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Energy system planning informed by consumer preference for the adoption of flexible electric vehicle chargers in Belgium

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Abstract

Belgium is part of the top countries with the most Watt PV installed per capita. The mismatch between the renewable electricity generation and the consumption of this electricity poses a challenge for the system and the distribution grid. Overproduction requires curtailment and underproduction requires installed capacity in other forms of electricity generation. Low voltage flexibility, e.g. a shift in time of use of charging an electric vehicle (EV), can reduce the mismatch between production and consumption. There is a certain technical potential but the real potential depends on the willingness of consumers to participate in demand response programs. The willingness to participate depends on their preferences, which are obtained through discrete choice experiments (DCEs). The goal of our work is to study the inclusion of consumer preferences for the adoption and use of flexible EV chargers in energy system planning models. While we recognise the potential of agent based modelling, we keep the focus on existing energy system planning models and modifications to these type of models. Existing energy system planning models can consider consumer preferences in a post analysis. In a post analysis of TIMES-BE, a tool to study different pathways for the energy system in Belgium, we calculate the available budget to compensate for the inconvenience of using flexible EV chargers as the difference between the cost of the energy system with and without flexible chargers. The available budget is then compared to the consumer preference for compensation for the adoption of flexible EV chargers derived from the implicit discount rate obtained from the DCE. Generally, there is sufficient budget, especially from 2035 and onwards when the need for flexibility measures increase.

The existing model provides insights in the budgets for flexible EV chargers but the direct competition between compensation for the adoption of flexible EV chargers and other flexibility measures, e.g. investments in stationary batteries, is not possible. To that end, the consumer preference needs to become part of the energy system planning model. Here, we present a formulation that makes this competition possible in a stylised model. To derive that formulation, we transform the utility functions from the DCE to probabilities for adopting and using flexible chargers and linearise these probabilities. As opposed to the existing model, for the stylised model we focus on the methodology instead of the analysis and as such only consider a limited setup. For such a limited setup, the results show that remuneration of flexible chargers is still preferred over investments in batteries. Despite functional and useful, the equations tend to become non linear, impacting the computational performance of this approach. Therefore, for future research we suggest to study how our approach holds up against an agent based model.

Nomenclature

DCE Discrete choice experiment; survey where participants need to choose between distinct options.

EV Electric vehicle.

HP Household heat pump.

LV Low voltage

MV Medium voltage

PV Photovoltaic or solar panel for generation of electricity.

V2G Bidirectional charging of an EV.

V2H Bidirectional charging of an EV, limited to the use of the appliances at home.

1 Consumer preference for low voltage flexibility in the context of Belgium

With a production of 761 kWh per capita in 2024, Belgium is among the top countries with the most Watt PV installed per capita [12]. These PV systems pose a challenge for the distribution grid; especially when there is a significant mismatch between the PV production and the demand in the grid. The voltages in the grid can reach prohibitive levels at times of overproduction, possibly resulting in curtailment of the PV systems. Underproduction on the other hand requires other forms of electricity production to pick up the slack; which implies a sufficient installed capacity of these generation units. Low voltage flexibility, or more commonly called demand response at residential level, is the shift in time of use of an asset such as, e.g. charging of an EV and use of a HP. Low voltage flexibility can reduce the mismatch between production and consumption and as such lower the capacity requirements of other generation units.

Technically, there are little barriers for the use of low voltage flexibility. The willingness to adopt these measures is a different issue [13]. Low voltage flexibility has an impact on the daily life of a consumer. Consumers have certain habits and preferences for the use of their assets and need sufficient compensation or benefits to adjust their behaviour.

At the planning stage of investments in additional capacity, it is hard to take the consumer preference into account. Often, scenarios are considered for the extreme cases where no one participates in flexibility measures or where the full potential can be used [4, 3]. The real potential is somewhere in between. To obtain a scenario in between, a common approach is to make a distinction between comfort, cost and environment and design different consumer profiles with different emphasis on these categories [15]. Although these scenarios provide insights in the flexibility potential, the actual flexibility potential remains unclear.

It is more rare for energy system planning models to directly integrate consumer preference in the modelling. Zhang, Caramanis and Baillieul include consumer preference for the control of idle (cooling) appliances in a stochastic dynamic programming problem for regulation service reserves [21]. Sachdev and Singh consider the demand response as a trade-off between different goods when deciding to participate in demand response or not in a cost optimisation problem for the grid [16]. However, both works use theoretical utility functions that are based on certain common principles but are not derived directly from a survey.

The goal of our study is to embed the consumer preference from the DCEs in an energy system planning process to obtain a more realistic potential of low voltage flexibility in the energy system. To that end we need to obtain consumer preferences and form a modelling strategy.

Discrete choice experiments, a form of surveys, are a common tool to obtain consumer preferences. Table 1 provides a non exhaustive overview of consumer preferences for low voltage flexibility in literature.

Table 1: Consumer preferences for low voltage flexibility in literature.

Technology	Location	Time	preference	reference
EV	highway, shopping centre	2024	Sensitive to the charging price; trade off between waiting and price.	[5]
EV	home, work	2024	Willingness to wait is higher.	[5]
EV, smart home	home	2024	Interest to participate is more important than finances and environment.	[19]
appliances	Colombia	2020, 18-24h	Higher interest to participate in (manual demand response in) the evening.	[11]
demand response	Poland	2023	Stay in control of their own assets, clear communication, user-friendly interface, predictable changes in short frequent intervals	[17]
all	all	all	Participation in demand response programs require financial benefits.	[11, 5, 17]
all	all	all	Young, educated people tend to be more open for participation.	[5, 19]

It is clear that consumer preference is context specific. As such, for the context of Belgium, we collaborate with related work on a discrete choice experiment for the consumer preference on the adoption and use of flexible EV chargers [6]. Accordingly, the focus of our study will also be on flexible EV chargers.

The scope of two separate DCEs are described in Tables 2 and 3. The first DCE is concerned with the adoption of a flexible charger with certain attributes whereas the second DCE focuses on ceding control to a third party. More specifically, the baseline for the first DCE is a simple charger with the electricity contract that they currently have (typically a volumetric contract or in some cases a day/night contract). In that DCE, the individual has the choice between keeping the simple charger or changing to a charger with certain attributes, e.g. a charger that is controlled by an energy retailer and is able to charge as well as discharge to the grid. The baseline of the second DCE is that they already have a bidirectional charger but they did not cede control to a third party (and as such chances are that they are not fully used) because of financial and privacy concerns or driving range anxiety. The second DCE inquires how the presence of certain attributes, e.g. a portable battery bank, alleviates these concerns and allow for the control of the bidirectional charger to be ceded to a third party (and as such be fully used).

In our study, we are rather concerned with the availability of flexibility from flexible EV chargers to the energy system. In principle, to obtain a clear picture on the adoption and control of flexible EV chargers and as such the full availability of flexibility in the energy system, we have to combine the two DCEs. However, combining the results of two DCEs is not trivial and not within the scope of our work. Therefore, for all intents and purposes, the two DCEs are to be treated completely separately. This separation implies that the availability of flexibility is lower than it could have been, which can be considered as a lower bound of the available flexibility.

Table 2: Attributes considered in the first DCE on the adoption of flexible chargers with certain features.

Attribute type	Attribute	Description
Control	solar charging	Charging your EV mostly with your PV.
	dynamic load management	Reduce the peak consumption of the home.
	smart controller at home	A local solution for controlling your EV.
	energy retailer	The retailer directly controls the charging of your EV.
	smartphone	You control the charging of the EV yourself through your smartphone.
Bidirectional charging	home	Allow discharging of your EV, but only for your own appliances.
	home and grid	Allow discharging of your EV to your own appliances and/or the local grid.
Financial	reward	An annualised financial benefit. The financial benefit can come from the optimal use of the battery or as a subsidy on the investment.
	price	Investment cost of the charger

Table 3: Attributes considered in the second DCE on ceeding control of flexible chargers to a third party.

Attribute type	Attribute	Description
Battery	minimum battery level	A minimum state of charge is guaranteed before the charger is used flexibly.
	portable battery bank	You have access to a portable battery bank, as if you would carry a jerrycan in your gasoline car.
	road side charging insurance	When you run out of battery charge during your trip, a service vehicle shows up to charge your battery enough to get to the next charging station.
Privacy	data encryption	Data exchange between you and the energy retailer is encrypted.
Financial	fee	A reduction on your energy bill savings that are used by your retailer to provide the features above.

There are different possible modelling strategies to embed the consumer preference into energy system planning models. Here, we consider a post analysis of an existing energy system planning model and a new formulation for energy system planning models that embed the consumer preference directly.

We also recognise the potential for agent based models in this context. However, there are few rigorously validated models and the correct interpretation can be problematic [8]. For that reason, transmission grid operators may be reluctant to adopt these kind of approaches. And for the same reason, we focus here on strategies that are closer to current common modelling practices. Though, we do suggest to compare an agent based model to our own approach in future work.

For the post analysis, TIMES-BE is an appropriate tool to determine pathways for the energy system in Belgium, including investments in electricity generation for a given maximum share of flexible EV chargers. By comparing different scenarios with and without flexible chargers TIMES provides insights in the available budget for compensating the adoption and use of flexible chargers. The post analysis studies whether that budget is in line with the stated preference of consumers for compensation (from the first DCE).

The post analysis only provides insights in the budgets and does not allow for, e.g., stationary batteries to compete directly with remuneration strategies for the adoption of flexible EV chargers. To make direct use of the consumer preference in energy system planning models, we create a new formulation in a stylised model for energy system planning model. With this stylised model the focus shifts from the analysis to the methodology; the setup for the stylised model has a smaller scope. Due to the smaller scope, the results of the stylised model are not usable in absolute terms but due to the use of the TIMES model in the first approach, the results of the stylised model can be used in relative terms to the results from the TIMES model.

The interactions of the two energy system planning models with the DCEs are shown in Figure 1. That figure also serves as the overview of our study. We have already discussed the consumer preference for low voltage flexibility in Belgium. The next section deals with the scenario analysis and the the post analysis of the TIMES-BE model where the results are compared to the results of the DCE. Thereafter follows the stylised model with its formulation aligned to the DCEs and with its data aligned to the TIMES-BE scenarios. Afterwards, the overall results are further discussed.

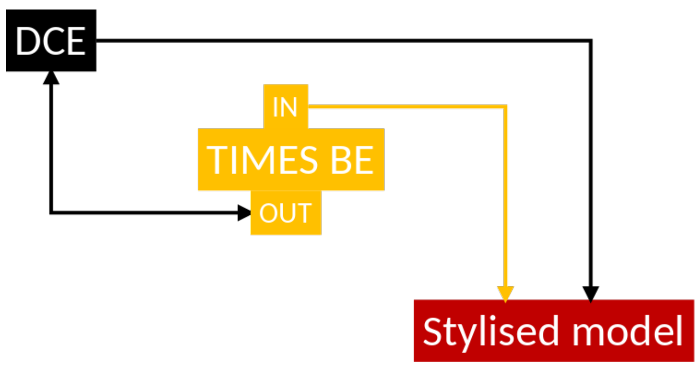


Figure 1: Modelling overview: TIMES-BE considers the DCE in a post analysis whereas the stylised model uses the DCE internally and uses similar input as the TIMES-BE model.

2 Scenario analysis with TIMES-BE on the potential of flexible EV chargers

TIMES-BE is used for many different studies. A general description of the model is provided in Appendix B. Here, we focus on the flexibility that flexible EV chargers can provide to the energy system in Belgium. With a scenario analysis we can explore different energy systems with different availability of flexible EV chargers (Subsections 2.3 and 2.4). Whether these scenarios are realistic can be determined from a comparison to the stated preferences for financial benefits from the DCE (Subsection 2.5). But, before heading to these results, we will briefly explain the setup for Belgium (Subsection 2.1) with a particular focus on the modelling of EV chargers (Subsection 2.2).

2.1 TIMES-BE setup for Belgium

The TIMES-BE model is a single-region model, representing Belgium as one aggregated energy system without regional disaggregation [9]. In terms of scope, the model explicitly covers the full chain of the energy system, including:

- Supply sector – including domestic resource extraction, imports, and production of energy carriers (excluding electricity)
- Power sector – detailed representation of all electricity generation technologies, storage, and grid-related infrastructure.
- End-use demand sectors, which are broken down into:
  - Buildings (Residential and Commercial)
  - Transport (including passenger and freight, both national and international)
  - Industry – detailed by subsectors and energy/material flows (e.g. steel, chemicals),
  - Agriculture

Due to the complexity of modelling all sectors, fuels, and transformation processes over long horizons, TIMES-BE does not operate on an hourly resolution for each year [9]. Instead, it employs a time-slicing approach using 10 representative days, selected through clustering algorithms to capture annual variability in demand, prices, and renewable generation patterns [14]. These days are resolved on a 2-hourly basis, a granularity shown in literature to offer comparable accuracy to hourly models, while significantly reducing computational burden [7].

2.2 Modelling EV charging

In TIMES-BE, the road transport sector is subdivided into four main categories: passenger cars, buses, freight, and motorcycles. Passenger cars are further disaggregated into four behavioural categories (Figure 2): Commuting / Non-Commuting, Long / Short Distance. Only the passenger car categories are associated with hourly (time-slice level) energy service demands; other vehicle types are characterized only at annual level [9]. The demand projections are sourced from the TREMOVE model, which foresees a 11–14% demand growth for passenger vehicles, buses, and motorcycles, and nearly 29% for trucks by 2050 [18].

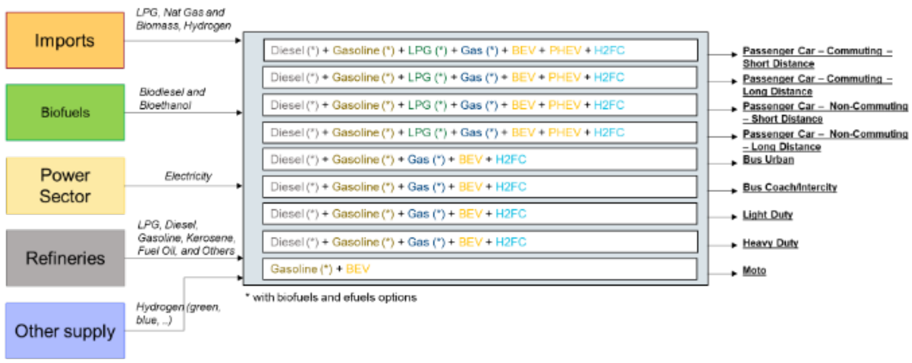


Figure 2: Road transport sector structure in TIMES-BE

Passenger electric vehicles (EVs) are linked to charging infrastructure through two sectors: residential (home charging) and commercial (workplace charging). The model represents charging infrastructure with availability factors dependent on the vehicle's physical presence at home or work, enabling a time-resolved optimisation of charging profiles. Charging technologies are grouped as follows (Figure 3):

- Standard Unidirectional Chargers (User-driven): Availability is capped by time-slice presence at home/work. Use is fixed during typical peak user-preferred periods, while optimized for system cost in all other periods.
- Flexible Unidirectional Chargers: Subject to the same availability caps, but charging time is only determined by (total) system cost optimisation.
- Bidirectional Chargers (V2H/V2B/V2G): Allow electricity to flow both into and out of the vehicle. The bidirectional flow can:
  - Support residential/commercial electricity demand (Vehicle-to-Home/Building),
  - Inject power into the local LV grid (Vehicle-to-Grid), where it can be stored in grid-scale batteries or sent to MV grid

Only commuting vehicle categories have access to both residential and commercial chargers, whereas non-commuting vehicles are limited to residential charging. Bidirectional chargers are pivotal for enabling EVs to act as distributed energy storage assets, supporting both user-level flexibility and wider grid integration.

A financial characterisation of each charger type is provided in the appendix, i.e. Table 2.3, while their availability factor (reflecting the times in which charging is possible for the user) is reported in Figure 4.

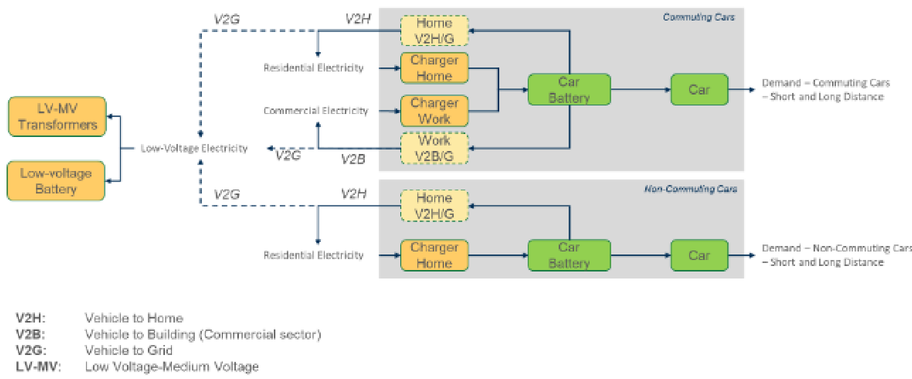


Figure 3: EV Passenger Cars Charging Infrastructure Modelling in TIMES-BE

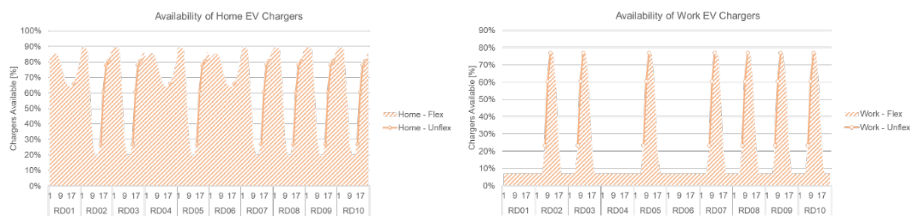


Figure 4: Availability of Home EV Chargers (left) and Work EV Chargers (right): for Flex chargers it is shown as an area, being it only an UPPER bound, while for Unflex chargers it is shown as a line, being a FIXED bound. Representative Days (RD): RD01, RD04, RD06 are weekend days.

2.3 Scenario setup

In this analysis, we choose to base our sensitivity exploration on the PATHS2050 scenarios, as they provide a well-established and extensively modelled set of storylines that serve as a robust reference for assessing future energy system transformations in Belgium [1]. The PATHS2050 study explores three distinct plausible transition pathways toward a climate-neutral Belgium by 2050. Each storyline reflects a different strategic emphasis:

- ROTORS prioritizes the maximal deployment of renewable electricity, particularly wind power onshore and offshore, while keeping nuclear energy to the current levels, and bound carbon capture deployment.
- IMPORTS emphasizes large-scale imports of clean hydrogen and derived synthetic fuels, reducing the domestic build-up of both renewables and nuclear
- REACTORS explores a future where nuclear energy is a key pillar, with

extended or new reactor capacity, reducing pressure on renewables and imports.

Across all three storylines, we impose a common boundary condition on the uptake of flexible EV charging and V2H/B/G (vehicle-to-home/building/grid) to reflect real-world behavioural and infrastructural constraints. This upper-bound constraint evolves over time: flexible charging adoption may rises from 7% in 2025 to 48% in 2050, while V2H/B/G may grows from 0% to 38%. These limits are grounded in the 2023 ELIA Adequacy and Flexibility Study [4] and TML's 2023 EPOC survey on public acceptance and readiness for flexibility in mobility [20].

To better explore the solution space and enable a more robust assessment of the remuneration budget (i.e. the cost savings compared to an energy system without flexible EV chargers, see Subsection 2.5) across different flexibility levels, the initial set of scenarios—based on the three core PATHS2050 storylines (ROTORS, REACTORS, IMPORTS)—was extended through a series of targeted sensitivities.

For each storyline, four flexibility configurations were constructed to capture varying degrees of societal and infrastructural acceptance of flexibility technologies:

- Full flexibility (100_100_100): Flex charging, V2H (Vehicle-to-Home), and V2G (Vehicle-to-Grid) are all allowed.
- No V2G (100_100_0): Only flex charging and V2H are accepted, V2G is restricted.
- Flex charging only (100_0_0): V2H and V2G are excluded.
- No flexibility (0_0_0): EVs are charged without any smart or bi-directional capability.

This extension allows the model to more accurately reflect real-world behavioural limits and infrastructure constraints while enhancing comparability between scenarios. To further enable comparability, a constraint on the global minimum charging capacity has been set in in all scenarios, to the minimum level in the original story lines, i.e. 1.5 million chargers (~11.3 GW). The detailed impacts of these sensitivities on system cost, grid utilisation, and required remuneration budgets are presented in Section 2.4. The full scenario matrix is summarised in Table 2.3.

Table 4: Set of scenarios, starting from the main story lines. Each scenario is defined by the maximum percentage of chargers can be of a particular type. For example, 48% Max Flex Chargers means that maximum 48% of the chargers can be unidirectional chargers that can be used flexibly. The other chargers need to be of another type. A charger can always be a unidirectional charger that is operated inflexibly.

Scenario	Base Storyline	Max Flex Chargers [%]	Max V2H/B [%]	Max V2G [%]
ROTORS	ROTORS	48%	38%	38%
RO100_100_100	ROTORS	100%	100%	100%
RO100_100_0	ROTORS	100%	100%	0%
RO100_0_0	ROTORS	100%	0%	0%
RO0_0_0	ROTORS	0%	0%	0%
IMPORTS	IMPORTS	48%	38%	38%
IM100_100_100	IMPORTS	100%	100%	100%
IM100_100_0	IMPORTS	100%	100%	0%
IM100_0_0	IMPORTS	100%	0%	0%
IM0_0_0	IMPORTS	0%	0%	0%
REACTORS	REACTORS	48%	38%	38%
RE100_100_100	REACTORS	100%	100%	100%
RE100_100_0	REACTORS	100%	100%	0%
RE100_0_0	REACTORS	100%	0%	0%
RE0_0_0	REACTORS	0%	0%	0%

2.4 Scenario results

The modelling results in Table 2.4 clearly show that the higher the level of flexibility and bidirectionality allowed in EV charging infrastructure, the greater the optimal installed capacity of such technologies in the system. This outcome reflects the system's preference for accessing distributed flexibility to support grid stability and reduce system costs.

In all scenarios where flexible chargers are allowed, they are consistently favoured over standard (non-flex) chargers, even if ~15% more expensive (Table B.1). Their ability to shift load and reduce peak demand makes them a valuable asset in the cost-optimal mix.

As for Flex chargers with V2H (Vehicle-to-Home), it is adopted in moderate quantities—up to around 25% of the installed capacity—and is always preferred over V2B (Vehicle-to-Building), primarily due to greater evening availability, a critical period when solar PV output drops and system stress increases.

V2G, however, is not adopted in any scenario. This is not due to lack of value per se, but rather due to a limitation of the model. TIMES takes a copper plate approach, i.e. aggregating all homes/buildings of the same type in a single node. As a result, excess electricity from one V2H-equipped home will not flow to the low-voltage grid, but would be consumed in other homes, avoiding associated distribution costs. Hence, the results of the scenarios with and without V2G enabled (100_100_100 and 100_100_0 respectively) are the same: for this reason, from now on, we will combine the scenario with and without V2G enabled into one (i.e. 100_100_100/0).

A general observation concerning the deployment of EV charging infrastructure is that the installed capacity of EV chargers ranges between 11.3 GW (approximately 1.5 million chargers) and 17.9 GW (around 2.5 million chargers) across the modeled scenarios. Given an estimated EV stock of 6 million vehicles by 2050, this corresponds to a charger-to-vehicle ratio between 1:4 and 1:2.5. This relationship is particularly relevant for the remuneration analysis, where two distinct approaches are considered: one that computes remuneration on a per-EV driver basis, and another that does so per charging device.

Table 5: Results – EV Chargers optimal capacity installed in 2050

	Chargers [GW]					Chargers [%]		
	Unflex	Flex	Flex + V2H/B	V2G	Total	Flex	Flex + V2H/B	V2G
ROTORS*	5.8	2.9	2.6	0.0	11.3	48%	23%	0%
RO100_100_100	0.1	13.8	3.3	0.0	17.2	100%	19%	0%
RO100_100_0	0.1	13.8	3.3	0.0	17.2	100%	19%	0%
RO100_0_0	0.2	11.0	0.0	0.0	11.3	98%	0%	0%
RO0_0_0	11.3	0.0	0.0	0.0	11.3	0%	0%	0%
IMPORTS*	5.8	3.0	2.5	0.0	11.3	48%	22%	0%
IM100_100_100	0.4	14.0	3.4	0.0	17.8	98%	19%	0%
IM100_100_0	0.4	14.0	3.4	0.0	17.8	98%	19%	0%
IM100_0_0	0.4	10.9	0.0	0.0	11.3	96%	0%	0%
IM0_0_0	11.3	0.0	0.0	0.0	11.3	0%	0%	0%
REACTORS*	6.1	2.7	2.9	0.0	11.8	48%	25%	0%
RE100_100_100	0.0	14.5	3.4	0.0	17.9	100%	19%	0%
RE100_100_0	0.0	14.5	3.4	0.0	17.9	100%	19%	0%
RE100_0_0	0.1	12.3	0.0	0.0	12.4	99%	0%	0%
RE0_0_0	11.3	0.0	0.0	0.0	11.3	0%	0%	0%

The integration of flexible EV charging infrastructure substantially shapes the energy system in 2050 (Figure 5 and Table 2.4), reinforcing its role as a cornerstone of system-wide flexibility. The main impacts include:

- Other flexibility technologies: Flexible EV charging notably reduces the reliance on stationary batteries. In scenarios without flexible charging, battery storage capacity can increase up to 8 times, especially in the absence of large-scale nuclear capacity. This highlights a strong substitution effect between mobile and stationary flexibility sources.

- Electrification effects: Allowing flexible charging raises total electricity demand modestly—up to +3%—as the system can economically accommodate more electrified end-uses due to better peak management.
- Import dependency: Without flexible charging, net electricity imports can rise by 2–5 TWh, as the domestic system struggles to meet peak demand with variable renewables and limited flexibility.
- Renewable integration and power infrastructure: High flexibility facilitates greater solar PV deployment, lowers the need for dispatchable generation (by 1.5–3 GW), and reduces distribution grid reinforcement needs.

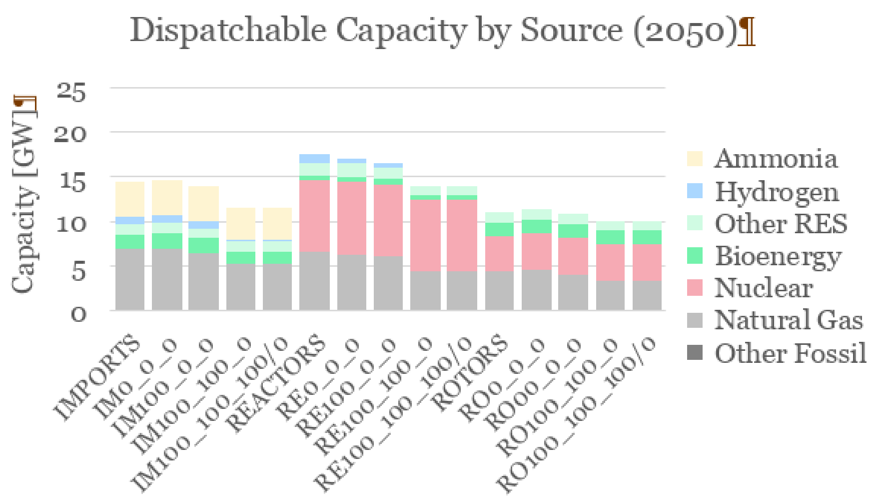


Figure 5: Dispatchabe Capacity by Source (2050)

Table 6: Impacts at energy system level of the different story lines.

	Other Flex [GW]		Total Flows [TWh]		Power Supply [GW]			Distr. Grid [GW]
	Batteries	Electrolyzers	Demand	Net Imp	PV	Wind	Dispatchable	Total
ROTORS	6.1	2.8	179.5	7.7	39.3	39.8	11.2	8.3
RO100_100_100/0	2.3	2.8	181.8	6.2	43.1	39.8	10.1	8.2
RO100_0_0	9.2	2.7	179.5	6.5	40.2	39.8	11.0	8.3
RO0_0_0	17.7	2.7	179.3	8.4	37.2	39.8	11.4	8.5
IMPORTS	6.9	0.0	159.4	32.4	46.5	23.2	14.5	8.2
IM100_100_100/0	3.7	0.0	160.2	30.2	50.3	23.2	11.6	7.8
IM100_0_0	8.2	0.0	158.8	31.7	46.2	23.2	14.0	8.1
IM0_0_0	23.8	0.0	159.0	31.7	47.1	23.2	14.5	8.1
REACTORS	6.7	1.9	163.2	8.2	44.1	23.1	17.5	9.6
RE100_100_100/0	3.3	2.1	163.3	4.4	50.1	23.1	14.0	9.1
RE100_0_0	9.5	2.1	162.2	8.6	43.4	23.1	16.6	9.5
RE0_0_0	10.8	2.1	161.9	9.5	41.8	23.2	17.1	9.7

In terms of system cost implications, the deployment of fully flexible EV charging yields significant economic benefits over time, clearly visible in the difference with inflexible scenarios (Figure 6).

By 2040, although higher upfront investments are required for EV charging infrastructure and expanded solar PV capacity, these are more than offset by carbon offsetting (the higher emissions in non-flex scenarios require costly offsets via instruments like the EU ETS, leading to potential savings of up to €1 billion per year) and savings in stationary battery savings (250-500 M€/year).

By 2050, the structure of savings evolves, with battery savings becoming dominant, reaching €700–800 million annually, followed by energy trading savings (power and commodity exchanges) with an additional €500–800 million/year.

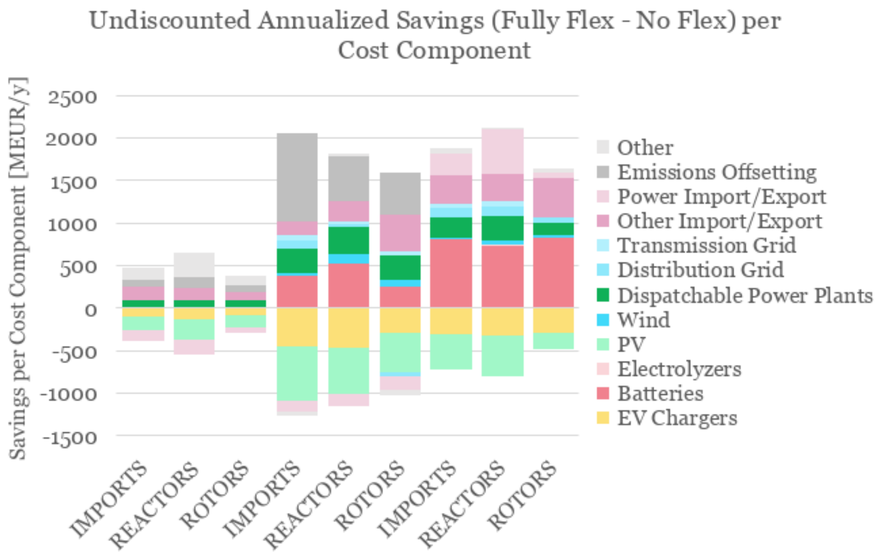


Figure 6: Cost savings expressed as a cost difference between Fully Flex (100_100_0) and Non-flex scenarios (0_0_0), per story line (imports, reactors and rotors) for 2030, 2040 and 2050.

2.5 Remuneration budget

To compute the remuneration budget for flexible EV charging and bidirectional applications (V2H/B/G), we apply several methodologies (all based on installed flexible technology capacities and not dependent of actual usage) based on differences in system costs and user counts derived from TIMES model outputs. Two sensitivity dimensions are individuated, one based on how the remuneration is split across flexibility technology adoption (Equal vs Technology dependent), and one based on across whom the remuneration is split (per Driver vs per Charger) :

- Technology independent, or Equal (in Figure 7): Total annualised system cost savings (vs no-flexibility baseline, e.g. RO/IM/RE0_0_0) are equally distributed across all chargers participating in flexibility schemes (equaling the number of chargers installed, computed as the ratio between capacity and typical size, Table B.1).
- Technology dependent, or Proportional (columns Flex and V2H in Figure 7): For each flexibility technology, the remuneration is computed by isolating its marginal contribution to system cost savings. Specifically, the system cost difference between a scenario without the flexibility technology and a scenario with full availability of the technology is assigned to its users. For example:

    - Flex charging: savings = RO/IM/RE0_0_0 – RO/IM/RE100_0_0
    - V2H/B: savings = RO/IM/RE100_0_0 – RO/IM/RE100_100_0
    - Each saving is then divided by the corresponding number of users chargers (e.g. number of flex chargers in 'Flex charging' or V2H-enabled devices in 'V2H/B').

- Per Charger (in Figure 7): Each saving is then divided by the corresponding number of chargers (e.g. number of flexible chargers in 1. or V2H-enabled devices in 2.).
- Per Driver (in Figure 7): The cost savings are now distributed over the number of EVs (therefore, instead of dividing the savings by the number of chargers, a number of EVs being associated with a flexibility strategy is derived proportionally from the total number of EVs).

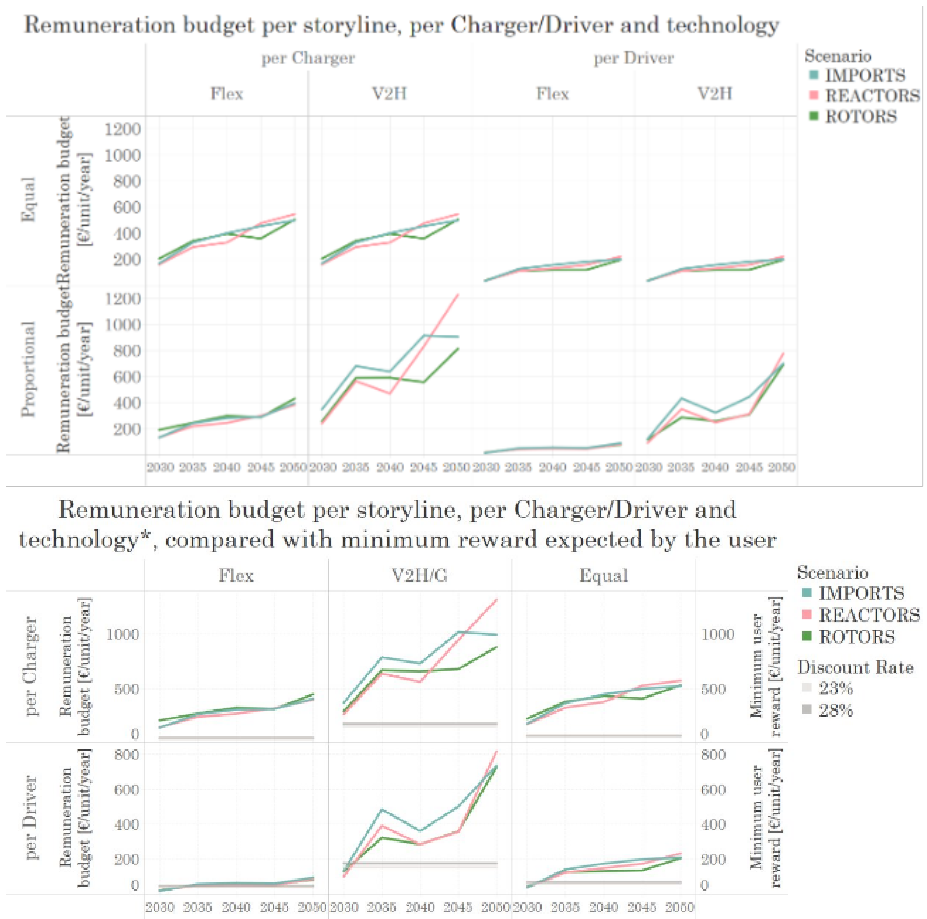
All approaches are rescaled to match the system cost savings, ensuring budget consistency and avoiding overcompensation.

Results are synthesized in Figure 7, offering a visual summary of all methods and their outputs.

It can be observed that under the "Equal" remuneration schemes, compensation levels are uniform across all users participating in flexibility, including both flexible charging and V2H adopters. In contrast, the proportional schemes (columns Flex and V2H) allocate higher remuneration to V2H adopters, who are fewer in number yet contribute significantly to system cost savings. This reflects the higher marginal value of V2H flexibility in the modelled energy system.

An important trend is that remuneration levels increase over time across nearly all scenarios and schemes. This indicates the growing economic value of flexible charging technologies as the energy transition progresses and system integration challenges intensify.

Nevertheless, remuneration levels vary widely depending on the adopted scheme and scenario. For instance, remuneration for flexible charging ranges from approximately €20/year (Flex, per Driver) to €200/year (Equal, per Charger) in 2030, and from €80/year (Flex, per Driver) to around €550/year (Equal, per Charger) by 2050. For V2H users, remuneration spans from the above mentioned €20/year, to €350/year (V2H, per Charger) in 2030, and from €80/year to as much as €1,200/year (V2H, per Charger) in 2050.



*The budgets and the rewards are computed basing on a typical charger size of 7.4 kW for comparability purposes across technologies

Figure 7: Remuneration budget in the different scenarios, for the different calculation methodologies.

To relate these results to the consumer preference of the DCE, the remuneration levels are compared with the minimum rewards expected by the users: they are computed starting from the IDR obtained from the DCE (28.5% for the sample average and 23% for the majority class) to annualise the difference in investment between each flexibility technology with the non-flexible equivalent (a simple one-directional charger). The time horizon taken into account is the lifetime of the charging technologies (15 years). During the comparison, note that the remuneration budgets are by milestone year, while the implicit discount rate reflect the savings over the lifetime of a charger.

The results in Figure 7 show that the remuneration budget exceeds the minimum reward expected in all scenarios and considering any remuneration sharing setup, starting from 2035 onwards, even when looking at Flexible charging (in the 'Proportional' sharing setup), and computing the remuneration per Driver.

3 Modelling energy system planning with consumer preference

In the scenario analysis with TIMES we saw the competition between, e.g., mobile and stationary batteries where the consumer preference was considered as an afterthought. In the next step we want to make the consumer preference an integral part to such a competition. The integration of the consumer preference in the energy system planning model requires modifications to the formulation model. Although, in principle, it is possible to make those modifications in the TIMES model, the model is quite large and cumbersome for such an experimental exercise. Instead, we choose to work with a stylised model and a limited scope. That approach offers more freedom in the design of the experiments. That also means that we shift the focus from the analysis to the modelling itself.

The stylised model is a relaxed clustered unit commitment model with considerations for adequacy. The full model is available in appendix C. Here, we focus on the part of the formulation that is relevant to the consumer preference for low voltage flexibility. Note that for simplicity we only consider a single electric vehicle and charger in these equations. The full formulation is different as it considers multiple electric vehicles and chargers.

The limited scope and the focus on the methodology make the results of the stylised model not usable in absolute terms. However, to be able to use the results in relative terms to the TIMES model, we repeat part of the analysis from Section 2 with the stylised model and compare the results of both models (Section 3.1).

Of course, in the comparison between the stylised model and the TIMES model, the stylised model will seem inferior. However, the stylised model is not supposed to outperform the TIMES model. The stylised model is meant to experiment with the formulation and allow for the consumer preference to take a part in the competition between, e.g., mobile and stationary batteries. To that end, we first need to prepare the equations (i.e. utility functions) from the DCE to fit a linear energy system planning model. That is covered in Section 3.2.

We will not cover every attribute of the DCE as, from the perspective of the model, there is some overlap in some of the attributes and not every attribute is directly within the scope of a linear model for the energy system.[1] Here we focus on financial concerns (Section 3.3) and driving range anxiety (Section 3.4). For the financial concerns we consider a compensation for the use of a

[1] By the design of the DCE, each of these features can chosen independently. As such we can choose the combination of features that makes most sense within the context of the energy system planning model.

flexible charger and for the driving range anxiety we consider a minimum state of charge. Note that these attributes originate from different DCEs and as such need to be treated separately. For both cases we use the same model but we enable/disable the equations related to the DCEs whenever relevant.

3.1 Post analysis with a stylised energy system planning model

The setup for the stylised model is aligned with that of the TIMES model whenever possible. However, some simplifications are in place to make the interpretation of the impact of the new equations easier. Among the simplifications are that the stylised model only considers the power sector and residential chargers. Also, the electric vehicles follow the same pattern, causing very extreme conditions of all vehicles and no vehicles to be (in)accessissible at the same time. The stylised model covers the time horizon from 2025 to 2050 (with milestone years every 5 years that are deemed representative for the years in between) whereas the TIMES-BE model starts from 2014. Otherwise, the data is mostly aligned with the TIMES-BE model.[2]

Another big difference is that the stylised model is meant to consider more than one node/region. In a single node setup, there are no links and as such no associated distribution costs.[3] In a multi node setup, electric vehicles can transfer electricity not only in time but also in space. V2G chargers may be advantageous in such a setup up. For the comparison to TIMES, we will have to consider a single node setup. However, to study the selection of the type of flexible charger, we will also look at a multi node setup as shown in Figure 8. In that setup we simplify the Belgian electricity system to five nodes. One node represents the TSO and has all the electricity generation units. In this node, the model can also choose to invest in additional units to increase capacity or flexibility to obtain an adequate system. The other nodes represent different DSOs. Each DSO has its own demand, HP, PV and EV adoption. The expected routes are also included in the model to track in what location the electricity is actually demanded. Each node has two electric vehicles; one to drive one node clockwise and back and one to drive one node counterclockwise and back. At every moment in time there is a vehicle available in a node. These routes are somewhat arbitrary. As the number of nodes and the number of (clustered) vehicles are limited (due to the limited setup), so are the routes. A more realistic approach is to monitor different routes and cluster them in a certain number of distinct vehicles and nodes. But that is beyond the scope of our study.

[2]Except for the demand, wind and solar profiles as well as the existing capacities which are taken directly from the transmission grid operator Elia. Though, those values should be very similar if not the same.

[3]Distribution costs are only indirectly present in the stylised model in the form of investment and maintenance cost of overhead lines.

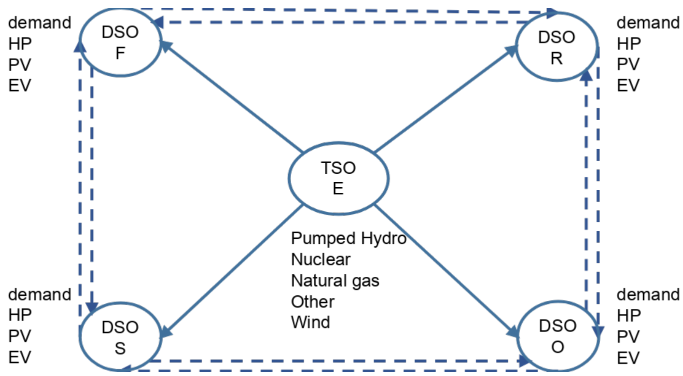


Figure 8: A stylised setup for the electricity system in Belgium with one node representing the TSO with all of the electricity generation units and several nodes representing different DSOs. Each DSO has its own demand, PV adoption and EV adoption. The solid lines represent electricity flows whereas the dashed lines represent vehicle routes.

For the single node setup and the multi node setup, similar to TIMES-BE, we simulate the energy system when there are no flexible EV chargers available and when the flexible EV chargers are fully available.

Flexible EV chargers do not appear in the solution of the stylised model for the values from TIMES. This is a consequence of the limited setup. For example, the extreme conditions of the charging pattern of the vehicles limit the use in time of the batteries of electric vehicles. While in theory, it is possible to create a setup with a better mix of patterns of electric vehicles, that quickly becomes too complex for the small setup we need to experiment with equations for the consumer preference for the adoption and use of flexible EV chargers. To obtain results that are more in line with the behaviour of TIMES, i.e. a more fair competition between flexible EV chargers and stationary batteries, we therefore opt instead to artificially increase the cost of stationary batteries by a factor of 4 and reduce the cost of flexible chargers by a factor of 4.

For the multi node setup and the two scenarios on flexible chargers respectively, Figures 9 and 10 show the charging pattern for 4 weekdays throughout the year for an electric vehicle in node S that is only used for driving to work and back. It is clear that in the scenario without flexible chargers the batteries of the vehicles are largely unused, whereas the batteries are constantly used in the scenario where all chargers can be converted to flexible chargers.

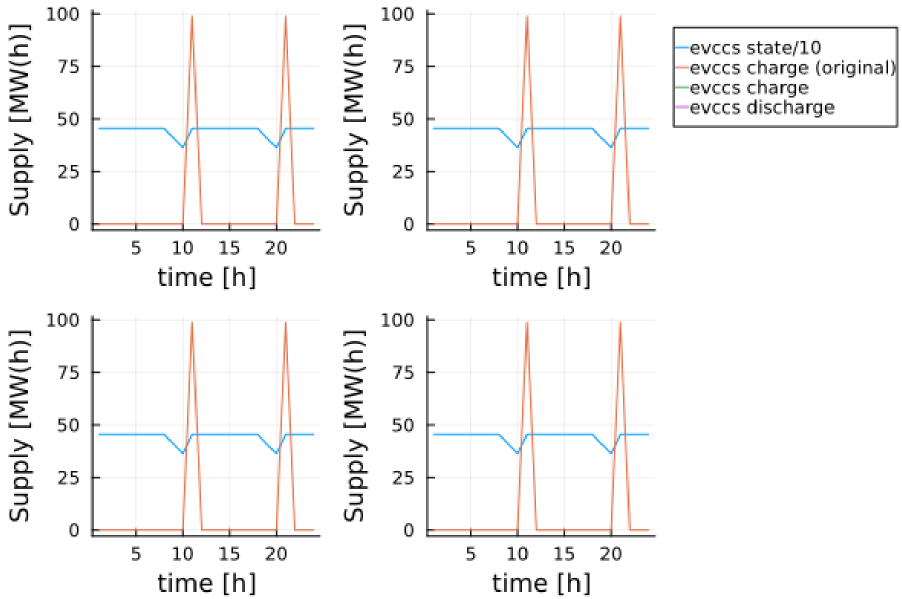


Figure 9: Charging pattern for 4 week days throughout the year for an electric vehicle associated to the S node in the case there is no access to flexible chargers.

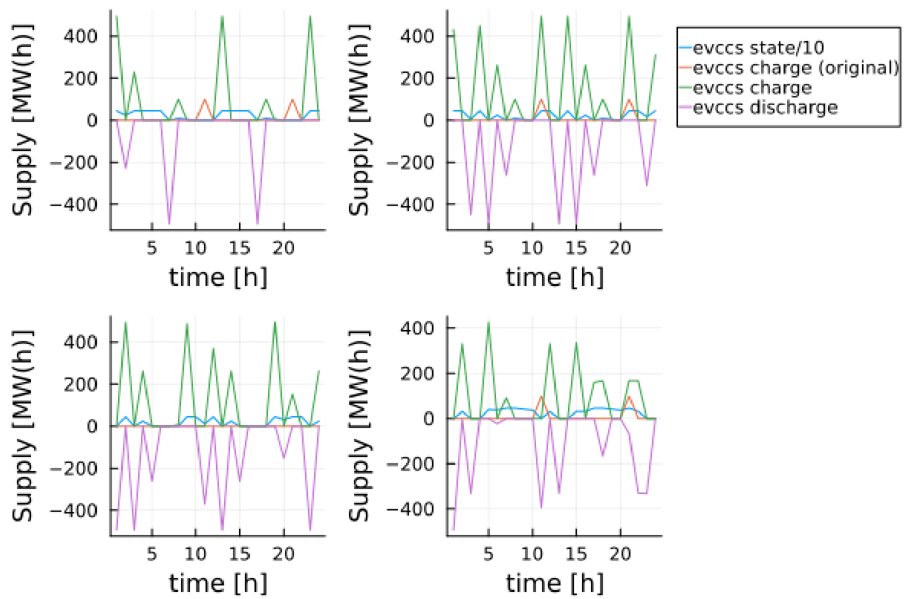


Figure 10: Charging pattern for 4 week days throughout the year for an electric vehicle associated to the S node in the case there is full access to flexible chargers.

Table 3.1 compares the results for the selected charger type and the cost savings (between the no flex and full flex scenarios) for the TIMES-BE model and the stylised model. As mentioned before, there is a big difference in scope and setup between the two models: TIMES-BE covers multiple sectors but only has one node whereas the stylised model only covers the electricity sector but has multiple nodes. In an attempt to make the models somewhat comparable, we also provide the results for the electricity sector in a single node for both models (for the time horizon of 2025-2050). Note that the calculation for the TIMES-BE model is a simplification that assumes that the use of flexible EV chargers mostly impacts the electricity sector.

It is striking that the TIMES-BE model only chooses for V2H chargers whereas the stylised model only chooses for V2G chargers. As mentioned before, the choice for V2H chargers was reasoned to be chosen over V2G chargers as the copper plate in the TIMES model is a limitation of the model that allows to avoid distribution costs with V2H chargers while providing the same functionality of V2G chargers. In the multi node setup of the stylised model, the multiple nodes do not allow for bypassing the V2G behaviour. However, the multiple nodes allow for the electric vehicles to move electricity from one node to another which makes V2G chargers favourable. In the single node setup of the stylised model, there is no distribution grid and as such the model cannot take advantage of the difference in location of electricity demand. That reduces the usability of flexible EV chargers and only the time component plays a role. Given the extreme charging pattern (all available or none available) stationary batteries are needed to provide flexibility in time instead.

For the cost savings, we can see that for the TIMES-BE model there is a big difference when considering multiple sectors and the electricity sector. That is, the flexible EV chargers have the highest impact on the electricity sector and the costs in the other sectors simply hide that impact. More importantly, we can also see that, relatively speaking, the results of the two models are in the same ball park. That indicates that we can potentially use the results of the stylised model relative to the TIMES-BE model.

Table 7: Cost savings and most flexible EV charger that each model chooses. The cost savings for the energy system planning models are the difference between a model run with and without flexible chargers.
* This is a simplified calculation where it is assumed that the contribution of the flexible chargers has the largest impact on the power system.

	cost savings [10^9 EUR24]	cost savings [%]	most flexible chosen charger type
TIMES-BE (multi sector, single node)	8.70	0.46	V2H
TIMES-BE (single sector, single node)*	8.06	7.12	V2H
stylised model (single sector, single node)	0.0	0.0	/
stylised model (single sector, multi nodes)	2.76	9.91	V2G

This comparison is merely meant to provide nuance to the results of the stylised model. In the following, we continue with the true purpose of the stylised model: to experiment with equations that represent consumer preference inside an energy system planning model.

In the following exercise we continue with the multi node setup. That setup makes more sense for when we consider a difference in consumer preference from short distance drivers and long distance drivers later on (Section 3.4). Also, instead of performing a full analysis as in Section 2, here we focus on the adoption and use of flexible chargers as a consequence of consumer preference. Though, first we will have to derive general equations from the DCE to fit the energy system planning model.

3.2 From DCE to energy system planning model

To integrate the results of the DCE in the energy system planning model we have to transform the obtained utility for the adoption of flexible chargers to a market share of flexible chargers. For this transformation we loosely follow the example of Byun, Shin and Lee [2]. The trick is to transform the utility to a probability first. Then, we assume that the probability for adopting a flexible charger is a good proxy for the market share of flexible chargers. For example, when an individual has a probability of 50% to adopt a charger with a particular feature (e.g. a V2H charger), we assume that 50% of a group (or cluster) of individuals actually adopt the charger.

The utility functions of the DCE can be simplified to:

$$V_{ik}(x) = \beta_0 + \beta_x \cdot x \tag{1}$$

With

V_{ik} the utility that individual i in latent class k has for attribute x, e.g. the utility that an individual from the class of 'likely adopters' has for a V2H charger

β_0 the baseline utility for the conducted survey (typically disappears when considering the difference in utility between two attributes)

β_x a coefficient for attribute x, determined from the DCE

x value for attribute x, x can be continuous for some attributes, e.g. 50% for the attribute of a minimum battery level, and x can be discontinuous for other attributes, e.g. whether an energy retailer has access to the charger or not.

In principle, the utility function also has interaction terms, i.e. the combined effect of two attributes. However, these interaction terms are dropped here as the DCE at hand does not consider these interaction terms either.

To obtain a probability function from the utility function, we need to assume a probability distribution. We consider a common logistic distribution:

$$P_k(x) = \frac{exp(V_k(x))}{exp(\beta_0) + exp(V_k(x))} \tag{2}$$

with

$V_k(x)$ the combined utility of all individuals in latent class k for attribute x

$P_k(x)$ the probability or market share of a charger with features x due to latent class k, e.g. 20% (P=20%) of the class of likely adopters (k=likely adopters) adopts flexible chargers that always charge to a minimum battery level of 40% (x=40% minimum charge)

The relation between P_k and x is non-linear. To make use of this relation in a linear model, we need to linearise the equation in a small interval and bind the values of the attributes to that interval.

$$P_k(x) \sim P_0 + \gamma_{kx} \cdot (x - x_0) \tag{3}$$

with

P_0 the probability of the point around which the probability function is linearised

x_0 the point around which the probability function is linearised

γ_{kx} a class specific linearised coefficient for the relation between the attribute value x and the market share for flexible chargers with these attributes

To obtain the full market share of the flexible chargers, we simply take the weighted sum of the probabilities of the different latent classes. For example, if the classes consist of likely adopters and unlikely adopters and these make up 20% and 80% of the entire group respectively, the weights for the sum are 20% and 80% for the probability of a likely adopter and the probability of an unlikely adopter to adopt a flexible charger respectively.

The insertion of this equation in the energy system planning model is very specific for each attribute. In the following we consider two examples, one for each DCE. For the first DCE we focus on the financial concerns of the consumer. For the second DCE we focus on the driving range anxiety of the consumers. For each of these attributes, the values from the DCE in the context of the equation for the linearised market share of flexible chargers can be found in Appendix A.

3.3 Energy system planning model for DCE on financial concerns

To address the financial concerns of the consumer, we consider a financial reward for adopting a charger with specific features. The financial reward is meant to be interpreted as yearly savings on the energy bill. Because there are no direct prices in an optimisation model (as opposed to an equilibrium model), the interpretation is taken to be a bit more general to a reward for the adoption of a charger.

To be clear, as in the baseline of the DCE, we start from a situation where there is already a unidirectional charger without optimal charging, i.e. the vehicle is always fully charged immediately after driving. The consumer then has a probability to adopt a flexible charger for a given reward. Similar to the scenario analysis with TIMES-BE, we consider flexible chargers that are optimally controlled[4] but with different directional capabilities, i.e. unidirectional charging, V2H chargers and V2G chargers.

Due to how the probabilities are calculated for this (partial) selection of charger types, the sum of the probabilities does not add to 1 and each charger type needs to be considered independently. In other words, we need to make a distinction between the unidirectional chargers (without optimal charging) that *can* be converted to, e.g., V2H chargers and chargers that *will* be converted to,

[4]It is possible to study the effect on the different control strategies, but it is assumed that in the long term, flexible chargers are used primarily to gain a financial benefit which should after some redesigns of electricity contracts grow towards optimal control.

e.g., V2H chargers. For the model that means that the market share has to be adjusted accordingly:

$$f_v \cdot P_v(r_v) \tag{4}$$

with

v set of charger types $[uni, V2H, V2G]$, i.e. optimal charging with a unidirectional charger, a V2H charger and a V2G charger

f_v representing the chargers that can change to charger type v

$P_v(r_v)$ representing the chargers that will change to charger type v, following equation 3 for the yearly reward for the adoption of charger type v

r_v the yearly reward associated to adopting a charger of type v

The interpretation of f_v depends on the scale. For a single charger, f_v is a binary that denotes whether the charger considers that charger type or not. For multiple chargers, f_v becomes an integer. For clustered chargers, we can relax f_v to a percentage (or fraction). Since we are already working with a clustered unit commitment model, we opt for the latter interpretation. Accordingly, the fraction of all charger types cannot exceed 1:[5]

$$\sum_v f_v \leq 1 \tag{5}$$

The market share for each charger is used in the charging pattern of the electric vehicles and the calculation of the costs of the rewards in the objective function.

For the charging pattern of electric vehicles p we initially assume that each charger charges without optimal charging. That charging pattern only depends on the driving pattern and as such is predetermined for the simulation, i.e. P^e.

When a charger converts to a flexible charger, the charging pattern of the cluster needs to be adjusted for the market share of the flexible charger $f_v \cdot P_v(r_v)$. Additionally we need to add variables for charging p^c (and discharging p^d if applicable). Finally, we need to repeat this for every charger type, resulting in the following equation:

$$p_{ch,t} = -P^e_{ev,t} \cdot (1 - \sum_v f_v \cdot P_v(r_v)) + \sum_v p^d_{ev,v,t} - p^c_{ev,v,t} \tag{6}$$

with

$p_{ch,t}$ the actual charging pattern of the clustered chargers ch at time t

[5]For the binary interpretation we would have the same constraint but with binary variables and for the integer interpretation the sum of f_v would have to be equal or smaller than the number of chargers.

$P^e_{ev,t}$ the expected charging pattern of electric vehicle ev at time t if the charger were a unidirectional charger without optimal control

$1 - \sum_v f_v \cdot P_v(r_v)$ the share of unidirectional chargers without optimal control, expressed as the remainder after the shares of the different types of flexible chargers

$p^c_{ev,v,t}$ the flexible charging of electric vehicle ev at charger type v in the cluster of chargers

$p^d_{ev,v,t}$ the flexible discharging of electric vehicle ev at charger type v in the cluster of chargers

Accordingly, the flexible charging and discharging of each charger type are bound by the market share of the corresponding charger type. In that same bound we can also include some specifications on the charging pattern. For example, optimal charging is only bound by the market share but solar charger is additionally bound by the solar pattern. Similarly, a V2H charger is not able to discharge so the bound should be 0 regardless of the market share. These additional caveats in the charging pattern are included in the parameter A.

$$p^c_{ev,v,t} \leq f_v \cdot P_v(r_v) \cdot C^p_{ch} \cdot A^c_v \tag{7}$$
$$p^d_{ev,v,t} \leq f_v \cdot P_v(r_v) \cdot C^p_{ch} \cdot A^d_v \tag{8}$$

with

C^p_{ch} the total capacity of the clustered chargers ch, equal to the maximum of $P^e_{ev,t}$

A^c_v the charging mode of charger type v, e.g. 1 for optimal charging and a solar profile for solar charging (though we only consider optimal charging here)

A^d_v the discharging mode of charger type v, e.g. 1 for bidirectional charging and 0 for unidirectional charging

For the fraction of inflexible chargers $(1 - \sum_v f_v \cdot P_v(r_v))$, there is also a constraint that guarantees that the vehicle is fully charged as soon as possible, taking into account when the vehicle is connected to a charger and the maximum charge output of the charger.[6] Both the docking and the charging rate are known upfront and as such are predetermined in the simulation.

$$(1 - \sum_v f_v \cdot P_v(r_v)) \cdot A^i_{ev,t} \cdot C^e_{ev} \leq e_{ev,t} \leq C^e_{ev} \tag{9}$$

with

[6] This equation is actually from the perspective of the fleet of electric vehicles and assumes that all types of chargers are available in the same ratio in each cluster of chargers. With the introduction of sets of which fleets pass by which cluster of chargers, we can make the necessary distinction. But for the simple setup for the stylised model there is no need for that.

$A^i_{ev,t}$ a binary parameter[7] that indicates when the battery of a vehicle attached to an inflexible charger should be full, i.e. as soon as possible

C^e_{ev} the maximum energy level of the battery of the vehicle

$e_{ev,t}$ the current energy level of the battery of the vehicle

That marks an end to the modifications to the formulation of electric vehicles and chargers in the energy system planning model. All that is left is to add the yearly reward to the additional investment cost of the flexible charger in the objective function.

$$\min \sum_v DF_1 \cdot I^{ch}_v \cdot f_v \cdot P_v(r_v) \cdot C^p_{chu} + \sum_v \sum_y \Delta DF_y \cdot r_v \cdot FAR_v \cdot C^p_{ch} \tag{10}$$

with

DF_y the discount factor in milestone year y

ΔDF_y the discount factor for each milestone year y and all the years the milestone year represents

I^{ch}_v the additional investment cost for a charger of type v

FAR_v an estimate of the fraction of charger type v due to the reward of adopting charger type v (used as a proxy of $f_v \cdot P_v(r_v)$ to avoid a non linear objective function)

With these adjustments of the formulation, we are able to address the financial concerns of the EV owners in the energy system planning model. As such we can study the competition between addressing the financial concerns of the EV owners (i.e. the model can provide a compensation per flexible charger) and additional investments in capacity for electricity generation or batteries.

In order for the equations above to be linear, either the fraction of different types of chargers can be a variable or the reward can be a variable but they cannot be variables at the same time. Logically, we first take the fraction of the different types of chargers as a variable with a fixed reward equal to x_0. The fractions that are obtained from that model run can then serve as the fixed values for the fractions in a run where the reward is variable.

Using the coefficients from the DCE (Tables 8 and 9), when we run the model with variable fractions, the model consistently chooses V2G chargers over V2H and unidirectional chargers. So, for the run with the variable reward, we only need to consider V2G chargers. To obtain a good estimate for the fraction of V2G chargers and inflexible chargers we take an iterative approach until the fixed fraction FAR_{V2G} is sufficiently close to $f_{V2G} \cdot P_{V2G}(r_{V2G})$ with $f_{V2G} = 1$ as all chargers are able to convert to V2G chargers.

[7]Not to be confused with a binary variable.

For this particular setup, the additional cost of the reward given to the owner of the flexible EV charger, does not limit the adoption and use of flexible EV chargers as can be seen from Figure 11. However, recall that the competition with stationary batteries has been artificially increased to correspond better to the results from the TIMES BE model. While it is not shown here, in a more competitive setup, the reward required by the consumers actually reduces the competitiveness of flexible EV chargers compared to stationary batteries. Implying an incentive to increase consumer acceptance of flexible EV chargers and as such reduce the required reward.

It is possible to go in much more detail of the case study, but here we want to focus on the modelling of DCEs in energy system planning model. The following section will cover another DCE with different equations for the same setup.

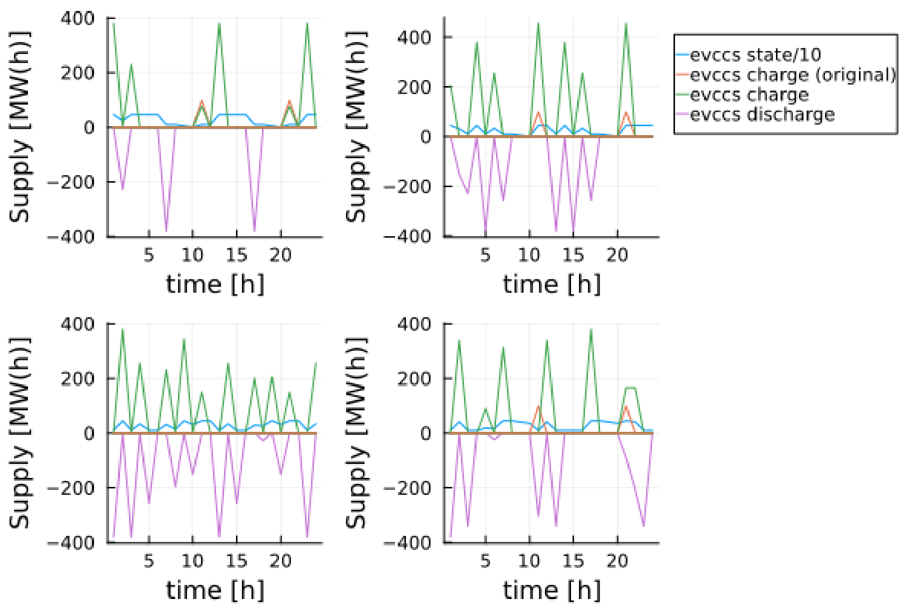


Figure 11: Charging pattern for 4 week days throughout the year for an electric vehicle associated to the S node in the case the model has access to flexible chargers. The charging profile is the charge pattern for the inflexible chargers (as well as the flexible chargers if they would be used inflexibly) whereas the flexible chargers follow the charge and discharge pattern.

3.4 Energy system planning model for DCE on driving range anxiety

To address the driving range anxiety, we only consider the minimum battery level (as the other options like road side services and an emergency battery are in principle similar to reserving a part of the battery for emergencies). However, in contrary to the case study on the financial concerns, the DCE is not about adopting a flexible charger but about ceding control to a third party. That implies that we do not need to make the distinction between the chargers that can be converted and those that will be converted. For simplicity, we further assume that the charger is not used optimally when the control of the charger is not ceded to a third party. In other words, the available flexibility from the EV chargers equals the probability that the consumer cedes control to a third party.

In this setup, we only consider 1 charger type and we separate the data from the second DCE in two latent classes. Typically, DCEs split the data according to 'likely adopters' and 'unlikely adopters'. Alternatively, some inspiration could be obtained from Sridhar et al. who challenge certain myths regarding various latent classes [19]. However, since we discuss the driving range anxiety, it is actually more interesting for our work to split the data into groups with a short driving range and those with a long driving range.

The bound on the flexible charging and discharging is similar to the previous setup. Though, instead of using the probability of adopting a flexible charger in function of the reward, we use the probability of ceding control in function of the minimum battery level.

$$p_{ch,t} = -P^e_{ev,t} \cdot (1 - P_{ve}(b_{ve})) + p^d_{ev,t} - p^c_{ev,t} \tag{11}$$

$$p^c_{ch,t} \leq P_{ve}(b_{ve}) \cdot C^p_{ch} \cdot A^c \tag{12}$$
$$p^d_{ch,t} \leq P_{ve}(b_{ve}) \cdot C^p_{ch} \cdot A^c \tag{13}$$

with

$P_{ve}(b)$ the linearised probability of vehicle owner class ve using the charger optimally when the battery level is b

The minimum battery level only affects the equation for the state of the battery. Similar to equation 9, the charging pattern needs to consider the driving pattern and the charging rate (combined in parameter A which is predetermined in the simulation). Different to equation 9, the minimum battery level of the fleet is split in two parts: for the chargers that are not controlled optimally $(1-P_{ve}(b_{ve}))$ the batteries are fully charged as soon as possible and for the the chargers that are controlled optimally $(P_{ve}(b_{ve}))$ the batteries are charged to the minimum battery level b as soon as possible.

$$(1 - P_{ve}(b_{ve})) \cdot A^i_{ev,t} \cdot C^e_u + FAB_{ve} \cdot b_{ve} \cdot A^{bl}_{ev,ve,t} \cdot C^e_u \leq e_{u,t} \leq C^e_u \tag{14}$$

with

$A^{bl}_{ev,ve,t}$ a binary parameter that indicates whether the minimum battery level needs to be accounted for vehicle ev, vehicle type ve and time t, taking into account the driving pattern and the charging rate (predetermined)

FAB_{ve} estimated fraction corresponding to the minimum battery level (used as a proxy of $P_{ve}(b_{ve})$ to avoid a non linear constraint)

With these adjustments of the formulation, we are able to address the driving range anxiety of the EV owners in the energy system planning model. The charging pattern in Figure 12 shows that the limit on the battery level is too restricting for the model to leverage the use of flexible EV chargers. The only reason there are flexible chargers installed is because of the bounds on the consumer preference for the minimum battery level set by the results of the DCE (see Table 9). That implies in this case we should have conducted the survey for lower rates of adoption (or assume the results are linear and allow them to go to zero).

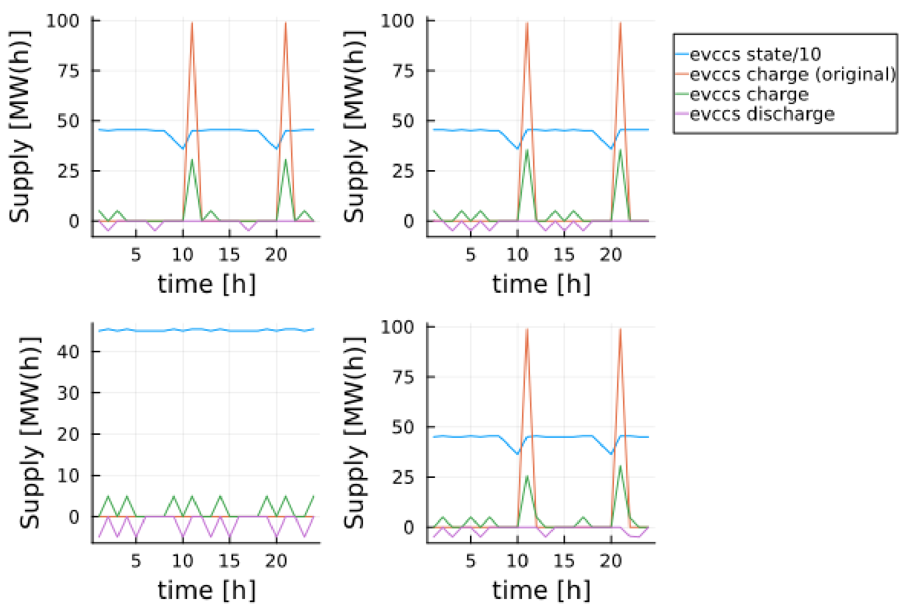


Figure 12: Charging pattern for 4 week days throughout the year for an electric vehicle associated to the S node in the case when there is a minimum battery level. The charging profile is the charge pattern for the inflexible chargers (as well as the flexible chargers if they would be used inflexibly) whereas the flexible chargers follow the charge and discharge pattern.

3.5 Comments on the modelling exercise

In the previous subsections we have modelled different attributes from different DCEs. While there is some common ground for the corresponding equations, there are also parts that are very specific for each of these attributes. That requires a careful design of the formulation. One part is the interpretation of the DCE. We have seen that some attributes are very similar from the point of view of the model (e.g. the emergency battery and the minimum battery level of the vehicle) allowing us to concentrate on only one of these attributes. We have also seen that the complexity of the equations is also different depending on the considered attributes/DCE (e.g. compare Subsections 3.3 and 3.4). Here, we have been working with existing DCEs, but, due to the specific design of the equations, it is clearly advantageous to design the survey and the energy model at the same time.

Even when the consumer preference is linearised, the equations become non-linear rather quickly due to multiplications of variables (typically quadratic as it is a multiplication of a variable with a fraction of chargers depending on that same variable). While it is possible to deal with quadratic equations, here we have opted to keep working with linear equations. In some cases that required us to use a best guess for some of the variables (e.g. when dealing with $f_v \cdot P_v(r_v)$) whereas in other cases that required us to take an iterative approach (e.g. when dealing with $r_v \cdot FAR_v$). In the former case, the quality of the results depend on the quality of the guess. In the latter case, with the iterative approach we venture into the domain of agent based modelling as the iterative approach is prevalent there. That raises the question how this methodology holds up against such an agent based model. However, that is left for future research.

Due to the limited setup and scope of the stylised model, the results of that model are not directly usable to make conclusions for the Belgian situation. Yet, by comparing the stylised model to the TIMES-BE model, we can provide some nuance to the results of the TIMES-BE model with the modelling insights of the stylised model. Though, we also need to take into account that import/export, curtailment and stationary batteries have been artificially altered to make the modelling exercise more clear. Regardless, while the setup of the stylised model without consumer preference prefers to use flexible chargers (see Section 3.1), we see that the consumer preferences pose constraints on the model that the model tries to avoid by various means (i.e. the aforementioned import/export, curtailment and stationary batteries). Any energy system planning model is quite sensitive to all of these constraints. On one hand that means that various pathways are possible and should be considered in scenarios and on the other hand that means that consumer preference is not to be neglected in a pathway that includes the use of flexible EV chargers.

4 Conclusion

Flexible EV chargers have a large technical potential to provide flexibility to the distribution grid. However, the potential is only as much as consumers are willing to adopt and use flexible EV chargers. Bringing consumer preference to energy system planning models is not a trivial task.

In our study, we have explored the indirect consideration for consumer preference in a post analysis with the TIMES-BE model as well as the direct integration of consumer preference in a stylised model. Whereas the indirect approach is immediately accessible for existing models (which may be particularly interesting for transmission system operators with their current adequacy modelling exercises), the direct approach leads to more accurate results for the actual availability and use of flexibility in the energy system.

In the indirect approach, we used TIMES-BE to study the adoption of flexible EV chargers in Belgium. For a given maximum availability of flexible chargers, the model can choose between unidirectional chargers, vehicle to home (V2H) chargers and vehicle to home and grid (V2G) chargers. However, due to the copper plate approach in the TIMES-BE model, the model is not able to effectively use the V2G chargers and as such only chooses V2H chargers. Regardless, the scenario analysis with the TIMES-BE model starts from the PATHS2050 scenarios and extends them with scenarios without access to flexible EV chargers and full access to flexible EV chargers. In post analysis, the difference in total system costs between the scenarios with and without flexible EV chargers provides a remuneration budget that can be used to reward adopters of flexible EV chargers. This remuneration budget is then compared to the stated expected return on investment from a DCE (in the form of an implicit discount rate). It is found that the remuneration budget generally satisfies the requirements of the consumer.

In the direct approach, we chose to build a new formulation for a stylised model to be able to experiment more freely with the model equations. The setup for this model is limited and accordingly the focus is more on the modelling than the actual results. Additionally, we had to artificially change settings for import/export, curtailment and stationary batteries to align the behaviour of the stylised model to the TIMES model. Part of the modelling exercise was general for any DCE but another part was very specific to each of the attributes in the DCE. We provided examples for two attributes from two different DCEs: the adoption of flexible EV chargers for a given reward and ceding control of flexible chargers for a given minimum battery level during charging. The results show that the consumer preferences pose important constraints to the problem which on one hand provides us a more accurate picture of the availability of flexibility from flexible EV chargers and on the other hand possibly steer the investments in flexibility towards other flexibility measures.

While the results of the stylised model are not usable in absolute terms, we can use the results relative to those of the TIMES-BE model. That is, the stylised model shows that consumer preference is important to consider during the decision process as it reduces the competitiveness of flexible EV chargers.

In conclusion, whether we use the direct or indirect approach, the consumer preferences impose an important constraint on the availability of flexibility from flexible EV chargers and need to be considered during energy system planning. For future studies, we need to consider consumer preferences (similar to the stylised model) at the decision process of a tool that is calibrated properly to represent the Belgian situation (similar to the TIMES-BE model). We also call for further collaboration between social sciences and energy system modelling as well as further studies on the role of our direct approach compared to agent based modelling.

Acknowledgement

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A DCE

This appendix contains the data from the DCEs for the energy system planning models. The data is split according to the two surveys that were conducted.

A.1 DCE on financial concerns

$$P_x(r) = P_0 + \gamma_x + \gamma_r \cdot (r - r_0) \tag{15}$$

where $x \in [uni, V2H, V2G]$ with uni for unidirectional charging, V2H for bidirectional charging at home and V2G for bidirectional charging with the grid.

Table 8: Parameters and values for the linearised equation from the DCE

Parameter	Value
P_0	0.612
r_0	400.0
r_{min}	30.0
r_{max}	810.0
γ_r	0.000349
γ_{uni}	0.0121
γ_{V2H}	0.0146
γ_{V2G}	0.0331

A.2 DCE on driving range anxiety

$$P_c(r) = P_{c,0} + \gamma_{c,b} \cdot (b - b_{c,0}) \tag{16}$$

where $c \in [short, long]$ with short for the class of short distance drivers and long for the class of long distance drivers.

Table 9: Parameters and values for the linearised equation from the DCE

Parameter	Value for short distance drivers	Value for long distance drivers
P_0	0.370	0.439
b_0	0.20	0.20
b_{min}	0.0	0.0
b_{max}	0.5	0.5
γ_b	0.303	0.346

B TIMES-BE

This analysis employs the TIMES modelling framework, a long-established tool developed under the IEA's Energy Technology Systems Analysis Program (ETSAP) for energy system planning [10]. TIMES enables the identification of cost-optimal transition pathways by minimizing total system costs under a wide range of technical and policy constraints [10]. It integrates detailed representations of current technologies, future demand projections, resource availabilities, and techno-economic parameters, producing outputs such as investment decisions, activity levels, and energy flows across the planning horizon [10].

B.1 Data for electric vehicle chargers

Table 10: Financial characterisation of EV chargers

Sector	Charger type	Typical size [kW]	CAPEX [€]	CAPEX [€/kW]	Source
Residential (Home)	Uncontrolled	7.4	1541.4	208.3	ICCT[10] , EV[9]
Residential (Home)	Flexible	7.4	1747.1	236.1	ICCT[10], Wallbox, EV[9]
Residential (Home)	Flex with V2H/V2G	7.4	2330.3	314.9	Wallbox, EV[9]
Commercial (Work)	Uncontrolled	7.4	2063.1	278.8	ICCT[10] , EV[9]
Commercial (Work)	Flexible	7.4	2153.4	291.0	ICCT[10] ,Wallbox, EV[9]
Commercial (Work)	Flex with V2B/V2G	7.4	3902.0	527.3	Wallbox, EV[9]

C Stylised model

This appendix provides the full linear formulation of the stylised model for adequacy with low voltage flexibility.

These are nodal equations. By convention, the power to a node is considered positive.[8]

[8]The terms 'power' and 'energy' are used in the general physics sense. Even more so, whenever 'power' is used in this formulation, it is meant as the accumulated energy during 1 time step. It is still called 'power' because the formulation still holds when the step duration is decreased to infinitesimally small values.

Also note that upper case or Greek letters represent parameters whereas lower case represents variables. Subscripts are indices and superscripts provide additional information.

For reference, we first share the general results of the model before providing the full model.

C.1 Results for Belgium

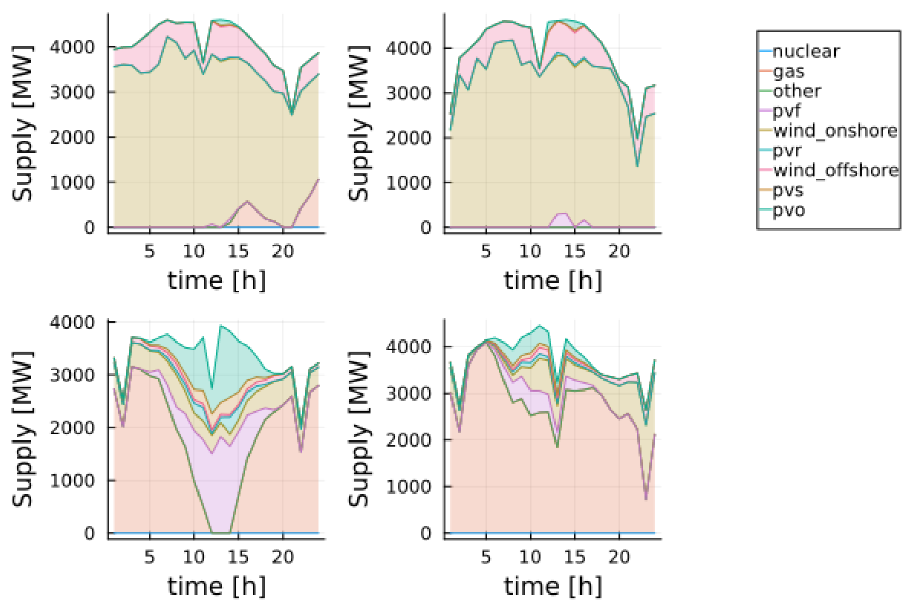

Figure 13: Power production for 4 week days throughout the year.

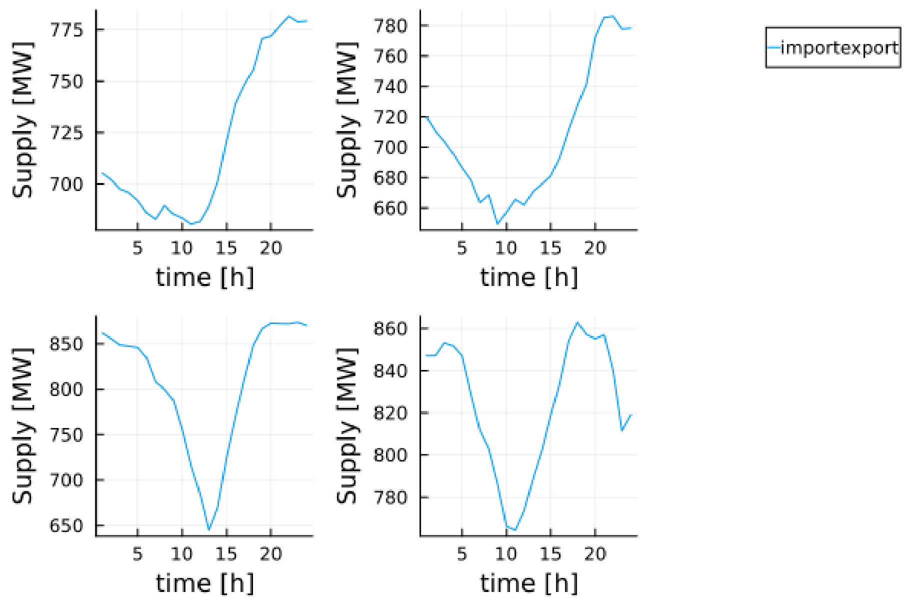

Figure 14: Import (positive) and export (negative) for 4 week days throughout the year.

C.2 Sets

v: charger mode

ve: ev types

$veev_{evu}$: map between ev and evtypes

vd: subset that triggers a self consumption constraint

n: node, defined by the units attached to it

l: link, comprised of two nodes

h: subset of node, home node containing, e.g., demand, HP, PV and EV, used to determine the monthly peak demand

hch_{chu}: subset of home, without charger

u: unit, e.g. conversion unit, demand, load shedding, flex, etc., excluding evu

lu: subset of unit, link ends

evu: electric vehicle clusters, each cluster can have different types (or users)

chu: subset of unit, charger clusters (or parking lot), each cluster can have different types

hup: subset of unit, heat pump

su: subset of unit, storage unit

du: subset of unit, demand unit

eu: subset of unit, export

iu: subset of unit, import

ru: subset of unit, renewables

gu: subset of unit, generation unit

$griechhpu$: subset of unit, generation, renewable, import/export, charger, heat pump

$grsdieu$: subset of unit, generation, renewable, storage, demand, import/export

$grsu$: subset of unit, generation, renewable and storage unit

dlu: subset of unit, demand and line

$shpevu$: subset of unit, storage, electric vehicle and heat pump

$passby_{chu}$: all electric vehicles that pass by the charger chu over all times

$pass_{chu,t}$: all electric vehicles that pass by the charger chu at time t

$route_{evu,t}$: all chargers that are part of the route of electric vehicle evu at time t

t: time steps, coincides with the lowest time scale, typically hours

d: days

m: months

y: years

Y_t: year corresponding to a time step

Y_m: year corresponding to a month

T_d: time steps of a day

T_m: time steps of a month

T_y: time steps of a year

mt_{sgru}: time steps at which unit u is under maintenance (for renewable units it is important to also adjust the profile)

ct_{evu}: time steps at which the electric vehicle evu needs to be full

$MUTt_{u,t}$: return the end and start time index corresponding to the MUT when committed in time t; this will only be exact for a constant step duration

$MDTt_{u,t}$: return the end and start time index corresponding to the MUT when committed in time t; this will only be exact for a constant step duration

$Ly_{u,y}$: return the start and end year index corresponding to the life time when installed in year y; this will only be exact for a constant year step duration, corresponding to milestone years

C.3 Parameters

ΔT_t**:** duration of a time step

ΔDF_t**:** conversion factor for the present value for each time step for the duration of the year

DF_y**:** conversion factor for the present value for each year

ΔDF_y**:** conversion factor for the present value for each year for the duration of the year

R^+**:** likelihood of worst upward scenario

R^-**:** likelihood of worst downward scenario

TAX^{CO_2}**:** tax on carbon emissions

$VOLL$**:** value of lost load

C^{peak}**:** cost for peak production in a month

$\gamma_v^{r,0}$**:** constant parameter for the linearised market coefficient between a financial reward and a charger mode

γ_v^r**:** coefficient (from DCE) for the linearised market coefficient between a financial reward and a charger mode

$A_v^{r,0}$**:** baseline for the financial reward for a charger mode

$A_v^{r,min}$**:** minimum value for the financial reward (due to the linear interval)

$A_v^{r,max}$**:** maximum value for the financial reward (due to the linear interval)

$\gamma_{ve,v}^{b,0}$**:** constant parameter for the linearised market coefficient between a battery level and a charger mode for a driver's preference

$\gamma_{ve,v}^{b}$**:** coefficient (from DCE) for the linearised market coefficient between a battery level and a charger mode for a driver's preference

$A_{ve,v}^{b,0}$**:** baseline for the battery level for a charger mode

$A_{ve,v}^{b,min}$**:** minimum value for the battery level (due to the linear interval)

$A_{ve,v}^{b,max}$**:** maximum value for the battery level (due to the linear interval)

θ**:** comfort band expressed in percentage of the indoor temperature

I_u **or** I_u^p**:** investment cost per installed power capacity

I_u^e**:** investment cost per installed energy capacity

I_v^{ch}**:** investment cost per installed power capacity of a charger of a particular type

SC_{grsu}^p**:** sunk power capacity

SC_{su}^e**:** sunk energy capacity

FOM_{grsu} or FOM^{p}_{grsu}: fixed operation and maintenance cost per installed power capacity

FOM^{e}_{su}: fixed operation and maintenance cost per installed energy capacity

$VOM_{grsdieu}$: variable operation and maintenance cost during operation per unit of energy (also used for demand response and import/export)

SUC_{gu}: start-up cost

L_{grsu}: lifetime

η_u: efficiency

η^{min}_u: part load efficiency

η^{s}_u: storage efficiency

η^{c}_u: charging efficiency

η^{d}_u: discharging efficiency

η^{l}_l: line efficiency

η^{ev}_u: charge/discharge efficiency of an electric vehicle (assumption that $\eta^c = \eta^d$ and η is the same for each charger)

$\eta^{gain}_{u,t}$: temperature (and thus time) dependent heat pump coefficient

$\eta^{loss}_{u,t}$: temperature (and thus time) dependent building coefficient

MUT_u: minimum up time

MDT_u: minimum down time

$F^{CO_2}_u$: fraction of the emissions that is not captured

F^{ramp}_u: fraction of the power capacity that can be ramped up or down during one time step

F^{Cramp}_u: fraction of the installed capacity that can be ramped up in consecutive years

$F^{response}_u$: fraction of available demand response

$F^{curtail}_u$: fraction of allowed curtailment

F^{shp}_u: fraction of smart heat pumps

F^{res}: fraction of the renewable capacity is used as the potential deviation of the prediction

F^{dres}: fraction of the peak demand is used as the potential deviation of the prediction

FAR_v: estimated fraction of charger types due to the reward

$FAB_{veev,v}$: estimated fraction of charger types due to the minimum battery level of vehicle type

$A^c_{v,t}$**:** charging pattern for a class/attributes; heuristic for dumb charging or solar charging and 1 for optimal charging

$A^d_{v,t}$**:** discharging pattern for a class/attribute; 0 for unidirectional or 1 for bidirectional

$A^{drive}_{evu,t}$**:** driving pattern

$A^{bl}_{evu,ve,v,t}$**:** activates the minimum battery level constraint for flexible chargers only when the electric vehicle is not driving and has had the chance to reach the minimum battery level (obtained with a heuristic).

$A^{bl,fix}_{evu,t}$**:** activates the minimum battery level constraint for inflexible chargers only when the electric vehicle is not driving and has had the chance to reach the minimum battery level (obtained with a heuristic).

$P^e_{u,t}$**:** power profiles for predicted demand, scheduled intermittent source, import/export signal (between 0 and 1) and electric vehicle charging

P^{drive}_u**:** power consumption while driving

$P^{peak}_{u,y}$**:** peak power

P^{min}_{gieu}**:** minimum (national or international) power production

P^{max}_{gieu}**:** maximum (national or international) power production

C^p_u**:** a cap on the installed power capacity

C^e_u**:** a cap on the installed energy capacity

C^{l+}_l**:** positive bound on capacity of a line in node i, set $C^{l+}_l = 0$ whenever $\eta^l_l \neq 1$ (because a directional line goes from i to j)

C^{l-}_l**:** negative bound on capacity of a line in node i, typically $C^{l-}_l = C^{l+}_l$ whenever $\eta^l_l = 1$

C.4 Variables

All variables are bound to be larger than zero, unless specified otherwise

f_v: feature or fraction of charger type

a^r_v: attribute level for financial reward considered by the DCE; for the current data set, a^r_v and $a^b_{ve,v}$ should not be in the model at the same time

$a^b_{ve,v}$: attribute level for financial reward considered by the DCE; for the current data set, a^r_v and $a^b_{ve,v}$ should not be in the model at the same time

$p_{u,t}$: operation power of unit u at time t, bidirectional by default

$p^e_{u,t}$: supporting variable used as a modified version of the operation power to create an absolute value, to enable curtailment, etc.

$p^c_{su,t}$: charge power

$p^d_{su,t}$: discharge power

$p^c_{evu,v,t}$: class/attribute specific charge power

$p^d_{evu,v,t}$: class/attribute specific discharge power

$p^{d,upperbound}_{chu,v,t}$: term used to lower the available capacity for reserves for V2H, it is lower than the upper bound for V2G and it is lower than the upper bound of the demand in the home node

$p^{ll}_{du,t}$: scheduled load shedding

$p^{response}_{du,t}$: demand response

$p^{response,e}_{du,t}$: positive difference between demand response and actual profile, used for cost calculations

$p^m_{h,m}$: monthly peak use of a connection (demand or supply) of a home

$c_{grsu,y}$: power capacity of unit u at time t

$c^u_{grsu,y}$: installed power capacity

$c^d_{grsu,y}$: removed power capacity

$n_{gu,t}$: number of committed units

$n^u_{gu,t}$: start up of committed units

$n^d_{gu,t}$: shut down of committed units

$e_{shpevu,t}$: state of energy storage

$c^e_{su,y}$: available energy capacity

$c^{e,u}_{su,y}$: installed energy capacity

$c^{e,d}_{su,y}$: removed energy capacity

$r^{+}_{griechhpu,t}$: upward spinning reserves of unit u at time t and scenario s

$r^{-}_{griechhpu,t}$: downward spinning reserves of unit u at time t and scenario s

$r^{c,+}_{su,t}$: upward spinning reserves of unit u that is charging at time t and scenario s

$r^{c,-}_{su,t}$: downward spinning reserves of unit u that is charging at time t and scenario s

$r^{d,+}_{su,t}$: upward spinning reserves of unit u that is discharging at time t and scenario s

$r^{d,-}_{su,t}$: downward spinning reserves of unit u that is discharging at time t and scenario s

$r^{e,+}_{shpevu,t}$: upward energy reserves

$r^{e,-}_{shpevu,t}$: downward energy reserves

$r^{ll}_{du,t}$: load shedding in upward reserves

$r^{l,+}_{dlu,t}$: transport of reserves in the upward balancing equation (also used for demand response), bidirectional

$r^{l,-}_{dlu,t}$: transport of reserves in the downward balancing equation (also used for demand response), bidirectional

C.5 Objective function

$$\min \sum_{h} \sum_{m} DF_{Y_m} \cdot p^{m}_{h,m} \cdot C^{peak} \tag{17}$$

$$+ \sum_{u \in chu} \sum_{v} \sum_{y} \Delta DF_y \cdot C^p_u \cdot FAR_V \cdot a^r_v \tag{18}$$

$$+ \sum_{chu} \sum_{evu \in passby_{chu}} \sum_{v} DF_1 \cdot I^{ch}_v \cdot f'_{evu,v} \cdot C^p_{chu} \tag{19}$$

$$+ \sum_{u \in du} \sum_{t} \Delta DF_t \cdot VOM_{u,t} \cdot \Delta T_t \cdot p^{response,e}_{u,t} \tag{20}$$

$$+ \sum_{u \in du} \sum_{t} \Delta DF_t \cdot VOLL \cdot \Delta T_t \cdot (p^{ll}_{u,t} + R^+ \cdot r^{ll}_{u,t}) \tag{21}$$

$$+ \sum_{u \in su} \sum_{y} DF_y \cdot I^e_u \cdot c^{e,u}_{u,y} + \Delta DF_y \cdot FOM^e_u \cdot c^e_{u,y} \tag{22}$$

$$+ \sum_{u \in su} \sum_{y} DF_y \cdot I^p_u \cdot c^{p,u}_{u,y} + \Delta DF_y \cdot FOM^p_u \cdot c^p_{u,y} \tag{23}$$

$$+ \sum_{u \in su} \sum_{t} \Delta DF_t \cdot VOM_u \cdot \Delta T_t \cdot p^e_{u,t} \tag{24}$$

$$+ \sum_{u \in su} DF_1 \cdot I^p_u \cdot (c^p_{u,1} - SC^p_u) + DF_1 \cdot I^e_u \cdot (c^e_{u,1} - SC^e_u) \tag{25}$$

$$+ \sum_{u \in ieu} \sum_{t} \Delta DF_t \cdot VOM_u \cdot (2 \cdot P^e_{u,t} - 1) \cdot \Delta T_t \cdot (p_{u,t} + R^+ \cdot r^+_{u,t} - R^-_{u,t} \cdot r^-_{u,t}) \tag{26}$$

$$+ \sum_{u \in ru} \sum_{y} DF_y \cdot I_u \cdot c^u_{u,y} + \Delta DF_y \cdot FOM_u \cdot c_{u,y} \tag{27}$$

$$+ \sum_{u \in ru} \sum_{t} \Delta DF_t \cdot VOM_u \cdot \Delta T_t \cdot (p^e_{u,t} - R^+ \cdot r^+_{u,t} + R^-_{u,t} \cdot r^-_{u,t}) \tag{28}$$

$$+ \sum_{u \in ru} DF_1 \cdot I_u \cdot (c_{u,1} - SC^p_u) \tag{29}$$

$$+ \sum_{u \in gu} \sum_{y} DF_y \cdot I_u \cdot c^u_{u,y} + \Delta DF_y \cdot FOM_u \cdot c_{u,y} \tag{30}$$

$$+ \sum_{u \in gu} \sum_{t} \Delta DF_t \cdot SUC_u \cdot n^u_{u,t} \tag{31}$$

$$+ \sum_{u \in gu} \sum_{t} \Delta DF_t \cdot TAX^{CO_2} \cdot F^{CO_2}_u \cdot \Delta T_t \cdot (p^e_{u,t} + n_{u,t} \cdot P^{min}_u) \tag{32}$$

$$+ \sum_{u \in gu} \sum_{t} \Delta DF_t \cdot TAX^{CO_2} \cdot F^{CO_2}_u \cdot \Delta T_t \cdot (R^+ \cdot r^+_{u,t} - R^-_{u,t} \cdot r^-_{u,t}) \tag{33}$$

$$+ \sum_{u \in gu} \sum_{t} \Delta DF_t \cdot VOM_u \cdot \Delta T_t \cdot (p^e_{u,t} + n_{u,t} \cdot P^{min}_u) \tag{34}$$

$$+\sum_{u \in gu} \sum_{t} \Delta DF_t \cdot VOM_u \cdot \Delta T_t \cdot (R^+ \cdot r^+_{u,t} - R^-_{u,t} \cdot r^-_{u,t}) \tag{35}$$

$$+\sum_{u \in gu} DF_1 \cdot I_u \cdot (c_{u,1} - SC^p_u) + \Delta DF_1 \cdot SUC_u \cdot n_{u,1} \tag{36}$$

C.6 Nodal constraints

$$\forall n, t:$$

$$\sum_{u \in n} p_{u,t} = 0 \tag{37}$$

$$\sum_{u \in n} r^{+}_{u,t} + \sum_{u \in su \cup n} r^{c,+}_{u,t} + r^{d,+}_{u,t} + \sum_{u \in dlu \cup n} r^{l,+}_{u,t} + \sum_{u \in du \cup n} r^{ll}_{u,t}$$
$$- \sum_{u \in du \cup n} F^{dres} \cdot P^{peak}_{u,Y_t} - \sum_{u \in ru \cup n} F^{res} \cdot c_{u,Y_t} = 0 \tag{38}$$

$$\sum_{u \in n} r^{-}_{u,t} + \sum_{u \in su \cup n} r^{c,-}_{u,t} + r^{d,-}_{u,t} + \sum_{u \in dlu \cup n} r^{l,-}_{u,t}$$
$$- \sum_{u \in du \cup n} F^{dres} \cdot P^{peak}_{u,Y_t} - \sum_{u \in ru \cup n} F^{res} \cdot c_{u,Y_t} = 0 \tag{39}$$

$$\forall h, m, t \in T_m$$

$$p^{m}_{h,m} \geq -\sum_{u \in h} p_{u,t} \tag{40}$$

$$p^{m}_{h,m} \geq \sum_{u \in h} p_{u,t} \tag{41}$$

C.7 Link

$$\forall (i,j) \in l, t:$$

$$p_{i,t} \leq C^{l+}_{l} \tag{42}$$

$$p_{i,t} \geq -C^{l-}_{l} \tag{43}$$

$$p_{i,t} + r^{l,-}_{i,t} \leq C^{l+}_{l} \tag{44}$$

$$p_{i,t} + r^{l,-}_{i,t} \geq -C^{l-}_{l} \tag{45}$$

$$p_{i,t} + r^{l,+}_{i,t} \leq C^{l+}_{l} \tag{46}$$

$$p_{i,t} + r^{l,+}_{i,t} \geq -C^{l-}_{l} \tag{47}$$

$$p_{i,t} + r^{l,+}_{i,t} + r^{l,-}_{i,t} \leq C^{l+}_{l} \tag{48}$$

$$p_{i,t} + r^{l,+}_{i,t} + r^{l,-}_{i,t} \geq -C^{l-}_{l} \tag{49}$$

$$p_{j,t} = -\eta^{l}_{l} \cdot p_{i,t} \tag{50}$$

$$r^{l,-}_{j,t} = -\eta^{l}_{l} \cdot r^{l,-}_{i,t} \tag{51}$$

$$r^{l,+}_{j,t} = -\eta^{l}_{l} \cdot r^{l,+}_{i,t} \tag{52}$$

C.8 Demand

$\forall u \in du, t:$

$$p_{u,t} = -(1 - F_u^{response}) \cdot P_{u,t}^e - p_{u,t}^{response} + p_{u,t}^{ll} \tag{53}$$

$$p_{u,t} \leq 0 \tag{54}$$

$$r_{u,t}^{ll} \leq -p_{u,t} + F^{dres} \cdot P_{u,Y_t}^{peak} \tag{55}$$

$$r_{u,t}^{l,+} \leq p_{u,t}^{response} \tag{56}$$

$$r_{u,t}^{l,-} \geq -p_{u,t}^{response} \tag{57}$$

$$p_{u,t}^{response} \geq 0 \tag{58}$$

$$\tag{59}$$

$$p_{u,t}^{response,e} \geq F_u^{response} \cdot P_{u,t}^e - p_{u,t}^{response} + R^+ \cdot r_{u,t}^{l,+} - R^- \cdot r_{u,t}^{l,-} \tag{60}$$

$$p_{u,t}^{response,e} \geq -F_u^{response} \cdot P_{u,t}^e + p_{u,t}^{response} - R^+ \cdot r_{u,t}^{l,+} + R^- \cdot r_{u,t}^{l,-} \tag{61}$$

$$\forall u \in du, d: \tag{62}$$

$$\sum_{t \in T_d} \Delta T_t \cdot p_{u,t}^{response} - \sum_{t \in T_d} \Delta T_t \cdot F_u^{response} \cdot P_{u,t}^e = 0 \tag{63}$$

$$\sum_{t \in T_d} \Delta T_t \cdot r_{u,t}^{l,+} = 0 \tag{64}$$

$$\sum_{t \in T_d} \Delta T_t \cdot r_{u,t}^{l,-} = 0 \tag{65}$$

C.9 Import/Export

$\forall u \in ieu, t:$

$$-(P_u^{max} - P_u^{min}) \cdot P_{u,t}^e + r_{u,t}^- \leq p_{u,t} \tag{66}$$

$$p_{u,t} \leq (P_u^{max} - P_u^{min}) \cdot (1 - P_{u,t}^e) - r_{u,t}^+ \tag{67}$$

C.10 Storage

$$\forall u \in su:$$

$$c_{u,1} \geq SC^p_u \tag{68}$$

$$c^e_{u,1} \geq SC^e_u \tag{69}$$

$$\forall u \in su, t:$$

$$p_{u,t} = \eta^d_u \cdot p^d_{u,t} - p^c_{u,t} \tag{70}$$

$$\begin{aligned} p^e_{u,t} &= \eta^d_u \cdot (p^d_{u,t} + R^+ \cdot r^{d,+}_{u,t} - R^- \cdot r^{d,-}_{u,t}) \\ &+ p^c_{u,t} - R^+ \cdot r^{c,+}_{u,t} + R^- \cdot r^{c,-}_{u,t} \end{aligned} \tag{71}$$

$$r^{c,+}_{u,t} \leq p^c_{u,t} \leq c_{u,Y_t} - r^{c,-}_{u,t} \tag{72}$$

$$r^{d,-}_{u,t} \leq p^d_{u,t} \leq c_{u,Y_t} - r^{d,+}_{u,t} \tag{73}$$

$$r^{e,+}_{u,t} \leq e_{u,t} \leq c^e_{u,Y_t} - r^{e,-}_{u,t} \tag{74}$$

$$r^{e,+}_{u,t} = (r^{c,+}_{u,t} + r^{d,+}_{u,t}) \cdot \Delta T_t \tag{75}$$

$$r^{e,-}_{u,t} = (r^{c,-}_{u,t} + r^{d,-}_{u,t}) \cdot \Delta T_t \tag{76}$$

$$\forall u \in su, t \in mt_u$$

$$p_{u,t} = 0.0 \tag{77}$$

$$\forall u \in su, y:$$

$$\begin{aligned} e_{u,T_y[1]} &= \eta^s_u \cdot e_{u,T_y[end]} \\ &+ \eta^c_u \cdot \Delta T_{T_y[1]} \cdot p^c_{u,T_y[1]} - \Delta T_{T_y[1]} \cdot p^d_{u,T_y[1]} \end{aligned} \tag{78}$$

$$c^u_{u,y} \leq C^p_u - c_{u,y} \tag{79}$$

$$c^{e,u}_{u,y} \leq C^e_u - c^e_{u,y} \tag{80}$$

$$\forall u \in su, y, t \in T_y[2:end]:$$

$$e_{u,t} = \eta^s_u \cdot e_{u,t-1} + \eta^c_u \cdot \Delta T_t \cdot p^c_{u,t} - \Delta T_t \cdot p^d_{u,t} \tag{81}$$

$$-p_{u,t} + F^{ramp}_u \cdot c_{u,Y_t} + p_{u,t-1} \geq 0 \tag{82}$$

$$p_{u,t} + F^{ramp}_u \cdot c_{u,Y_t} - p_{u,t-1} \geq 0 \tag{83}$$

$$\forall u \in su, y[2:end]:$$

$$c_{u,y} = c_{u,y-1} + c^u_{u,y-1} - c^d_{u,y-1} \tag{84}$$

$$c^e_{u,y} = c^e_{u,y-1} + c^{e,u}_{u,y-1} - c^{e,d}_{u,y-1} \tag{85}$$

$$-c_{u,y} + F^{Cramp}_u \cdot C^p_u + c_{u,y-1} \geq 0 \tag{86}$$

$$-c^e_{u,y} + F^{Cramp}_u \cdot C^p_u + c^e_{u,y-1} \geq 0 \tag{87}$$

$$\forall u \in su, (yi, yj) \in Ly[1] \tag{88}$$

$$\sum_{y=yi}^{yj} c_{u,y}^{d} \geq c_{u,1} \tag{89}$$

$$\sum_{y=yi}^{yj} c_{u,y}^{e,d} \geq c_{u,1}^{e} \tag{90}$$

$$\forall u \in su, (yi, yj) \in Ly \tag{91}$$

$$\sum_{y=yi}^{yj} c_{u,y}^{d} \geq c_{u,yi}^{u} \tag{92}$$

$$\sum_{y=yi}^{yj} c_{u,y}^{e,d} \geq c_{u,yi}^{e,u} \tag{93}$$

C.11 Electric vehicle and charger

$$f'_{evu,v} = f_v \cdot (\gamma_v^{r,0} + \gamma_v^r \cdot (a_v^r - A_v^{r,0})) + f_v \cdot (\gamma_{veev_{evu},v}^{b,0} + \gamma_{veev_{evu},v}^{b} \cdot (a_{veev_{evu},v}^{b} - A_{veev_{evu},v}^{b,0})) \tag{94}$$

$$\sum_v f_v \leq 1 \tag{95}$$

$\forall v$

$$0 \leq f_v \leq 1 \tag{96}$$

$$A_v^{r,min} \leq a_v^r \leq A_v^{r,max} \tag{97}$$

$\forall ve, v$

$$A_{ve,v}^{b,min} \leq a_{ve,v}^b \leq A_{ve,v}^{b,max} \tag{98}$$

$\forall chu, t$

$$p_{chu,t} = \sum_{evu \in pass_{chu,t}} -P_{evu,t}^e \cdot (1 - \sum_v f'_{evu,v}) + \sum_v -p_{evu,v,t}^c + p_{evu,v,t}^d \tag{99}$$

$$r_{chu,t}^+ \leq \sum_{evu \in pass_{chu,t}} \sum_v p_{evu,v,t}^c \tag{100}$$

$$\sum_{evu \in pass_{chu,t}} \sum_v p_{evu,v,t}^c \leq \sum_{evu \in pass_{chu,t}} \sum_v f'_{evu,v} \cdot C_{chu}^p \cdot A_{v,t}^c - r_{chu,t}^- \tag{101}$$

$$r_{chu,t}^- \leq \sum_{evu \in pass_{chu,t}} \sum_v p_{evu,v,t}^d \tag{102}$$

$$\sum_{evu \in pass_{chu,t}} \sum_v p_{evu,v,t}^d \leq \sum_v p_{chu,v,t}^{d,upperbound} - r_{chu,t}^+ \tag{103}$$

$\forall chu, v, t$

$$p_{chu,v,t}^{d,upperbound} \leq \sum_{evu \in pass_{chu,t}} f'_{evu,v} \cdot C_{chu}^p \cdot A_{v,t}^d \tag{104}$$

$\forall chu, v \in vd, t$ (105)

$$\sum_{evu \in pass_{chu,t}} p_{evu,v,t}^d \leq - \sum_{u \in hch_{chu}} p_{u,t} \tag{106}$$

$$p_{chu,v,t}^{d,upperbound} \leq - \sum_{u \in hch_{chu}} p_{u,t} \tag{107}$$

$\forall evu, v, t:$

$$p^{c}_{evu,v,t} \leq \sum_{chu \in route_{evu,t}} f'_{evu,v} \cdot C^{p}_{chu} \cdot A^{c}_{v,t} \tag{108}$$

$$p^{d}_{evu,v,t} \leq \sum_{chu \in route_{evu,t}} f'_{evu,v} \cdot C^{p}_{chu} \cdot A^{d}_{v,t} \tag{109}$$

$$\forall evu, t \tag{110}$$

$$r^{e,+}_{evu,t} = \sum_{chu \in route_{evu,t}} r^{+}_{chu,t} \cdot \Delta T_t \tag{111}$$

$$r^{e,-}_{evu,t} = \sum_{chu \in route_{evu,t}} r^{-}_{chu,t} \cdot \Delta T_t \tag{112}$$

$$\begin{aligned} e_{evu,t} &\geq r^{e,+}_{evu,t} + (1 - \sum_{v} f'_{evu,v}) \cdot A^{bl,fix}_{evu,t} \cdot C^{e}_{evu} \\ &+ \sum_{v} FAB_{veev_{evu},v} \cdot a^{b}_{veev_{evu},v} \cdot A^{bl}_{evu,veev_{evu},v,t} \cdot C^{e}_{evu} \end{aligned} \tag{113}$$

$$e_{evu,t} \leq C^{e}_{evu} - r^{e,-}_{evu,t} \tag{114}$$

$$\forall evu, t \in ct \tag{115}$$

$$e_{evu,t} = C^{e}_{evu} \tag{116}$$

$\forall evu, y:$

$$\begin{aligned} e_{evu,T_y[1]} &= e_{evu,T_y[end]} - P^{drive}_{evu} \cdot \Delta T_{T_y[1]} \cdot A^{drive}_{evu,T_y[1]} \\ &+ \Delta T_{T_y[1]} \cdot \eta^{ev}_{evu} \cdot P^{e}_{evu,T_y[1]} \cdot (1 - \sum_{v} f'_{evu,v}) \\ &+ \Delta T_{T_y[1]} \cdot \eta^{ev}_{evu} \cdot (\sum_{v} p^{c}_{evu,v,T_y[1]} - p^{d}_{evu,v,T_y[1]}) \end{aligned} \tag{117}$$

$\forall evu, t \in T_y[2:end]:$

$$\begin{aligned} e_{evu,t} &= e_{evu,t-1} - P^{drive}_{evu} \cdot \Delta T_t \cdot A^{drive}_{evu,t} \\ &+ \Delta T_t \cdot \eta^{ev}_{evu} \cdot P^{e}_{evu,t} \cdot (1 - \sum_{v} f'_{evu,v}) \\ &+ \Delta T_t \cdot \eta^{ev}_{evu} \cdot (\sum_{v} p^{c}_{evu,v,t} - p^{d}_{evu,v,t}) \end{aligned} \tag{118}$$

C.12 Heat pump

$$
\begin{aligned}
&\forall u \in hpu, t: \\
&\qquad p_{u,t} = -P^e_{u,t} - p^c_{u,t} + p^d_{u,t} && (119)\\
&\qquad p_{u,t} \leq 0 && (120)\\
&\qquad p_{u,t} \geq -C^p_u && (121)\\
& && (122)\\
&\qquad r^+_{u,t} \leq p^c_{u,t} && (123)\\
&\qquad p^c_{u,t} \leq F^{shp}_u \cdot (C^p_u - P^e_{u,t}) - r^-_{u,t} && (124)\\
&\qquad r^-_{u,t} \leq p^d_{u,t} && (125)\\
&\qquad p^d_{u,t} \leq F^{shp}_u \cdot P^e_{u,t} - r^+_{u,t} && (126)\\
& && (127)\\
&\qquad r^{e,+}_{u,t} = r^+_{u,t} \cdot \Delta T_t && (128)\\
&\qquad r^{e,-}_{u,t} = r^-_{u,t} \cdot \Delta T_t && (129)\\
& && (130)\\
&\qquad r^{e,+}_{u,t} + (1-\theta) \cdot C^e_u \leq e_{u,t} \leq C^e_u \cdot (1+\theta) - r^{e,-}_{u,t} && (131)\\
&\forall u \in hpu: && (132)\\
&\qquad e_{u,1} = C^e_u && (133)\\
&\forall u \in hpu, t \in T[2:end]: && (134)\\
&\qquad e_{u,t} = \eta^{loss}_{u,t} \cdot e_{u,t-1} - \Delta T_t \cdot \eta^{gain}_{u,t} \cdot p_{u,t} && (135)
\end{aligned}
$$

C.13 Intermittent source

$$\forall u \in ru$$

$$c_{u,1} \geq SC^p_u \tag{136}$$

$$\forall u \in ru, t:$$

$$p_{u,t} = P^e_{u,t} \cdot c_{u,Y_t} - p^e_{u,t} \tag{137}$$

$$r^+_{u,t} \leq p^e_{u,t} \tag{138}$$

$$p^e_{u,t} \leq P^e_{u,t} \cdot c_{u,Y_t} - r^-_{u,t} \tag{139}$$

$$p^e_{u,t} \leq F^{curtail}_u \cdot c_{u,Y_t} - r^-_{u,t} \tag{140}$$

$$\forall u \in ru, t \in mt_u \tag{141}$$

$$p_{u,t} = 0.0 \tag{142}$$

$$\forall u \in ru, y:$$

$$c^u_{u,y} \leq C^p_u - c_{u,y} \tag{143}$$

$$\forall u \in ru, y[2:end]$$

$$c_{u,y} = c_{u,y-1} + c^u_{u,y-1} - c^d_{u,y-1} \tag{144}$$

$$-c_{u,y} + F^{Cramp}_u \cdot C^p_u + c_{u,y-1} \geq 0 \tag{145}$$

$$\forall u \in ru, (yi, yj) \in Ly[1]$$

$$\sum_{y=yi}^{yj} c^d_{u,y} \geq c_{u,1} \tag{146}$$

$$\forall u \in ru, (yi, yj) \in Ly \tag{147}$$

$$\sum_{y=yi}^{yj} c^d_{u,y} \geq c^u_{u,yi} \tag{148}$$

C.14 Generator

$$\forall u \in gu:$$

$$c_{u,1} \geq SC^p_u \tag{149}$$

$$\forall u \in gu, t:$$

$$p_{u,t} = (1 - \frac{\eta_u}{\eta_u^{min}}) \cdot P_u^{min} \cdot n_{u,t} + \eta_u \cdot p^e_{u,t} \tag{150}$$

$$P_u^{min} \cdot n_{u,t} + r^-_{u,t} \leq p_{u,t} \leq P_u^{max} \cdot n_{u,t} - r^+_{u,t} \tag{151}$$

$$\forall u \in gu, t[2 : end] \tag{152}$$

$$n_{u,t} = n_{u,t-1} + n^u_{u,t-1} - n^d_{u,t-1} \tag{153}$$

$$-p_{u,t} + F_u^{ramp} \cdot c_{u,Y_t} + p_{u,t-1} \geq 0 \tag{154}$$

$$p_{u,t} + F_u^{ramp} \cdot c_{u,Y_t} - p_{u,t-1} \geq 0 \tag{155}$$

$$\forall u \in gu, t \in mt_u$$

$$p_{u,t} = 0.0 \tag{156}$$

$$\forall u \in gu, (ti, tj) \in MUTt \tag{157}$$

$$n^d_{u,ti} \leq n_{u,ti} - \sum_{t=tj}^{ti-1} n^u_{u,t} \tag{158}$$

$$\forall u \in gu, (ti, tj) \in MDTt \tag{159}$$

$$n^u_{u,ti} \leq \frac{c_{u,Y_{ti}}}{P_u^{max}} - n_{u,ti} - \sum_{t=tj}^{ti-1} n^d_{u,t} \tag{160}$$

$$\forall u \in gu, y[2 : end] \tag{161}$$

$$c_{u,y} = c_{u,y-1} + c^u_{u,y-1} - c^d_{u,y-1} \tag{162}$$

$$-c_{u,y} + F_u^{Cramp} \cdot C^p_u + c_{u,y-1} \geq 0 \tag{163}$$

$$\forall u \in gu, y:$$

$$c^u_{u,y} \leq C^p_u - c_{u,y} \tag{164}$$

$$\forall u \in gu, (yi, yj) \in Ly[1] \tag{165}$$

$$\sum_{y=yi}^{yj} c^d_{u,y} \geq c_{u,1} \tag{166}$$

$$\forall u \in gu, (yi, yj) \in Ly \tag{167}$$

$$\sum_{y=yi}^{yj} c^d_{u,y} \geq c^u_{u,yi} \tag{168}$$

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