	11.1	3023	602	3.3
15:00	4565	3284	10.9	4314	3186	11.0	3369	1997	10.7	2191	377	3.0
16:00	5941	4712	10.7	4914	3874	11.4	3809	2794	10.7	1542	257	2.8
17:00	7693	6604	10.7	5917	4877	11.3	5574	4486	10.5	1087	164	3.4
18:00	10049	9008	10.5	7694	6887	11.3	8336	7321	10.0	658	83	3.4
19:00	12494	11700	10.3	10442	10016	11.1	10614	10032	9.7	378	44	3.4
20:00	15003	14107	10.1	12268	11942	11.0	13214	12560	9.4	234	15	4.4

21:00	16107	15032	9.9	13822	13485	10.8	14708	13789	9.3	136	7	1.5
22:00	16867	15456	9.7	15055	14560	10.6	16780	15301	9.1	92	15	1.0
23:00	15975	14122	9.6	14511	13836	10.6	16015	14039	9.2	92	0	0.0

The charging behaviour for workplace charging, as estimated by the model, reaches a peak between 10:00 and 11:00 at 5.4 [MW] and a reduction potential of 2.8 [MW].

The graphs further depict the steady smart charging strategies “max delay” and “modulated charging” - their character remains unaltered by the upscaling. Hence, via a constant maximum delay (dashed line) of all charging cycles, within the limits of the described flexibility model, the night time charge would be shifted towards the morning, creating a even higher morning peak at about 18 [MW] around 5:00 o’clock. In this extreme case, the evening peak could be reduced to even below 3 [MW]. Also the damping effect of a modulated charging power strategy is visualized on above graphs, reaching less peak reduction as compared to a “max delay” strategy.

Communal level

Allocating the EV charging activity and respective flexibility from **home charging** to the individual communes is done by the share of privately owned EVs registered per commune (SNCA). Also here, the absolute numbers (instant. flexibility) for today are considered less important, but the availability of the flexibility across the national territory should be estimated.

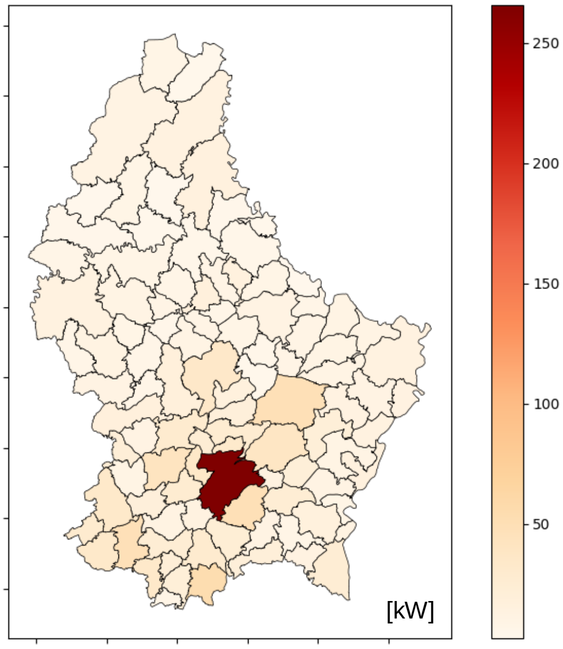


Figure 91 - Communal distribution of average instantaneous flexibility from home charging

By far the highest share of (privately owned) EVs is registered in the capital, with 14.2 % in the City of Luxembourg. The following communes are Dudelange (2.9 %), Hesperange (2.7%), Junglinster (2.6 %), Sanem (2.6 %), Mamer (2.3 %), Niederanven (2.1 %), Strassen (1.9 %), Mersch (1.9 %) and Esch-sur-Alzette (1.8 %).

Via these shares the home charging baseline and flexibility profiles have been allocated to the communes, visualized in Figure 91 and numbers given in the table in the annex.

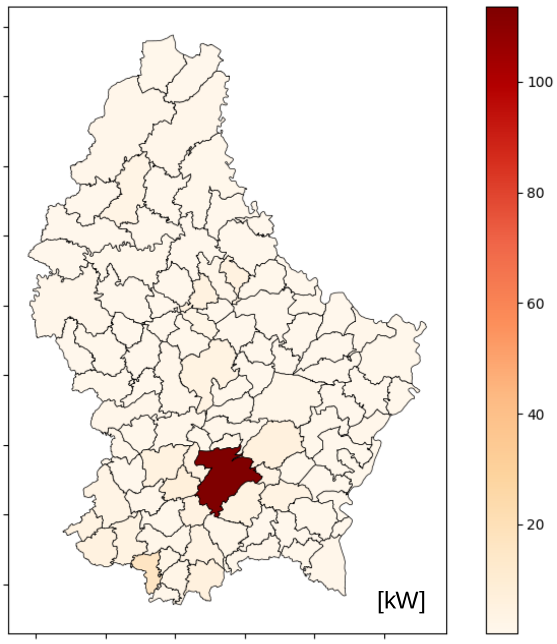


Figure 92 - Communal distribution of average instantaneous flexibility from work charging

The allocation of workplace charging is done via the amount of jobs (held by residents) per commune.

Obviously, the large majority of jobs are situated in Luxembourg (39.2 %), hence the work-place charging has been allocated with that share to the capital city. The following communes are Esch-sur-Alzette (5.6 %), Bertrange (2.5%), Dudelange (2 %) and Niederanven (2 %) while other communes have a share below 2% (Figure 92).

Also here, the absolute values can be found in the annex.

9.5. Overall results on national level – 2030 & 2040

The above described results for nation-wide EV charging baseline and flexibility represented the current state of EV penetration, based on the public charging data from 2023 to 2024 and the total number of full electric vehicles of 34’819 cars, as reported by the SNCA.

To upscale those profiles for higher amounts of EVs in the country in 2030 and 2040, the scenarios presented in 9.2 were used. Those scenarios, based on the CREOS Scenario report data in the 2024 version, were accounting for about 154’100 EVs in 2030 and 430’500 EVs in 2040. The upscaling doesn’t affect the dynamics, flexibility durations and schedules resulting from the EV model, but provide absolute numbers for all three charging locations in 2030 and 2040, for weekdays and weekends.

According to the modelling results depicted in Figure 93, the baseline peak consumption for **home charging** (at 22:00) reaches up to 75 MW in 2030 and almost 210 MW in 2040. During these evening and night periods, instant flexibility is also the highest, between 50 – 68 MW in 2030 and 145 – 190 MW in 2040. This flexibility during the evening / night time hours is a valuable measure to mitigate the evening peak, as described in 1.4 on flexibility use cases. Weekend show similar profiles, with slightly lower peak consumptions and higher flexibility characteristics.

The steady flexibility strategies “max delay” and “modulated charging” showcase again the extend to which the peaks can be reduced or completely shifted towards the morning hours, respectively how the profile could be smoothened.

2030 | **2040**

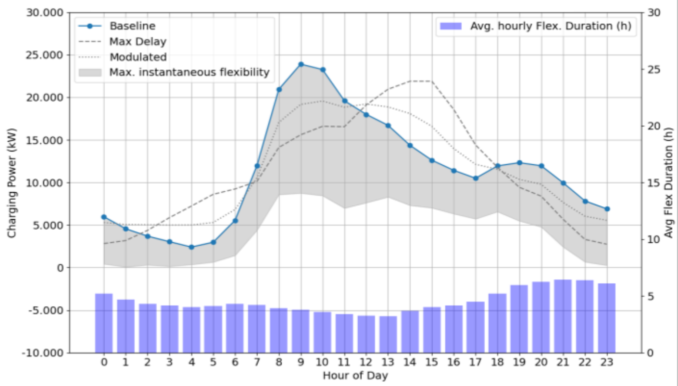
Weekday / home- and work-charging | **Weekday / home- and work-charging**

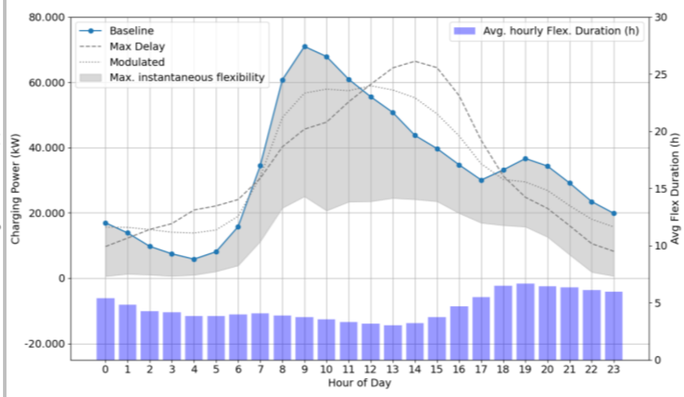
Weekend (Sat.) / home- and work-charging | **Weekend (Sat.) / home- and work-charging**

Figure 93 – Baseline- and flexibility profiles for home charging and workplace, for 2030 and 2040

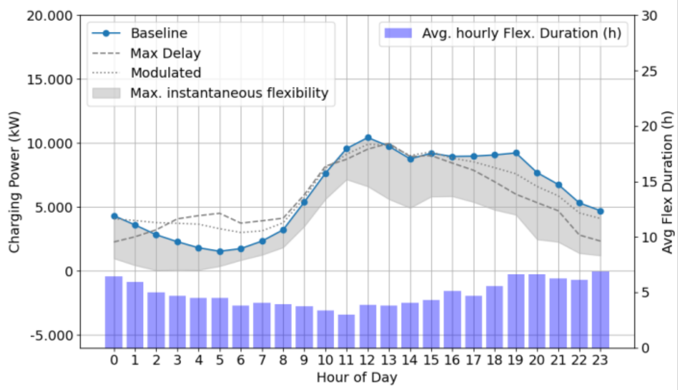
The **workplace charging** baseline consumption profile reaches a peak of 24 MW in 2030 (weekday, 10:00) and 67 MW in 2040. The highest instant flexibility would be available around 09:00 o'clock at approximately 12 MW (2030), respectively 35 MW (2040) – for weekdays.

2030	2040
Weekday public charging	**Weekday public charging**





Weekend public charging	Weekend public charging



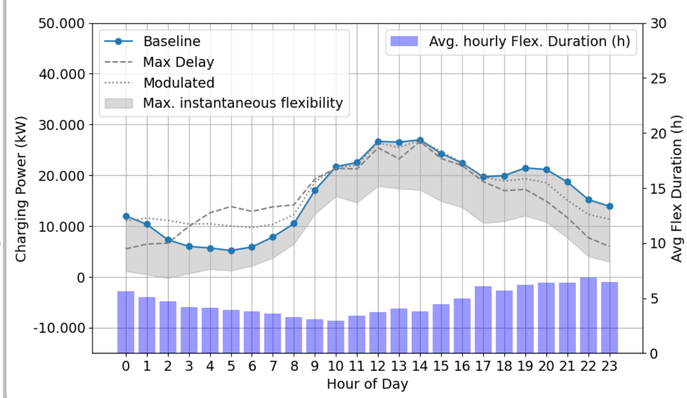


Figure 94 - Baseline- and flexibility profiles for public charging, for 2030 and 2040

Upscaling **public charging** to the 2030 scenario, as shown in Figure 94, results in a peak consumption of almost 24 MW (9:00) and 71 MW for 2040, respectively, on weekdays. During the whole morning, the modelling results in highest instant flexibility of about 16.5 – 24 MW from 8:00 – 13:00 (50 - 71 MW in 2040). The weekend profiles indicate much lower peak and average values.

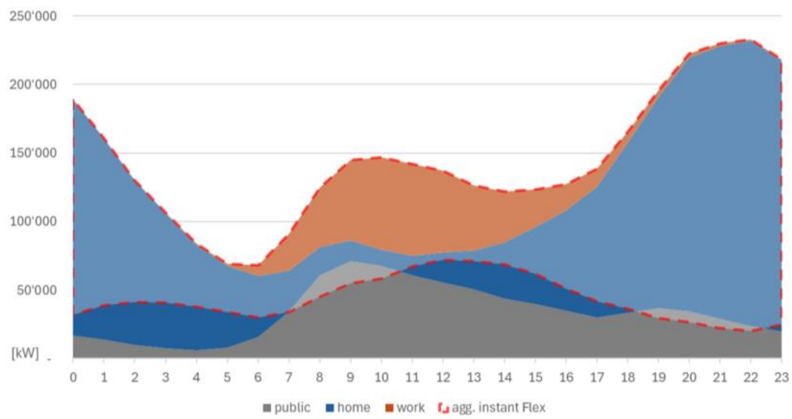


Figure 95 – Aggregated baseline profiles for three charging types, and aggregated instant flexibility (weekday, 2040)

Aggregating all baseline charging profiles of the three charging types for a weekday in the 2040 scenario is resulting in Figure 95. The shaded area, depicted as overlay between the red dashed lines, is the sum of instant flexibility from all three charging types. According to the model results, the aggregated charging baseline peaks in the evening hours at 233 MW, mainly from home charging, while a smaller peak (147 MW) during the day (10:00) results to about 90% from public and workplace charging. The aggregated instant flexibility has a minimum of 34 MW in the early morning hours, stemming to 75% from home charging flexibility. The maximum potential of about 210 MW can be expected around 23:00, originating to 90% from home charging.

Comparing the average instant flexibility from the different charging locations indicates clearly the importance of mobilising flexibility from home charging (Figure 96). With an average of about 73 MW (2040 scenario) this outweighs clearly public and private charging, and could reach up to 180 – 210 MW during the evening and night periods – very relevant for the evening peak shaving. While workplace- and public charging show much smaller potential and are drastically reduced on weekends, these might be easier to mobilise and have temporal correlation with the PV peak at noon.

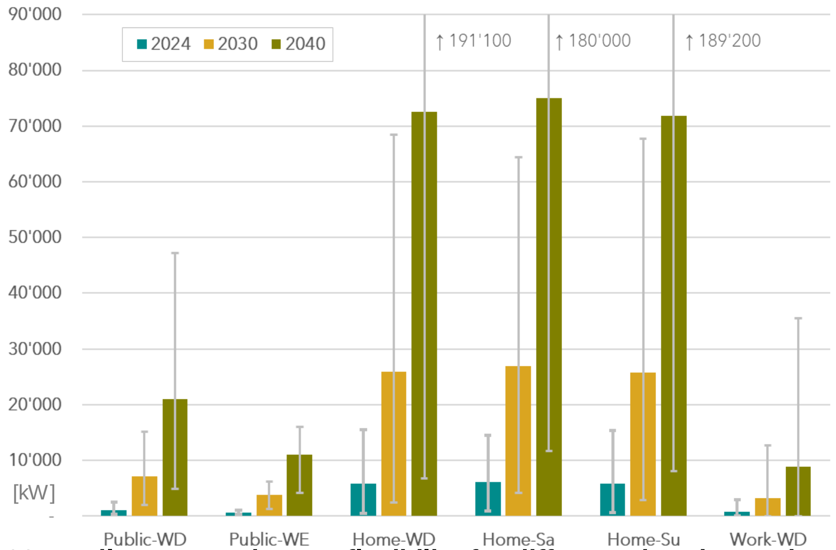


Figure 96 – Daily average, instant flexibility for different charging options and scenario years (error bars indicating the daily fluctuation (min/max)

9.6. Limitations of the model

All above-described results are based on a model which is explained in some details in chapter 9.1, and underlies assumptions, scenarios for future EV penetration and limitations, which should be mentioned in the bullet point below.

- The used data from public EV charging stations, and even more the artificial mobility profiles, are based on past mobility behaviour. No changes in mobility habits or plug-in behaviour have been considered. Also, no incentivisation of more frequent plug-in is considered. Hence, EVs are only plugged in and are only grid-available once recharging is required. This is a rather conservative assumption, and other studies come to much higher results (regarding EV flexibility) by assuming a plug-in period at each parking duration.
- Above mentioned is specifically true in case of vehicle-to-grid (V2G) usage, which could only unlock their potential in case of high grid-availability. This study did not consider V2G charging.
- The results in this chapter account for full electric battery electric vehicles - plug-in hybrid vehicles are not included.
- The smart charging model of this study and the assumptions on a minimum State-of-charge (SoC_{min}) and charging threshold have a moderate to high influence on the results and could be considered to be studied in further detail.
- Due to lack of data and responses form the stakeholders, the study did not include transition towards electro-mobility for bus-fleets and heavy-duty vehicles.

10. Conclusions and recommendations

Luxembourgish electricity consumers can contribute to flexibility provision by adjusting their load profiles in response to external signals. The assessment of the technical demand response potential across the industrial, tertiary, residential and mobility sectors identified substantial potentials. Each sector was analysed independently, applying specific methodologies tailored to its characteristics and the fundamental differences in technologies, data availability, or levels of complexity.

10.1. Conclusions – Flexibility potentials

The assessment of technical flexibility potentials across sectors in Luxembourg shows that demand-side resources can provide substantial contributions to future grid- and system operation. While the magnitude, temporal patterns and availability differ strongly by sector, the following overall conclusions can be drawn:

In the **industrial sector**, the analysis shows an average **upward (load reduction) potential** of around 20.2 MW today, with values ranging from 11.3 MW (pessimistic scenario) to 38.8 MW (optimistic). The duration is highly process-dependent: ranging from as little as 15 minutes to several hours. This makes industrial flexibility large but heterogeneous and site-specific. In the medium to long term, the plastic manufacturing sector is expected to provide temporary additional flexibility between 2030 and 2050, primarily due to the electrification of steam production. The actual magnitude of this contribution will depend on the rate of electric boiler adoption and the degree of simultaneity in investments across companies, ranging from 15,2 MW to up to 54,8 MW. This flexibility is expected to diminish once gas boilers are fully phased out, at which point additional inflexible electric loads will be introduced into the system. Although temporary, this flexibility can be particularly valuable for CREOS, as it provides a critical window of opportunity to prepare the power grid, allowing time for necessary infrastructure upgrades such as capacity expansions, transformer replacements, and network reinforcements. The potentials are concentrated at a few sites, making them highly effective for congestion management if geographically well located and easier to mobilise, due to the low number of stakeholders involved.

Tertiary sector: Cooling, ventilation and air-conditioning loads offer more than 188 MW of **downward flexibility** in summer peaks and up to -260 MW **upward flexibility**. The modelling assumed one-hour activations to limit impacts on indoor comfort levels – although process and site-specific configurations may allow longer activations. Flexibility is therefore rather high, but seasonal limited to warmer periods, while during cold periods the potentials drop towards +/- 20 MW, for both directions, roughly. Its effective deployment requires cascading activation strategies to stretch availability across longer periods, which require regeneration times between activations and rebound effects need to be considered.

The **residential sector** provides a range of smaller, distributed resources.

Residential Heat pumps show substantial potential, considering the huge growth potential with expected 56% of residential buildings being equipped with heat pumps by 2040. Depending on the activation signal and operation mode, the flexibility varies vastly. **Upward flexibility:** Blocking signals can sustain reductions of up to 120 minutes, with average power reductions between –90 and –230 MW in winter months, for the 2040 scenario, but the system needs to be designed accordingly. Other upward flexibility activations (SGR-off) last 20 – 55 minutes on average, at similar or slightly higher power levels. **Downward activations** through buffer charging can sustain 225–345 MW for ~1 – 1,5 hours, if temperature set points are increased (if not, durations are very short: 10 min. on avg.). Besides the high numbers for the 2040 scenario, the downside of the seasonal variation of heat pump flexibility is the fact that heat pumps provide the least flexibility, in term of duration, when it might be needed the most. During cold winter days, where grid load is expected to be high, heat pumps contribute increasingly to the future load increase, but the flexibility duration is very short in these days (for SGR-modes). If heat pump systems are designed for a 2 hour shut-off, the duration is drastically increased.

Large **electric water heaters**, as used for centralized hot water preparation, also provide highly controllable flexibility. **Downward** (load increase) potentials reach up to 92 MW for 6–8 minutes, while

upward (load reduction) potentials are more modest at around 5–6 MW lasting up to 9 minutes. Even these short durations can only be reached, when temperature setpoints are adapted, in addition to the On/Off control. The short durations and potential rebound effects require adequate activation strategies.

White ware devices, such as washing machines, tumble dryer and dish washers, contribute smaller power levels, but at very high penetration rates in the households. The aggregated power flexibility for a delay of the load by one hour has been estimated with 11 MW, on daily average, with a peak of up to 22 MW in the evenings. Longer deferral windows are possible, but the rebound effect is high, since the load is only shifted and requires smart activation strategies.

PV-battery systems show flexible charging and discharging durations of up to 1 hour, if charged at nominal power. Longer durations are possible at modulated power, or via cascaded activation strategies. But anyhow, huge seasonal differences need to be considered: **Downward flexibility in summer**, when batteries are often fully charged, is limited to 0 – 20 minutes, being unavailable during the solar peak. While **in winter**, the charging capacity can sustain downward flexibility on average between 20–40 minutes. **Discharging towards the grid** is typically possible during sunny periods for 40-60 minutes, while in winter upward flexibility windows are shorter (15–40 minutes). With increasing penetration rates, aggregated potentials rise from ~75 - 125 MW in 2030 to 330 - 415 MW in 2040. Hence, the growth potential is huge, but the practical availability during summer PV peaks, in the current operation mode, focusing on optimisation of self-consumption only, is very limited. This could be improved to unlock a substantial potential to mitigate the PV peaks by incentivisation of smarter operation modes. Beyond the incentivisation of a charging during PV peak hours, additional potential arises from a potential charging from the grid during off-peak times to provide additional capacity during peak times e.g. by applying dynamic tariffs.

Regarding flexibility from **electro-mobility**, the model results indicate that flexibility, and specifically its availability, strongly depends on charging location. For today’s fleet (≈35,000 EVs), **home charging** offers instantaneous flexibility of around 15 MW (at peak times), with average durations close to 10 hours if vehicles remain plugged in until departure. This flexibility could grow up to around 145-190 MW for the 2040 scenario with more than 430.000 EVs. **Workplace** charging flexibility peaks today at around 2.9MW (35 MW in 2040) with durations of 3–4 hours, while **public charging** provides 1.0 – 2.5 MW (50 to 71 MW in 2040) with typical durations between 3.3 and 6.5 hours. Since the flexibility from different charging locations occurs during different times, the aggregated national potentials for 2040 rise up to 212 MW during evening peaks, dominated by home charging.

The Table 38 gives an overview on the potentials by simplifying the complexity to single numbers for upward- and downward flexibility for each sector and year. Keeping in mind the above-described dependency on schedules, seasons, temperatures, operation modes or the diurnal cycle, the numbers below are averages, but give a comparative perspective which needs to be considered carefully.

Table 38 – Summary, average technical flexibility potentials across sectors & qualitative assessment indicators

		Industry sector	Tertiary sector	Heat pumps	White ware / EWH	PV-Battery	EVs
	Technical maturity	●	◑	◕	◑	◑	◕
	Ease of implementation	◑	◑	◑	◔	◔	◑
avg. flexibility potential [MW]							
2024	Upward Flex.	-20.2	-29	-3.6	-16	-6.6	-17
avg. Pot.	Downward Flex.		48	7.9	74	4.8	
2030	Upward Flex.	-41.0	-29	-60	-16	-122	-76
avg. Pot.	Downward Flex.	20.8	48	130	74	92	
2040	Upward Flex.	-61.7	-29	-123	-16	-401	-212
avg. Pot.	Downward Flex.	41.5	48	265	74	299	
avg. flexibility duration [min.]							
	Upw. Duration	*15-240*	*60**	*20-120*	*60* / 5.6*	*20-60*	*180-600*
	Downw. Duration		*60**	*9-80*	*- / 3.6*	*0-40*	

* the marked durations are no modelling results, but assumed model inputs

Beside the plain numbers characterizing the flexibility potential in terms of power and duration, there are other factors that should be taken into account when considering the mobilisation of these potentials. Not all the technologies have comparable technical maturity and might hold different challenges concerning their implementation. These soft factors have been qualitatively assessed below and led to the indicators comprised in above overview table.

Technological readiness – using flexibility from different assets and sectors requires technical solutions and a level of standardisation that is quite different for each sector. The maturity of technical solutions (e.g. communication, automation and standardisation of control interfaces) plays a crucial role in assessing how quickly a flexibility potential could be mobilised. This qualitative assessment has been summarized in Table 38.

- Flexibility from (large scale) industries are already today used for balancing flexibility in other European countries.
- Also heat pumps are used for economic optimization purposes by energy suppliers and some manufacturers offer (almost) standardized control interfaces. Hence, the technical maturity for those assets can be considered moderately high, although it’s usage for network needs is not established today. Further, the currently used approaches are often low-tech solutions, while more granular, nuanced control options and bi-directional communication is hardly established.
- “Smart EV charging” solutions exist, although these are mainly implemented for shared use of limited, local power capacities, and less common for network needs – but pilot projects and start-ups exist, testing solutions in operational environments. A technical standard is available and is being pushed, but it is not very stringently defined, leaving a lot of room for interpretations.
- Some aggregators and energy service companies offer furthermore flexibility from tertiary sector facilities, often linked to other services (e.g. energy saving contracts) or electric water heaters. Latter mainly in markets where those devices are widespread (e.g. France) – although these solutions are much less common.
- For white ware, the larger scale activation of those potentials would require a local automation and control instance, such as an energy management system, and compatible devices.

- Flexibility from PV battery storage is today only used by some of the battery manufacturers themselves, offering business models e.g. on balancing markets, but many products offer functionalities (e.g. production peak shaving or forecast based injection modes), that are basic functions for a smart, flexible operation. Also regarding this technology, a lack of standardisation and transparency hinders the large-scale usage of this potential, complicating the control and incentivisation of smarter solutions.

Ease of implementation – besides the technical aspects other factors influence the complexity and challenges of mobilising the flexibility potentials:

- Within the industry sector, a small number of stakeholders hold a large part of the potential, which is a huge advantage as compared to the potentials from the residential sector, that is very scattered in large amounts of small units. On the other hand, the tight economic pressure in the industry and focus on their core business, requires tailored solutions to minimize the impact on their production processes.
- Similarly, the tertiary sector is driven by economic pressure and a focus on their core business, hence their resources are rather constrained by daily routines. Opportunities might arise when building- and energy management is outsourced to specialized companies.
- The impact on user comfort is another factor, specifically regarding flexible use of white ware devices, where consumer interaction is required. This is a clear advantage of heat pumps and storage-based water heaters, that could provide flexibility with minimum impact on the user's comfort, if well implemented. Mobilisation of the comparably low potentials from white ware and electric water heaters is further hampered by the scattered nature of these assets. Additionally, the lack of a heat pump tariff, which would imply the option of a flexible switch-off and would lead to a more flexible system design (eventually including larger storage volumes), as well as the lack of experience of the installers with such smart solutions, hinders the mobilisation of this potential.
- The impact of flexibility provision from PV BESS on user comfort is also minimal, but the strong economic interest of the PV system owner for self-consumption optimisation and resentments regarding battery degradation, might stand against this use-case (although studies seem to proof that win-win scenarios are possible). While technical solutions for a smarter operation exist, though not highly standardized, the economic incentive is lacking. This might change with more attractive dynamic electricity tariffs, adapted injection time-of-use grid tariffs or even dynamic grid fees.
- Further, smart EV charging at workplace or public charging stations could be implemented with less effort, considering the ownership of charging stations and contractual situation. But flexibility from home charging has been proven to be more interesting for network needs, although appears to be more complex to be mobilized. Hence, a real smart charging option for home charging is not straightforward due to technical challenges. But a user-driven grid-relieving charging behaviour, via a delayed charging or modulated charging power induced by the user, can be incentivised, via time-of-use tariffs for example.

10.2. Matching flexibility potentials and needs

Some of the network needs for flexibility (see 1.4) are characterised by specific properties regarding where and when these conditions occur. These characteristics need to be matched by the characteristics of the individual flexibility potential to effectively alleviate the stress on the network. Specifically, two flexibility use cases have clear characteristics, that could be matched by some flexibility options:

Distribution (LV) and MV-networks will be increasingly experiencing congestions and voltage-issues due to **high PV-production during the spring- and summer periods**, which specifically concerns rural areas with long distribution lines and low demand – but not only. Downward flexibility from tertiary sector would be suitable during this period but is situated mainly in urban areas. Heat pumps are seasonally not well suited but could only contribute to a limited extend via domestic hot water production, such as electric water heaters can deliver this downward flexibility. EV-based flexibility is limited during mid-day, since mainly public- and workplace charging are available, but technically suitable, as far as located in the relevant location. If PV BESS are purely operated for optimisation of self-supply (as done today), the grid-relieving effect is minimal, but they could contribute very targeted flexibility if operated smartly, by e.g. forecast-assisted charging over noon.

Concluding the above-described characteristics of temporal and seasonal availability of the flexibility potential and the spatial distribution, tertiary sector flexibility and EV charging at workplace and public could potentially fit the flexibility needs of PV peak production, but with a focus on urban areas, which might be less pertinent. But if a smarter, more peak-production oriented charging behaviour of PV BESS could be incentivised, as some of the manufacturers already include similar functionalities, this appears as the best fit to alleviate the PV peak induced grid stress.

Table 39 - Qualitative assessment of the suitability of flexibility to alleviate the grid during PV peak periods

Flexibility use case: high PV peak production mid day, spring/summer locations: LV and MV, (urban &) rural	**Industry sector**	**Tertiary sector**	**Heat pumps**	**White ware / EWH**	**PV-Battery**	**EVs**
Suitability rating		◑	◔	◑	○ (◑)	◑
seasonal suitablity		++	-	+	-- (+)	+
diurnal cycle		+	+	+	-- (+)	-
location (voltage level, urban/rural)		-	+	+	+	+

** rating in brackets () only valid if batteries are operated smartly to charge over noon*

The already existing **evening peak**, specifically during winter, is expected to be fortified by the home-charging of EVs and intense operation of heat pumps in the cold period. To alleviate potential congestions, upward flexibility by reducing or postponing loads could be activated. Specifically, home-charging EVs have the potential to be very effective for this use case, being available at the suitable time and location, while the average durations to shift their charging is long enough. Heat pumps themselves, having long and frequent operation cycles during cold periods, are limited in the flexibility duration during that season. If heat pump systems are designed with the option to be switched off for a limited, but long enough period (e.g. 2h), reducing impacts on user comforts, a smart activation strategy can help reducing grid stress. White ware and EWH could potentially shift loads into the night but are limited in potential. Also, PV battery systems are potentially available to feed energy back to the households, but their average state of charge during winter evenings is low, resulting in short durations. If the PV BESS would be charged from the grid during the day, deviating from the pure self-supply-oriented operation today, the potential is obviously largely increased.

Hence, home charging EVs could potentially provide the best fit for this flexibility need, regarding timing and location. Additionally, shifting white ware electricity demand towards nights. Besides this, the flexibility-oriented design of heat pump systems, that could be incentivised by heat pump electricity tariffs holding that flexibility option, would open up larger potentials, in combination with smart activation strategies.

Table 40 - Qualitative assessment of the suitability of flexibility to alleviate the load peaks at winter evening

Flexibility use case: Heat pump and EV peak evenings, winter locations: LV, urban & rural	**Industry sector**	**Tertiary sector**	**Heat pumps**	**White ware / EWH**	**PV-Battery**	**EVs**
Suitability rating	○	◔	◑	◑	◔	◕
seasonal suitablity	+	-	-	+	-	+
diurnal cycle	+	-	-	+	+	+
location (voltage level, urban/rural)	- -	+	++	+	+	++

Other of the defined use cases of high flexibility needs (1.4) are located on MV to HV level, hence are less location specific.

- Suspended lines with higher line sag during hot summer days could be tackled by tertiary sector flexibility, originating from cooling- and AC-processes, due to good temporal alignment, or industry flexibility.
- Downward flexibility to buffer simultaneous PV and wind generation during transition periods could potentially be provided from several resources: Heat pumps, industry- and tertiary sector flexibility could alleviate grid stress temporarily. Similarly to the PV peak, smartly operated batteries could contribute to the solution as well.

In addition to their value for network operation, parts of the identified flexibility potentials are also relevant for **system balancing**. With increasing shares of variable renewable generation, balancing needs are expected to rise due to forecast errors, rapid ramping behaviour and deviations in BRP schedules. Balancing products such as FCR, aFRR or mFRR typically require shorter activation durations but fast and reliable response, often delivered in larger bid blocks. Among the assessed assets, industrial loads with short interruption capability, electric water heaters, and residential heat pumps are well suited to provide such short-duration, rapid-response flexibility, provided aggregation can deliver sufficient bid volumes. PV-battery systems and EV charging could also contribute, as they can react quickly to signals and be controlled in a highly decentralised manner.

While the present report has focused on grid-oriented use cases, these results indicate that demand-side resources in Luxembourg could also support system-level balancing needs, especially if aggregation and digital control are scaled up.

10.3. Prioritisation and recommendations, based on our findings

Considering the identified flexibility potentials, their technical characteristics, their suitability for specific flexibility needs, and the limiting factors that constrain their effective use, the following recommendations and priorities can be formulated:

I. **Heat pump systems,** even if not designed for longer blocking periods, could still provide flexibility e.g. via “smart grid ready” functionalities. But their flexibility under SGR-modes in colder periods can be quite limited, specifically in duration. In this case, durations remain short and the potential contribution to the reduction of winter evening peaks — one of the most critical periods — is minimal. To avoid a technological lock-in, policy should incentivise the design and installation of systems that are able to provide longer-duration upward flexibility, for example through the integration of adequate thermal storage or other design principles. Tariff structures including dedicated “flexibility options” or support programmes could ensure that new installations are capable of providing two-hour blocking flexibility without jeopardising comfort.

II. **PV-battery systems** are also widely supported, but their current operation has very limited grid-relieving effect. While these systems have the potential to absorb excess PV generation and thereby reduce local congestion, this is not the way they are typically operated today. Existing support schemes could therefore be reviewed to incentivise operation modes that explicitly target grid support, for example by aligning charging with midday PV peaks or by enabling discharging during evening demand peaks. This requires that batteries are not solely used for self-consumption of the local PV generation, but that they are also charged from and discharged to the grid.

III. **Electric vehicles.** Smart charging of EVs at home could become one of the most effective means of alleviating evening peak loads. To harness this potential, it should be assured that private wall boxes are on future-proof technical standards, such as interoperability with smart charging protocols (evtl. via checking if the support schemes are specific enough).

IV. **Pilot projects** could test specifically such approaches in practice (regarding heat pumps, EV wall boxes & PV BESS) and inform the design of long-term support schemes.

V. **Industry**. Industrial consumers provide large, site-specific flexibility, which could be mobilised both for high-voltage grid management and for balancing services. Due to the small number of stakeholders and the high individual power levels, industrial flexibility may be easier to activate than more fragmented residential or tertiary potentials. Even though balancing responsibility in Luxembourg lies with Amprion, the relevance of balancing flexibility is increasing, and mechanisms to valorise industrial contributions should be explored. Moreover, the ongoing electrification trend in industry — such as the replacement of gas boilers with electric steam generation as observed in FlexBeAn — should be monitored closely, as it will significantly shape future flexibility potentials.

VI. The **tertiary sector** offers large cooling and HVAC-related flexibility, especially in summer, coinciding with times of PV surplus and temperature-induced grid stress. While the effective duration may be limited (simulated for around one hour), these potentials could still provide valuable relief if aggregated. Partnerships with energy service companies could be leveraged: for example, energy efficiency contracting models could integrate additional revenues from flexibility provision, making use of synergies between efficiency and demand response.

VII. **White ware and electric water heaters** - Although the individual flexibility of appliances and domestic water heaters is very small and fragmented, the aggregate potential across households is significant. Unlocking this potential requires digitalisation and automation, in particular through the deployment of home energy management systems capable of coordinating multiple small devices. Such developments should be followed closely, as they could provide scalable and automated flexibility in the medium term.

10.4. Activation strategy

The flexibility potentials quantified in this report represent an upper bound, calculated as the maximum power deviation each asset or technology could provide. However, these maximum values are typically only available for short durations. In practice, system operators or aggregators are rarely interested in activating all resources at once. Instead, they seek to design activation strategies that combine and sequence different asset groups in order to sustain flexibility provision over longer periods and at the desired temporal and spatial resolution.

A central element of such strategies is **cascaded activation** (see example in Figure 97). Rather than mobilising the full pool of devices simultaneously, sub-groups are activated step by step, thereby prolonging the provision of flexibility. While this results in lower instantaneous power compared to the technical maximum, it enables a more reliable and predictable supply of flexibility over a defined time window.

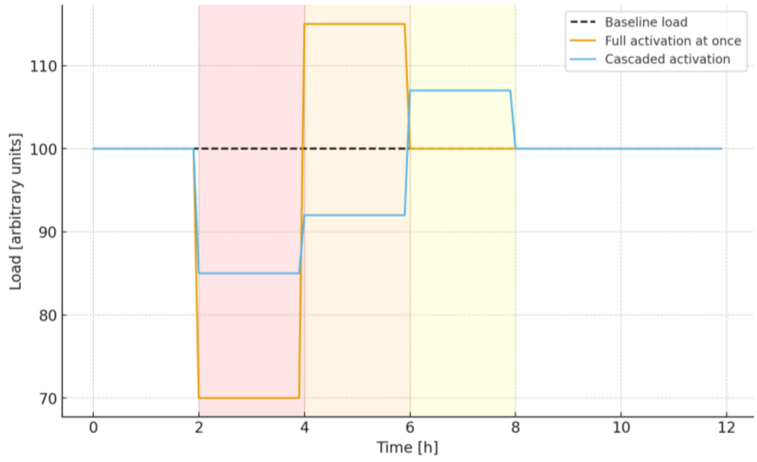


Figure 97 – Illustration of a cascaded activation strategy and rebound effect

When designing activation strategies, several key aspects need to be taken into account:

- **Magnitude, duration, and energy content of flexibility**. Each technology has a specific profile of maximum power, decline of the flexibility provision, (average) duration, and total shiftable energy. Activation schemes must be tailored to these characteristics to avoid overestimating the available potential. On the other hand, a preceding activation in opposite direction can increase the available potential – such as pre-heating buffer storages to increase the duration of a planned curtailment of heat pump operation for example.
- **Stability of the flexibility response**. Some device groups, such as heat pumps or water heaters, show very high power responses at the start of activation, but the effect diminishes over time as thermal buffers deplete. For system operation, it is therefore more relevant to consider average power levels and sustained delivery than short-term maxima.
- **Rebound effects**. Many technologies exhibit a rebound after activation—for example, a heat pump that was curtailed may subsequently consume more to restore indoor temperature. When cascading groups of devices, such rebounds can overlap with the activation of subsequent groups, thereby reducing the net flexibility delivered. Compensation strategies, such as activating additional resources in parallel, are needed to mitigate this effect.
- **Device-specific constraints**. Each technology differs in technical controllability, response rate and -time and user comfort limitations. For example, water heaters can provide very fast but short-lived flexibility, while white wares can be deferred potentially over hours but contribute only small instantaneous power.

In summary, the effectiveness of flexibility provision depends not only on the size of the technical potential, but equally on the activation strategy employed. Coordinated, cascaded, and device-specific activation allows distributed resources to provide targeted flexibility over extended periods while mitigating rebound effects. Such strategies are essential to translate the upper-bound technical potentials identified in this study into usable, reliable services for network and system operation.

10.5. Closing words

Finally, the results of the FlexBeAn project demonstrate that Luxembourg holds a significant technical demand response potential in terms of the potential power flexibility, although the durations that flexibility could be sustained are, for some assets, rather limited on average. If harnessed effectively by an adequate activation strategy, the available flexibility could, nevertheless, play a crucial role in addressing the challenges posed by the Luxembourgish power system decarbonization, i.e., alleviating grid congestion, better integration of RES, and contributing to price stability in electricity markets. As shown, especially household assets such as heat pumps, PV batteries and EV hold a significant flexibility potential in the future, suiting network flexibility needs, if implemented and operated in an adequate manner.

The practical activation of those potentials can be a demanding challenge and requires concerted actions of all involved stakeholders to set the right framework conditions and incentivise grid relieving usage of the available flexibility potential. The necessary steps towards a targeted implementation of demand side flexibility are documented in our policy advice paper: “*The beating heart of the Luxembourgish energy transition - How flexible energy consumers contribute to a reliable and low-carbon energy system in Luxembourg”*.

If you are interested in further interesting insights in the additional activities of the project, the final reports from all project work packages can be found on the project’s website, as well as the individual project partners websites, at CREOS, LIST and SnT.

11. References

Aghajanzadeh, A., Wray, C., & Mckane, A. (2015). Opportunities for Automated Demand Response in California Wastewater Treatment Facilities.

Alarfaj, O., & Bhattacharya, K. (2019). Material flow based power demand modeling of an oil refinery process for optimal energy management. IEEE Transactions on Power Systems, 34(3), 2312–2321. https://doi.org/10.1109/TPWRS.2018.2889773

Alcázar-Ortega, M., Álvarez-Bel, C., Escrivá-Escrivá, G., & Domijan, A. (2012). Evaluation and assessment of demand response potential applied to the meat industry. Applied Energy, 92, 84–91. https://doi.org/10.1016/j.apenergy.2011.10.040

Artelys Optimization solutions. (2023). TERRE Activation Optimization Function Public Description LIBRA Platform.

Bahrami, S., Wong, V., & Huang, J. (2019). Demand Response for Data Centers in Deregulated Markets: A Matching Game Approach. 2019 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm).

BDEW Bundesverband der Energie- und Wasserwirtschaft e.V., VKU, & GEODE. (2016). Leitfaden_20160630_Abwicklung-Standardlastprofile-Gas.

BGW Bundesverband der deutschen Gas- und Wasserwirtschaft. (2006). Anwendung von Standardlastprofilen zur Belieferung nicht-leistungsgemessener Kunden. www.wvgw.de

Bundesverband Wärmepumpen e.V. (2020). Regularium für das Label "SG Ready" für elektrische Heizungs-und Warmwasserwärmepumpen und kompatible Systemkomponenten. www.waermepumpe.de

Cai, Y., Zhu, L., Ye, Q., Hu, Z., Chen, W., & Zhang, C. (2023). The potential of load identification and regulation in the textile industry. Journal of Physics: Conference Series, 2584(1). https://doi.org/10.1088/1742-6596/2584/1/012035

Cao, Y., Cheng, M., Zhang, S., Mao, H., Wang, P., Li, C., Feng, Y., & Ding, Z. (2022). Data-driven flexibility assessment for internet data center towards periodic batch workloads. Applied Energy, 324. https://doi.org/10.1016/j.apenergy.2022.119665

Cioara, T., Anghel, I., Bertoncini, M., Salomie, I., Arnone, D., Mammina, M., Velivassaki, T. H., & Antal, M. (2018). Optimized flexibility management enacting Data Centres participation in Smart Demand Response programs. Future Generation Computer Systems, 78, 330–342. https://doi.org/10.1016/j.future.2016.05.010

CREOS, & Schroeder, C. (2024). CREOS - Scenario Report 2040 v2024.

Cupelli, L., Schutz, T., Jahangiri, P., Fuchs, M., Monti, A., & Muller, D. (2018). Data center control strategy for participation in demand response programs. IEEE Transactions on Industrial Informatics, 14(11), 5087–5099. https://doi.org/10.1109/TII.2018.2806889

De Vos, K., Hahati, B., Coates, D., Feito-Kiczak, R., & Donnadieu, JM. (n.d.). Assessment of required flexibility needs and available flexibility means in power systems: the implementation of a quantitative method in Belgium. Http://Dx.Doi.Org/10.2139/Ssrn.4165655. Retrieved September 2, 2025, from http://dx.doi.org/10.2139/ssrn.4165655

Degefa, M. Z., Sael, H., Petersen, I., & Ahcin, P. (2018). Data-driven Household Load Flexibility Modelling: Shiftable Atomic Loads.

Delbrassinne, M., & Michels, A. (2023). CREOS - Scenario Report 2040, version 2022. www.creos.net

D'hulst, R., Labeeuw, W., Beusen, B., Claessens, S., Deconinck, G., & Vanthournout, K. (2015). Demand response flexibility and flexibility potential of residential smart appliances: Experiences from large pilot test in Belgium. Applied Energy, 155, 79–90. https://doi.org/10.1016/j.apenergy.2015.05.101

DSO entity, & ENTSO E. (2024). Definition of the type and format of data and the methodology for the analysis by transmission system operators and distribution system operators of the flexibility needs at national level. www.entsoe.eu

European Commission. (2002). Energy consumption in the services sector : surveys of EU member states : data 1995-1999. Office for Official Publications of the European Communities.

Faria, P., Soares, J., & Vale, Z. (2015). Definition of the Demand Response Events Duration Using Differential Search Algorithm for Aggregated Consumption Shifting and Generation Scheduling. 18th International Conference on Intelligent System Application to Power Systems.

Ferro, Y., Gerber, P., Pigeron-Piroth, I., & Caruso, G. (2024). A GROWING POLARIZATION OF HOME-WORK TRAVEL IN LUXEMBOURG.

Feta, A., van den Broek, M., Crijns-Graus, W., & Jägers, G. (2018). Technical demand response potentials of the integrated steelmaking site of Tata Steel in IJmuiden. Energy Efficiency, 11(5), 1211–1225. https://doi.org/10.1007/s12053-018-9623-y

Fischer, D., Wolf, T., Wapler, J., Hollinger, R., & Madani, H. (2016). Model-based flexibility assessment of a residential heat pump pool. https://doi.org/10.1016/j.energy.2016.10.111

Gaete-Morales, C., Kramer, H., Schill, W. P., & Zerrahn, A. (2021). An open tool for creating battery-electric vehicle time series from empirical data, emobpy. Scientific Data, 8(1). https://doi.org/10.1038/s41597-021-00932-9

Ghalandari, V., Majd, M. M., & Golestanian, A. (2019). Energy audit for pyro-processing unit of a new generation cement plant and feasibility study for recovering waste heat: A case study. Energy, 173, 833–843. https://doi.org/10.1016/j.energy.2019.02.102

Ghatikar, G., Ganti, V., Matson, N., & Piette, M. A. (2012). Demand Response Opportunities and Enabling Technologies for Data Centers: Findings From Field Studies.

Gholian, A., Mohsenian-Rad, H., Hua, Y., & Qin, J. (2013). Optimal Industrial Load Control in Smart Grid: A Case Study for Oil Refineries. IEEE Power and Energy Society General Meeting.

Gils, H. C. (2014). Assessment of the theoretical demand response potential in Europe. Energy, 67, 1–18. https://doi.org/10.1016/j.energy.2014.02.019

Golmohamadi, H. (2022). Demand-side management in industrial sector: A review of heavy industries. In Renewable and Sustainable Energy Reviews (Vol. 156). Elsevier Ltd. https://doi.org/10.1016/j.rser.2021.111963

Gong, F., Han, N., Li, D., Chen, S., Xiao, M., & Yu, Y. (2020). A method for calculating steel demand response potential based on AOE network. 2020 IEEE 9th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), 890–894. https://doi.org/10.1109/ITAIC49862.2020.9338773

Hannan, A., Naz, M. N., Siddique, M., Altaf, M. W., & Imran, A. (2019). Demand Side and Response Side Joint Energy Management Strategy Towards Economical and Environmental Benefits of Sugar Industry. International Symposium on Recent Advances in Electrical Engineering.

He, Z., Xu, J., Tran, K. P., Thomassey, S., Zeng, X., & Yi, C. (2021). Modeling of textile manufacturing processes using intelligent techniques: a review. The International Journal of Advanced Manufacturing Technology, 116(1–2), 39–67. https://doi.org/10.1007/s00170-021-07444-1

Heitkoetter, W., Schyska, B. U., Schmidt, D., Medjroubi, W., Vogt, T., & Agert, C. (2021). Assessment of the regionalised demand response potential in Germany using an open source tool and dataset. Advances in Applied Energy, 1(September 2020), 100001. https://doi.org/10.1016/j.adapen.2020.100001

Heleno, M., Matos, M. A., & Lopes, J. A. P. (2015). Availability and flexibility of loads for the provision of reserve. IEEE Transactions on Smart Grid, 6(2), 667–674. https://doi.org/10.1109/TSG.2014.2368360

Herre, L., Tomasini, F., Paridari, K., Söder, L., & Nordström, L. (2020). Simplified model of integrated paper mill for optimal bidding in energy and reserve markets. Applied Energy, 279. https://doi.org/10.1016/j.apenergy.2020.115857

Kirchem, D., Lynch, M., Bertsch, V., & Casey, E. (2018). Market effects of industrial demand response and flexibility potential from wastewater treatment facilities. 15th International Conference on the European Energy Market (EEM).

Klein, C., & Peltier, F. (2017). Regards 13 - sur le stock des batiments et logements.

Koster, D., Fiorelli, D., Bruneau, P., & Braun, C. (2022). Single-site forecasts for 130 PV systems at Distribution System Operator Level, Using a Hybrid-Physical Approach, to Improve Grid-Integration and Enable Future Smart-Grid Operation. Solar RRL, 2200652(Special Issue: World PV Conference-Milano). https://doi.org/10.1002/solr.202200652

Koster, D., Minette, F., & O'Nagy, O. (2014). PV-FORECAST: REGIONALISED FORECASTING OF ENERGY PRODUCTION FROM PHOTOVOLTAIC AND THEIR DYNAMICS BY A COMBINED APPROACH OF MODELLING AND REAL TIME MEASUREMENTS OF REFERENCE SYSTEMS. 29th European Photovoltaic Solar Energy Conference and Exhibition, 2225–2232.

Li, J., Bao, Z., & Li, Z. (2015). Modeling demand response capability by internet data centers processing batch computing jobs. IEEE Transactions on Smart Grid, 6(2), 737–747. https://doi.org/10.1109/TSG.2014.2363583

Lidbetter, R. T., & Liebenberg, L. (2013). Load-shifting opportunities for typical cement plants. Journal of Energy in Southern Africa, 24(1).

Liu, J., Yin, R., Yu, L., Piette, M. A., Pritoni, M., Casillas, A., Xie, J., Hong, T., Neukomm, M., & Schwartz, P. (2022). Defining and applying an electricity demand flexibility benchmarking metrics framework for grid-interactive efficient commercial buildings. Advances in Applied Energy, 8. https://doi.org/10.1016/j.adapen.2022.100107

Luo, Z., Peng, J., Zhang, X., Jiang, H., & Lv, M. (2024). Load flexibility quantification of electric water heaters under various demand-side management strategies and seasons. Journal of Building Engineering, 97. https://doi.org/10.1016/j.jobe.2024.110724

MEA, & MECD. (2018). NECP - Luxembourg's integrated national energy and climate plan for 2021-2030.

MEA, & MECD. (2024). Plan national intégré en matière d'énergie et de climat du Luxembourg pour la période 2021-2030 - Mise à jour.

Noor, I. M., Thornhill, N. F., Fretheim, H., & Thorud, E. (2015). Quantifying the Demand-Side Response Capability of Industrial Plants to Participate in Power System Frequency Control Schemes. IEEE Eindhoven PowerTech.

Obaidat, M., Al-Ghandoor, A., Phelan, P., Villalobos, R., & Alkhalidi, A. (2018). Energy and exergy analyses of different aluminum reduction technologies. Sustainability, 10(4). https://doi.org/10.3390/su10041216

Pflugradt, N., Stenzel, P., Kotzur, L., & Stolten, D. (2022). LoadProfileGenerator: An Agent-Based Behavior Simulation for Generating Residential Load Profiles. Journal of Open Source Software, 7(71), 3574. https://doi.org/10.21105/joss.03574

Plaum, F., Ahmadiahangar, R., Rosin, A., & Kilter, J. (2022). Aggregated demand-side energy flexibility: A comprehensive review on characterization, forecasting and market prospects. In Energy Reports (Vol. 8, pp. 9344–9362). Elsevier Ltd. https://doi.org/10.1016/j.egyr.2022.07.038

Rodríguez-García, J., Álvarez-Bel, C., Carbonell-Carretero, J. F., Alcázar-Ortega, M., & Peñalvo-López, E. (2016). A novel tool for the evaluation and assessment of demand response activities in the industrial sector. Energy, 113, 1136–1146. https://doi.org/10.1016/j.energy.2016.07.146

Ruhnau, O., Hirth, L., & Praktiknjo, A. (2019). Time series of heat demand and heat pump efficiency for energy system modeling. Scientific Data, 6(1). https://doi.org/10.1038/s41597-019-0199-y

S. I. P. . FfE. (2022). Industrial demand-side flexibility data.

Sardeshpande, V., Gaitonde, U. N., & Banerjee, R. (2007). Model based energy benchmarking for glass furnace. Energy Conversion and Management, 48(10), 2718–2738. https://doi.org/10.1016/j.enconman.2007.04.013

Schäfer, M., Hobus, I., & Schmitt, T. G. (2017). Energetic flexibility on wastewater treatment plants. Water Science and Technology, 76(5), 1225–1233. https://doi.org/10.2166/wst.2017.308

Schlomann, B., Gruber, E., Eichhammer, W., Kling, N., Diekmann, J., Ziesing, H.-J., Rieke, H., Wittke, F., Herzog, T., Barbosa, M., Lutz, S., Broeske, U., Merten, D., Falkenberg, D., Nill, M., Kaltschmitt, M., Geiger, B., Kleeberger, H., & Eckl, R. (2004). Energieverbrauch der privaten Haushalte und des Sektors Gewerbe, Handel, Dienst-leistungen (GHD).

Schlomann, B., Steinbach, J., Gruber, E., Mai, M., & Gerspacher, A. (2013). Energy consumption of the tertiary sector (trade, commerce and services) for the years 2007 to 2010.

Seo, K., Edgar, T. F., & Baldea, M. (2020). Optimal demand response operation of electric boosting glass furnaces. Applied Energy, 269. https://doi.org/10.1016/j.apenergy.2020.115077

Shoreh, M. H., Siano, P., Shafie-khah, M., Loia, V., & Catalão, J. P. S. (2016). A survey of industrial applications of Demand Response. In Electric Power Systems Research (Vol. 141, pp. 31–49). Elsevier Ltd. https://doi.org/10.1016/j.epsr.2016.07.008

Sofana Reka, S., & Ramesh, V. (2016). Industrial demand side response modelling in smart grid using stochastic optimisation considering refinery process. Energy and Buildings, 127, 84–94. https://doi.org/10.1016/j.enbuild.2016.05.070

STATEC. (2024). POMPES À CHALEURS DANS LE SECTEUR RÉSIDENTIEL.

Summerbell, D. L., Khripko, D., Barlow, C., & Hesselbach, J. (2017). Cost and carbon reductions from industrial demand-side management: Study of potential savings at a cement plant. Applied Energy, 197, 100–113. https://doi.org/10.1016/j.apenergy.2017.03.083

Sun, H. S., & Lee, S. E. (2006). Case study of data centers' energy performance. Energy and Buildings, 38(5), 522–533. https://doi.org/10.1016/j.enbuild.2005.08.012

Tang, C. J., & Dai, M. R. (2012). Demand response control strategies for on-campus small data centers. Proceedings - IEEE 9th International Conference on Ubiquitous Intelligence and Computing and IEEE 9th International Conference on Autonomic and Trusted Computing, UIC-ATC 2012, 217–224. https://doi.org/10.1109/UIC-ATC.2012.97

Tang, C. J., Dai, M. R., Chuang, C. C., Chiu, Y. S., & Lin, W. S. (2014). A load control method for small data centers participating in demand response programs. Future Generation Computer Systems, 32(1), 232–245. https://doi.org/10.1016/j.future.2013.07.020

The TIR Consulting Group. (2016). The 3rd industrial revolution "Lëtzebuerg." 140.

Tristán, A., Heuberger, F., & Sauer, A. (2020). A methodology to systematically identify and characterize energy flexibility measures in industrial systems. Energies, 13(22). https://doi.org/10.3390/en13225887

Zeng, K., Wang, H., Lan, X., Wang, C., Liu, J., Le, L., Dong, C., & Xiaomeng, A. (2020). A Bi-level Programming Guiding Electrolytic Aluminum Load for Demand Response. 2020 IEEE IAS Industrial and Commercial Power Systems Asia.

Zhang, X., & Hug, G. (2015). Bidding Strategy in Energy and Spinning Reserve Markets for Aluminum Smelters' Demand Response. ISGT 2015 : Innovative Smart Grid Technologies.

Zhao, X., Bai, H., Shi, Q., Lu, X., & Zhang, Z. (2017). Optimal scheduling of a byproduct gas system in a steel plant considering time-of-use electricity pricing. Applied Energy, 195, 100–113. https://doi.org/10.1016/j.apenergy.2017.03.037

12. Annex

Annex – E-mobility (I)

Table 41 – example: average daily instantaneous flexibility, per commune (weekday, 2024)

Commune (2024)	avg. flex. HOME [kW]	avg. flex. PUBLIC [kW]	avg. flex. WORK [kW]
Beaufort	6.89	1.29	0.75
Bech	10.43	0.17	0.35
Beckerich	10.99	1.19	0.75
Berdorf	10.06	2.27	0.52
Bertrange	27.19	48.74	7.23
Bettembourg	29.80	12.00	4.05
Bettendorf	8.19	0.82	0.75
Betzdorf	21.60	11.26	1.07
Bissen	9.87	3.64	0.84
Biwer	13.60	4.24	0.52
Boulaide	7.26	0.87	0.38
Bourscheid	6.33	2.31	0.43
Bous-Waldbredimus	16.76	0.64	0.87
Clervaux	14.15	4.83	1.30
Colmar-Berg	9.31	2.97	2.89
Consdorf	10.06	0.98	0.55
Contern	24.96	12.61	4.05
Dalheim	8.19	1.59	0.46
Diekirch	14.90	12.31	5.50
Differdange	33.34	13.11	5.50
Dippach	19.00	3.12	1.16
Dudelange	54.01	18.81	5.79
Echternach	10.62	11.22	1.33
Ell	6.70	0.57	0.49
Erpeldange-sur-Sûre	9.50	2.33	1.74
Esch-sur-Alzette	34.08	59.46	16.20
Esch-sur-Sûre	8.57	0.89	0.81
Ettelbruck	17.32	12.74	5.50
Feulen	6.89	0.49	0.64
Fischbach	3.91	0.24	0.38
Flaxweiler	10.43	1.10	0.64
Frisange	20.30	2.17	1.22
Garnich	10.06	0.71	0.58
Goesdorf	4.47	0.22	0.46
Grevenmacher	13.78	6.24	1.24
Groussbus-Wal	9.87	0.22	0.64
Habscht	17.32	2.69	1.36
Heffingen	8.75	1.20	0.49
Helperknapp	18.62	1.11	1.33
Hesperange	49.54	45.96	4.63
Junglinster	48.98	3.65	2.03
Käerjeng	34.08	6.07	3.18
Kayl	21.05	4.13	2.31
Kehlen	29.24	3.96	1.50
Kiischpelt	2.42	0.94	0.29
Koerich	11.17	2.41	0.72
Kopstal	24.21	2.38	0.81
Lac de la Haute-Sûre	4.84	0.25	0.55
Larochette	5.77	1.66	0.52
Lenningen	10.99	2.59	0.61
Leudelange	14.34	11.48	4.92
Lintgen	16.20	4.33	1.04

Lorentzweiler	19.18	3.50	1.10
Luxembourg	265.78	259.94	113.60
Mamer	42.09	9.73	5.50
Manternach	10.99	1.23	0.61
Mersch	34.64	8.38	4.63
Mertert	13.60	4.36	1.07
Mertzig	9.31	0.73	0.61
Mondercange	24.58	4.33	1.65
Mondorf-les-Bains	13.60	8.88	1.10
Niederanven	38.93	11.95	5.79
Nommern	8.19	0.23	0.41
Parc Hosingen	14.90	1.37	1.04
Pétange	30.17	22.70	4.63
Préizerdaul	7.64	0.42	0.49
Putscheid	5.03	0.03	0.32
Rambrouch	13.78	2.38	1.16
Reckange-sur-Mess	11.92	1.84	0.78
Redange/Attert	12.29	1.45	0.81
Reisdorf	2.61	1.10	0.29
Remich	11.92	5.95	0.64
Roeser	23.09	12.77	1.82
Rosport-Mompach	14.71	3.89	1.01
Rumelange	8.19	4.52	1.22
Saeul	7.45	0.73	0.26
Sandweiler	14.34	3.42	3.76
Sanem	48.42	7.38	4.63
Schengen	24.03	3.28	1.33
Schieren	6.70	1.13	0.52
Schifflange	22.72	6.95	2.72
Schuttrange	21.05	3.20	1.04
Stadtbredimus	7.64	0.80	0.55
Steinfort	22.72	13.03	1.27
Steinsel	27.19	1.78	1.45
Strassen	35.76	28.09	4.92
Tandel	5.59	0.18	0.64
Troisvierges	7.64	1.29	0.84
Useldange	6.89	0.53	0.55
Vallée de l'Ernz	10.99	0.84	0.69
Vianden	3.91	1.46	0.49
Vichten	5.59	0.21	0.41
Waldbillig	9.50	0.33	0.52
Walferdange	31.66	7.12	2.08
Weiler-la-Tour	11.36	1.40	0.64
Weiswampach	3.91	0.95	0.46
Wiltz	8.57	4.26	3.18
Wincrange	10.99	0.58	1.16
Winseler	3.17	3.57	0.32
Wormeldange	15.46	3.95	0.78

Annex – E-mobility (II)

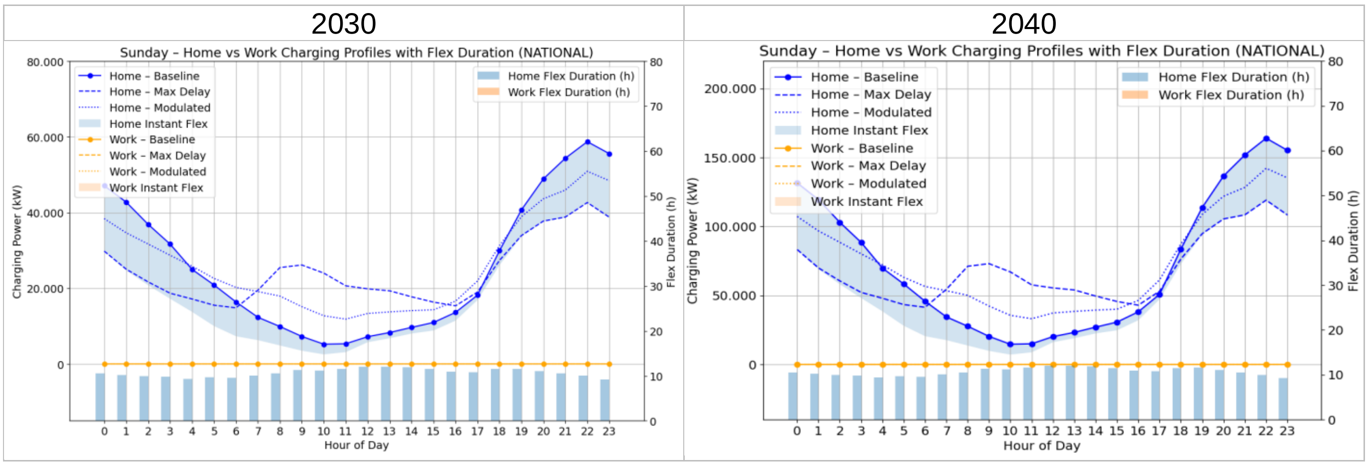


Figure 98 - Baseline- and flexibility profiles for home charging (workplace is zero) on Sundays, for 2030 and 2040

Annex – PV-BESS (I)

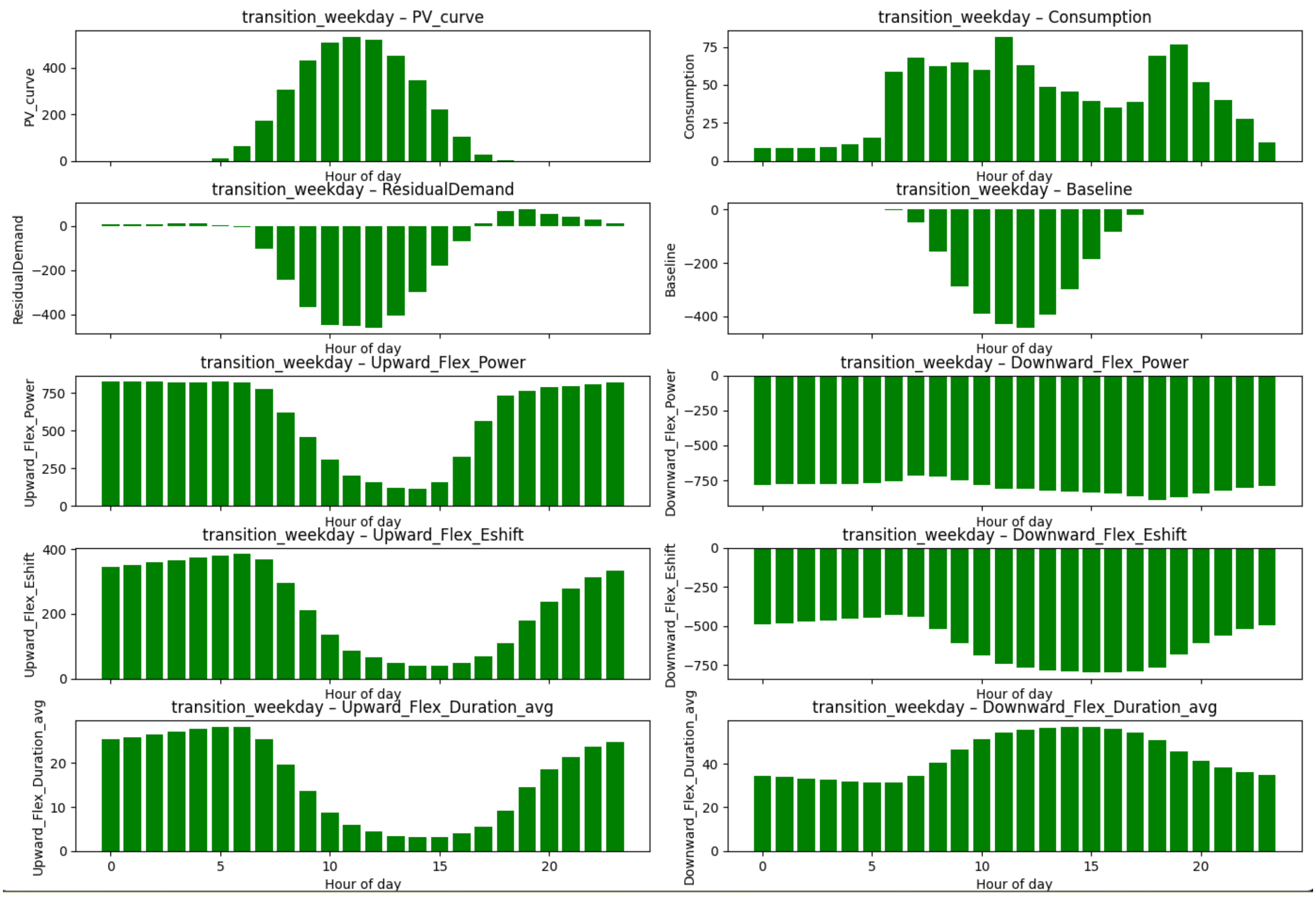


Figure 99 - PV BESS flexibility profile – transition period (100 PV BESS)