The REINVENT modelling environment

D2.1

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About REINVENT

In 2030 and beyond, multiple energy vectors (electricity, gas, heat, green molecules) will play a role in an interconnected energy system. Increased electrification will support sector integration between end user segments. To benefit maximally from the advantages of sector coupling, a fundamental rethinking of market design, business models and financing models is needed. ReInvent will define a roadmap for sector coupling in Belgium. The ReInvent approach is based on **4 pillars** and is a combination of 1) conceptual analysis, 2) sound modelling, 3) proofing of concepts by relevant test cases, and 4) an ambitious impact assessment and replication strategy.

The **first pillar** will analyse the role of different energy vectors (gas, power, heat, green molecules…) in the Belgian energy mix. This includes the impact on infrastructure, market design and business models for different energy end user groups. Based on discussions with project partners and relevant stakeholders, different concepts for both supply-side and demand-side sector integration will be proposed. In addition to the operational implications of sector integration, the financial implications in terms of risk, return, and uncertainty will be analysed.

The **second pillar** will develop the ReInvent modelling and simulation. This multi-sectoral simulation environment will capture the different dynamics of different vectors in multiple timeframes, for multiple scenarios, for multiple market design options, for multiple services, including different end-use sectors and different layers of the physical networks and their interconnection. Innovations modelled in ReInvent aim at the overarching goal of augmenting and realizing the potential of sector coupling in providing key flexibility, balancing, and adequacy services to the multi-energy system and the electric grid.

The **third pillar** will look at a selection of reference test cases that represent main use cases of sector coupling/integration. These applications will provide real data that allow proofing of the developed models in the second pillar. In addition, the models of the second pillar will provide necessary insights to the test cases about the impact of the ReInvent solutions on the operational and financial stability of the presented solution. The ReInvent test cases address different vectors, end user segments and applications and are selected based on the technologies and applications that will play a central role in a future integrated system but still face barriers today that hinder their expected breakthrough.

The **fourth pillar** will define a roadmap for improved sector coupling and sector integration for Belgium. This includes an impact assessment of a wide roll-out of the solutions for the Belgian energy system, in particular the implications for security of supply and system balancing.

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List of Abbreviations and Acronyms

Acronym	*Meaning*
5GDHC	5th-Generation District Heating and Cooling
AF	Availability Factor
aFRR	automatic Frequency Restoration Reserve
ATES	Aquifer Thermal Energy Storage
BEP	Best Efficiency Point (electrolyser)
BESS	Battery Energy Storage System
BRP	Balancing Responsible Party
BUC	Business Use Case
CAPEX	Capital Expenditure
CCGT	Combined-Cycle Gas Turbine
CCS	Carbon Capture and Storage
CHP	Combined Heat and Power
CIGRE	International Council on Large Electric Systems (Conseil International des Grands Réseaux Électriques)
CO_2	Carbon Dioxide
CRM	Capacity Remuneration Mechanism
CSV	Comma-Separated Values (file format)
CvaR	Conditional Value at Risk
DER	Distributed Energy Resources
DER-BTM	Distributed Energy Resources Behind the Meter
DHC	District Heating and Cooling
DOC	Demand Overlap Coefficient
DSF	Demand Side Flexibility
DRI	Direct Reduced Iron
DSO	Distribution System Operator
EBECS	EnergyVille Building and Energy Characterization System
EC	Energy Community
EHB	European Hydrogen Backbone
EHB+I	European Hydrogen Backbone plus extra-European imports (infrastructure setting)
EPC	Energy Performance Certificate
EPEX	European Power Exchange
EPSG	European Petroleum Survey Group (coordinate reference system code)
ERAA	European Resource Adequacy Assessment
EU	European Union
EV	Electric Vehicle
FCR	Frequency Containment Reserve
GBM	Gradient-Boosted Machine
GFPP	Gas-Fired Power Plant

Acronym	*Meaning*
GG	Gas Grid (hydrogen routing)
GSHP	Ground Source Heat Pump
H/C	Heat and Cooling
H_2	Hydrogen
HP	Heat Pump
ISO	Isolated hydrogen production without backbone access (infrastructure setting)
KPI	Key Performance Indicator
KUL	KU Leuven
LCOE	Levelised Cost of Electricity
$LCOH_2$	Levelised Cost of Hydrogen
MCR	Maximum Continuous Rating (power level)
MES	Multi-Energy System
MILP	Mixed-Integer Linear Programming
MIQP	Mixed-Integer Quadratic Program
MSOL	Minimum Stable Operating Level (electrolyser)
NPV	Net Present Value
NSIM	North Sea Integration Model
OPEX	Operating Expenditure
PAR	Peak-to-Average Ratio
PEM	Proton Exchange Membrane
POMMES	Python for Operations and Markets Modelling of Energy Systems
PPA	Power Purchase Agreement
PV	Photovoltaics / Photovoltaic generation
RAT	Revenue-Adequate Tariff
REC	Renewable Energy Cooperative
RES	Renewable Energy Sources
RFNBO	Renewable Fuels of Non-Biological Origin
ROC–AUC	Receiver Operating Characteristic – Area Under the Curve
ROI	Return on Investment
SCIP	Solving Constraint Integer Programs (solver)
SCOP	System Coefficient of Performance (as defined in this report)
SEW	Socio-Economic Welfare
SH	Space Heating
SLP	Standard Load Profile
SM	Smart Meter
SMO	Shared Mobility Operator
SoC	State-of-Charge
TAM	Technology Acceptance Model
TIMES	The Integrated MARKAL-EFOM System (energy system model)

Acronym	*Meaning*
TIMES-BE	TIMES model of Belgium
ToU	Time-of-Use (tariff)
TPT	Two-Part Tariff
TSO	Transmission System Operator
TT	Tube Trailer (hydrogen routing)
TYNDP	Ten-Year Network Development Plan
ULB	Université libre de Bruxelles
UMONS	Université de Mons
V2H/B/G	Vehicle-to-Home/Building/Grid
VITO	Vlaamse Instelling voor Technologisch Onderzoek (Flemish Institute for Technological Research)
WH	Water Heating
WP	Work Package

Executive Summary

This deliverable presents the final evaluation of the REINVENT Work Package 2 (WP2) modelling environment. WP2 has developed a multi-scale, multi-horizon simulation environment to analyse cross-sector coupling across electricity, thermal energy, hydrogen and mobility, so that the Business Use Cases (BUCs) of WP3 can be evaluated quantitatively and WP4 can assess system-level impacts and derive policy recommendations. The environment spans from the local and community level to the system and wholesale level, and from short-term operation to long-term planning.

Table 1 summarises the thirteen modelling tracks identified in WP2, distributed across the four WP2 tasks, together with the partners involved and the links to WP3 and WP4 activities.

Table 1: Overview of the WP2 modelling tracks distributed across tasks

Task 2.1 – Integrated multi-energy system models (planning & system perspective)		
Modelling track	**WP2 partner**	**Links**
Track A – Comprehensive Coverage of Demand-Side Flexibility, Including Heat Flexibility	VITO, KUL	BUC 7 and Task 4.2.
Track B – Supply-side flexibility via domestic Onshore & Offshore Hydrogen Production under Varying Demand-Side Flexibility	VITO, Fluxys	BUCs 7 and 8 and Task 4.2.
Track C – A European Multi-Energy System Model for Electricity and Hydrogen	KUL	BUC 7 and Task 4.2.
Track D – Myopic investment behaviour in multi energy markets: a case study of hydrogen investments in the steel industry	KUL	BUC 7 and Task 4.2.
Task 2.2 – Multi-carrier wholesale markets (operation & markets)		
Modelling track	**WP2 partner**	**Links**
Track A. Analysis of Integrated Multi-Energy Market Designs	VITO	Task 4.2.
Track B. Integration of BESS for managing sourcing and imbalance costs/risks of renewable energy cooperatives' portfolios	VITO	BUC 4 and Task 4.2.
Task 2.3 – End-users & energy communities (local perspective)		
Modelling track	**WP2 partner**	**Links**
Track A – Cross-Sectoral Technologies for Individual Consumers & Communities	VITO	BUC 2a, 10
Track B – Investment Models for Multi-Sector Communities	UMONS	BUCs 3, 5
Track C – Optimal Dispatch Models & Market Designs for Coupled Electricity & Heat/Cold Networks	UMONS, VITO	BUC 1
Track D – Optimised DER user adoption and usage	VITO	BUC 3
Track E – Hidden flexibility in vulnerable households	VITO	BUC3
Task 2.4 – Efficient incorporation of sector-integrated end-users (user-centric investment & flexibility).		
Modelling track	**WP2 partner**	**Links**
Track A. Revenue Stacking for End-Users Participating in Local & System-Level Flexibility Markets	ULB	BUC 6
Track B. Operation of an Electrolyser System Participating in the Belgian aFRR flexibility market	KUL	BUC 9

A summary of each task, including the objectives, modelling approach and key findings, is given below:

Task 2.1 – Integrated multi-energy system models (planning & system perspective)

- **Track A – Demand-side flexibility including heat**

Objective: to extend the TIMES-BE model to comprehensively represent demand-side flexibility from EVs and buildings, including heat storage using the building's thermal inertia, dedicated heat storage, and demand-response elasticity (e.g., through smart thermostats).

Modelling: TIMES-BE model currently already includes advanced EV flexibility and literature-grounded water and space heating models are implemented to capture the heat flexibility strategies mentioned above.

Key findings Across the nine scenarios, water-heating buffers are adopted almost to their full potential wherever they are available (98–99%). Building thermal inertia is used in about one third of the building stock (34–36%), and the remaining buildings keep a fixed heat-demand profile. Space-heating buffers are too costly to play a role (0% in all scenarios).

- **Track B – Domestic H_2 supply under varying flexibility**

Objective: to study the impact of energy-system demand flexibility on national H_2 supply, both in terms of domestic production and of imports.

Modelling: The hydrogen and synthetic-molecule supply routes of TIMES-BE (centralised and sector-specific electrolysis, imports) are evaluated on the nine scenarios, i.e. the three PATHS2050 storylines at three levels of building flexibility. The results are analysed in terms of hydrogen supply level and origin (domestic production or imports) and technology. Then the model explores the solution space of different storylines, and at different levels of flexibility to quantify the impact on the molecules supply at all levels of flexibility.

Key findings: Heating flexibility unlocks system savings of 2.5–5 B€/year (5.3–6 B€/year by 2050), mainly through lower insulation investment and fuel imports. Its impact on the hydrogen supply is visible only in storylines with non-low prices, and quite limited. However, a more in-depth analysis, also linking the North Sea Integration Model (NSIM) by Fluxys, has been carried out in Task 4.2 (linked to BUC 7).

- **Track C – European multi-energy model, POMMES**

Objective: to develop an EU-scale multi-energy model for electricity and hydrogen to assess investment robustness under alternative H_2 infrastructure pathways.

Modelling: POMMES (Python, cost-minimising, multi-horizon framework) was adapted into a single POMMES-EU instance combining European Resource Adequacy Assessment (ERAA) 2024 (2030–2035) and Ten-Year Network Development Plan (TYNDP) 2024 (2040–2050), covering 4 investment horizons × 3 weather years.

Key findings: Hydrogen backbone, carbon capture and storage (CCS), and storage infrastructure cut European system costs by up to 11% and lower emissions, though cheaper extra-EU imports raise energy sovereignty concerns. For Belgium, this same infrastructure keeps hydrogen prices stable near 2.5 €/kg and enables near-full self-sufficiency, whereas lacking it drives prices up to 3.7 €/kg as demand grows.

- **Track D – Myopic investment in steel**

Objective: to investigate the limitations of cap-and-trade systems as a tool for driving investments in low-carbon industrial technologies and to assess how imperfect carbon-price signals and myopic investor behaviour affect decarbonisation pathways in steel, with a focus on hydrogen-based Direct Reduced Iron (DRI).

Modelling: We develop a partial equilibrium model that explicitly incorporates such imperfect behaviour in cap-and-trade systems. We use a rolling horizon setup and carbon-market imperfections to show delayed switching to H_2-DRI and prolonged blast-furnace use; models and data are openly available.

Key findings: We find that such imperfections can distort carbon price trajectories, leading to suboptimal technology choice and delayed investments in low-carbon technologies. Vice versa, imperfect behaviour of investors due to other external factors may influence the carbon price trajectory if the group of affected agents is sufficiently large to influence carbon prices. The results indicate a need for complementary policy instruments to address these carbon market imperfections. To better align model outcomes with the reality of carbon markets, we advocate that modellers use techniques that capture imperfect market behaviour.

Task 2.2 – Multi-carrier wholesale markets (operation & markets)

- **Track A – Market designs**

Objective: to design and compare wholesale market clearings for isolated, coordinated, and fully integrated multi-energy markets using optimisation-based market models.

Modelling: an optimization-based market simulation tool implements the three designs and publishes prices, costs, socio-economic welfare (SEW) and surplus metrics; isolated electricity and gas market models are already operational.

Key findings: shortening day-ahead gas and hydrogen products to 6 hours raises annual profit by up to about 21% for a gas-fired plant, 5% for a combined heat and power (CHP) unit and 45% for an electrolyser, while shifting the market-day start hour has little effect; the gain shrinks when automatic frequency restoration reserve (aFRR) is accessible, so electricity, gas, hydrogen and balancing markets must be designed jointly.

- **Track B – BESS for REC portfolios**

Objective: to quantify how a battery energy storage system (BESS) in a renewable energy cooperative (wind-PPA) can mitigate sourcing/profiling and imbalance costs/risks.

Modelling: a single-level optimisation with device/market constraints evaluates perfect-forecast, stochastic risk-neutral, and risk-averse cases, using stochastic imbalance prices and 15-minute daily scheduling; this directly addresses BUC 4.

Key findings: battery deployment can help deal with sourcing and imbalance costs. Numerical simulations show that both under risk-averse and risk-neutral scenarios, positive net revenue can be obtained by leveraging the battery for day-ahead positioning and imbalance settlement.

Task 2.3 – End-users & energy communities (local perspective)

• Track A – Cross-sectoral technologies for individuals & communities

Objective: to assess the contribution of using a BESS to the financial stability of a large-scale renewable energy cooperative (REC) (Case 1 – BUC 2a) and to quantify the flexibility potential of electric vehicles (EVs) while accounting for technical, user behavioural, and manufacturer constraints (Case 2 – BUC 10).

Modelling: An optimization-based end-user simulation tool, capturing various technologies, including BESS and EVs, has been developed. For Case 1, the optimisation tool minimises total community and individual-member electricity costs to evaluate the benefits of BESS operation. For Case 2, the optimisation tool minimises household electricity costs using a detailed EV model that includes user behavioural and manufacturer constraints.

Key findings: for Case 1, the use of BESS increases the benefits of integrating RES within the REC and reduces the total cost of energy procurement. For Case 2, the results show that incorporating actual EV driving profiles, user-specific battery SoC preferences, behavioural constraints, and manufacturer-imposed limits has a significant impact on the estimated EV flexibility potential.

• Track B – Community investment models

Objective: to develop a customer-centred investment model for multi-sector energy communities (e.g., IDETA/Wapigreen and Klimaan/Otterbeek), with a focus on the electricity and mobility sectors, in order to optimise the electricity generation mix (production capacity, location, ownership), flexible resources (storage and shared mobility assets sizing) and sharing conditions (local prices, keys of repartition).

Modelling: a two-step optimisation model has been developed. The first optimisation model solves a generation expansion planning problem including constraints specific to communities (sharing rules, investment strategies, etc.). It defines the renewable production, storage and EV fleet capacity that minimises the total life-cycle cost of the community, accounting for investment and operational costs. The second problem is solved to identify the optimal internal exchange price structure for a fair distribution of the community benefits among its members. This problem is subject to competitiveness (collective exchanges must be incentivised with respect to retailers) and individual return on investment (everyone must recover their investment) constraints.

Key findings:

Investment ownership: Considering investment strategies specific to energy communities, i.e., joint investment, allows one to better take advantage of each member's production potential.

Sharing rules embedding: Integrating specific energy sharing rules, applied in the short-term, in the (long-term) investment process enables one to faithfully estimate the revenues of the community and of each member.

Prices definition: The main limitation of the two-step approach is that individual profitability is not guaranteed as the first step problem tries to minimise collective cost and disregards the individual objective. Furthermore, the second problem only has one degree of freedom to share benefits fairly among members. Future works will address this issue by proposing a single-step formulation of the problem while facing the problem convexity challenge.

- **Track C – Optimal dispatch & pricing for coupled electricity-heat/cold**

Objective: to deliver cost-optimal annual operation and welfare-preserving pricing for Thor Park's 5GDHC network (BUC 1a) and quantify the value of its aggregated electrical flexibility in a local flexibility market (BUC 1b).

Modelling: BUC 1a is a single-level mixed-integer linear programming (MILP) model over an annual hourly horizon coupling four prosumer buildings (heat pumps, chillers, direct cooling, photovoltaic (PV), gas backup) to the bidirectional thermal network and the supplier energy hub with its ground source heat pump (GSHP), chiller, free-cooling exchanger, accumulator and aquifer thermal energy storage (ATES) doublet; four pricing schemes are compared: centralised planner, revenue-adequate tariff, price cap and the proposed two-part tariff. BUC 1b extends this to a bilevel programme in which the operator bids into a DSO-run distribution local flexibility market. KPIs: system cost, SCOP, local-RES share, operational CO_2 and flexibility revenue.

Key findings:

Operation: the network runs at high seasonal efficiency with free cooling alone covering the cooling demand, but heating and cooling demand overlap is too little for prosumer-to-prosumer sharing to close the campus balance, and the aquifer cannot self-balance within a calendar year, suggesting a multi-year balancing or an auxiliary technology for balancing the ATES.

Pricing: the proposed two-part tariff reproduces central-planner welfare while keeping the supplier profitable and every prosumer no worse off than its stand-alone alternative, whereas a regulatory price cap (cost-based pricing) sacrifices total welfare for the thermal supplier gain.

Flexibility market: participation is profitable on all representative days and most attractive in the mixed-demand season but raises CO_2, arguing for a carbon-linked flexibility signal. Flexibility market

access regulation for aggregated 5GDHC networks should be considered as a relevant future direction.

- **Track D – DER adoption & usage**

Objective: to model drivers of distributed energy resource (DER) adoption and analyse EV-sharing behaviour in vulnerable communities.

Modelling: a Hasselt household survey was merged with spatial/building data to train predictive models and identify adoption clusters. an EV-sharing system model for the Otterbeek social-housing pilot is in development with data access underway.

Key findings: in the Hasselt proof of concept (67 households), non-linear models predict PV adoption well, EV and HP adoption moderately and smart-meter ownership not at all; innovation-oriented values, social influence, building characteristics and spatial context are useful predictors, but a larger, more representative dataset is needed before operational use.

- **Track E – Hidden flexibility in vulnerable households**

Objective: to assess electricity-use patterns in vulnerable households and identify opportunities for PV-aligned EV charging and shared mobility.

Modelling: Hourly consumption of 43 Mechelen-Noord households (Klimaan/Fluvius data) was reconstructed from grid import, PV production and grid injection, normalised into seasonal daily load shapes and clustered with k-means; the clusters were then compared on peak-to-average ratio, annual consumption and PV production, injection and self-consumption profiles.

Key findings: three profiles emerged: morning peak, balanced and evening peak. Evening-oriented households show the highest peak concentration and annual consumption, while substantial daytime PV exports across all groups suggest opportunities for solar-aligned EV charging. However, the analysis identifies promising conditions rather than directly demonstrating demand flexibility or shared-EV feasibility.

Task 2.4 – Efficient incorporation of sector-integrated end-users (user-centric investment & flexibility).

- **Track A – Revenue stacking**

Objective: to quantify whether stacking implicit/explicit flexibility revenues (focus on frequency containment reserve - FCR) improves end-user business cases via a multi-energy, customer-centred investment model.

Modelling: A two-stage stochastic investment model, in which the first stage sizes the conversion and storage technologies and the second stage optimises their hourly operation over several historical years of climate and EPEX price data, with linear input–output and storage constraints and the full energy bill (grid costs, regional tariff schemes). The framework computes KPIs (optimal capacities, energy shares,

CAPEX/OPEX, ROI/NPV). the framework sizes and operates technologies using hourly profiles and linear tech/storage constraints, computes KPIs (optimal capacities, energy shares, CAPEX/OPEX, ROI/NPV), and has been adapted to BUC 6 (“Wind to trucks”) with electrolyser, H_2 storage, heat-recovery and reversible fuel-cell validation.

Key findings: dynamic electricity prices are the main economic lever for the hydrogen-for-trucks system, cutting the $LCOH_2$ from 9.00 to 8.73 €/kg H_2 with the capacity tariff, with no battery needed. The capacity tariff roughly halves peak grid withdrawals; capping the grid share at 5% almost doubles the $LCOH_2$, and the interannual variability of the electricity bill (k€373–453 per year) justifies the stochastic multi-year design.

- **Track B – Electrolyser in Belgian aFRR-down**

Objective: to optimise the operation of an electrolyser participating in aFRR-down while maintaining (Renewable Fuels of Non-Biological Origin) RFNBO compliance.

Modelling: a Pyomo mixed-integer quadratic programming (MIQP) with piecewise-linear H_2 production, dynamic routing via economic incentives, calendar-aware constraints, and a two-part aFRR revenue model is implemented; the tool directly serves BUC 9.

Key findings: offering aFRR-down capacity to Elia is profitable for the Zeebrugge electrolyser without limiting hydrogen deliveries or RFNBO compliance. The value comes mainly from low-price day-ahead hours; the capacity that can be offered is limited by the market rules (4-hour bid blocks and the minimum-load requirement) rather than by the technical headroom, and the activated volumes are capped by the gas-grid injection limits.

1 Introduction

1.1 Purpose of the Document

This document aims to present the final status of the REINVENT modelling tasks. It serves as an evaluation of the REINVENT modeling environment.

1.2 The REINVENT Modelling Environment

Modelling activities in the REINVENT project are conducted in the framework of Work Package 2 (WP2). More precisely, WP2 aims at developing a simulation environment able to model cross-sector coupling opportunities to support the Business Use Cases (BUCs) of WP3 (see REINVENT Deliverable 3.1) and the impact assessment and recommendations of WP4. The simulation environment, depicted in Figure 1, considers:

- Two different spatial levels: the local level (e.g., end-user level) and the energy system level (e.g., at the wholesale level, for electricity and molecules).
- Two different time scales: short-term (e.g., daily with a quarter-hourly resolution to model optimal dispatch) and long-term planning horizons for which investment decisions in energy assets must be taken.
- Two market granularities: emerging local markets (such as electricity/thermal/mobility at the community level) and wholesale markets (for electricity and molecules).

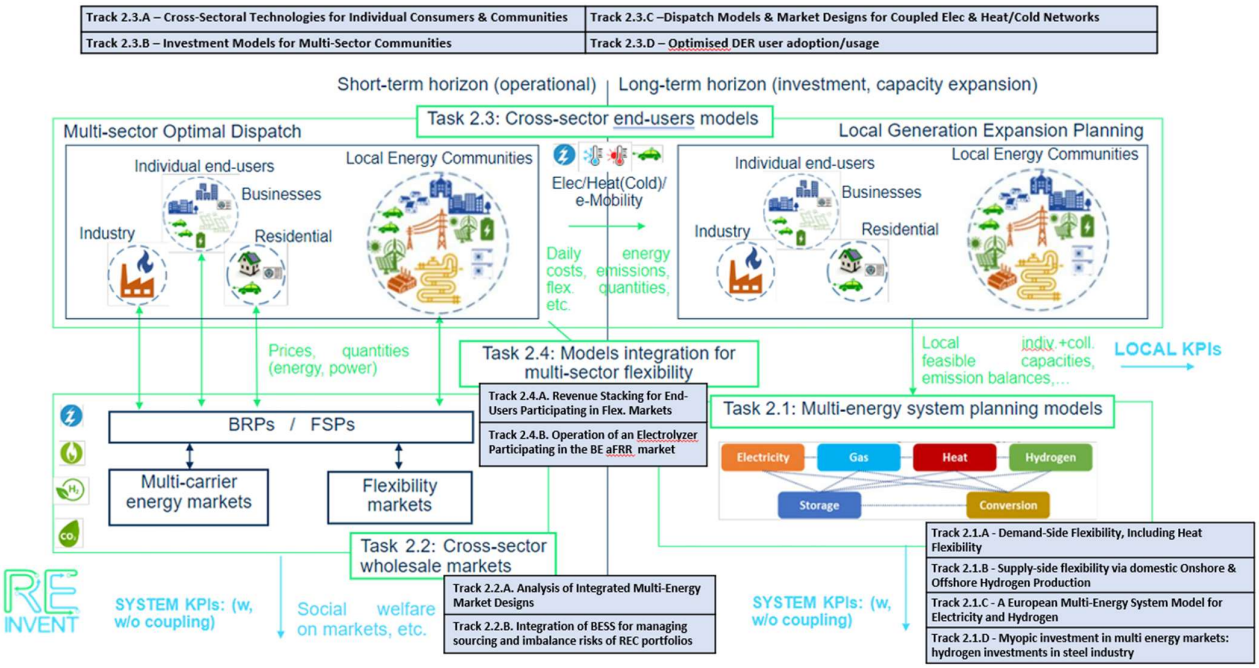


Figure 1: REINVENT modelling environment

As such, it addresses four main topics:

- The development and improvement of energy system planning models (Task 2.1), accounting for different sources of flexibility (residential, conventional power plants, connections between different energy carriers, utility-scale batteries, etc.), arising from cross-sector coupling (system level, long term).
- Analysing new market designs for multi-carrier markets (Task 2.2) and addressing the impact of cross-sectoral technologies on the operation of new markets (system level, short term).
- Cross-sector coupling opportunities for local end-users (individuals and communities) between electricity, heat/cold, and mobility (more particularly EVs), from the short-term (dispatch) and long term (planning) perspectives. This work draws from the end-user-oriented business model designs (Task 2.3).
- Considering flexibility provision from multi-sectoral coupling opportunities (Task 2.4).

1.3 Document Structure

Each task is divided into different modelling tracks according to the BUC and WP4 needs. For each modelling track, we start by framing the scope and objectives of the modelling activity, before outlining the model characteristics and the status of accomplished work. We continue by highlighting links with BUCs and WP4 activities and finally describe the key findings of the considered track. We close the report with a conclusion section.

2 Task 2.1 – Development of an Integrated Multi-Energy System Model

2.1 Modelling Track A – Comprehensive Coverage of DSF, Including Heat Flexibility

2.1.1 Scope and objectives

The representation of demand-side flexibility (DSF) is central to modelling sector coupling, as it strongly affects how the electricity system evolves over time and how renewable integration challenges are managed. Energy system models such as TIMES (and in the case of Belgium, TIMES-BE) are particularly well suited to capture these dynamics, since they can represent not only electricity generation but also storage technologies and sector-coupled solutions. Previous work has already demonstrated, for example in the transport sector, how enabling flexible EV charging can reduce peak power requirements, lower the need for stationary storage, facilitate the integration of variable Renewable Energy Sources (RES), and reduce overall system costs and price volatility. Similarly, electrification in buildings, particularly through heat pumps, introduces significant additional interactions between demand and supply.

For transport demand, the modelling of demand-side flexibility is already relatively advanced in TIMES-BE, particularly with respect to the representation of charging and discharging profiles. However, a key source of uncertainty, and a crucial determinant of the realisation of flexibility potential, remains the adoption level of flexible charging technologies, such as Smart Chargers and Vehicle-to-Home/Building/Grid (V2H/B/G) solutions, see Figure 2. While a more complete sensitivity analysis on this will be performed in the framework of the work for the deliverable of WP4, this source of flexibility is also taken into account in the work performed for Modelling Tracks A and B.

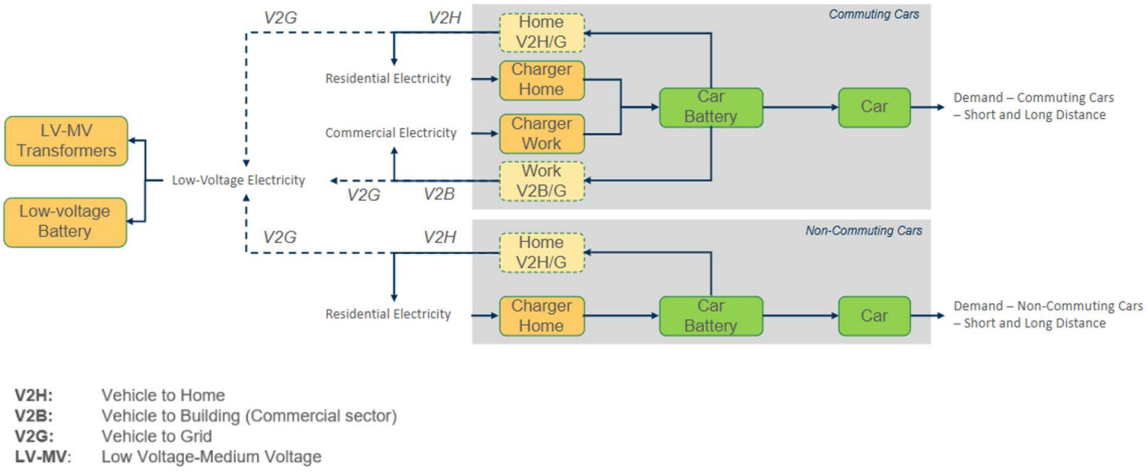


Figure 2: Design of the charging infrastructure in TIMES-BE for passenger cars

In addition, this modelling track focuses on providing a more accurate representation of heating demand in buildings in TIMES-BE. This track aimed to capture a broader set of mechanisms, such as the thermal inertia of buildings and the role of dedicated heat storage. These elements are essential for reflecting the complexity of how buildings can contribute to power system flexibility, beyond the relatively rigid profiles of current heating demand representations.

2.1.2 Accomplished work and general model outline

For what concerns the modelling of flexibility in buildings, a literature review has revealed potential strategies used in other modelling studies, which have been implemented and tested in TIMES-BE.

The space and water heating (SH and WH, respectively) structures in TIMES-BE have been revised to explicitly represent flexibility for technologies using time-varying commodities, namely heat pumps, electric heaters, and district heating. For space heating, the residential commodity (electricity, heat) is converted into (intermediate) heat commodity by the SH technology, which is constrained by an availability factor (AF) that limits its dispatch flexibility, avoiding an overestimation of the potential of heating flexibility. This intermediate heat commodity can then be stored in two technologies with bidirectional flow between them: a buffer (a dedicated heat storage device) or "Thermal inertia" (the building's own thermal mass). The intermediate heat is then converted to the SH commodity via an intermediate technology, before reaching the building technology and final demand. This explicit link between buffer and thermal inertia allows the model to shift space heating load across the day without violating comfort constraints, using either storage or the building envelope itself as flexibility sources (Figure 3).

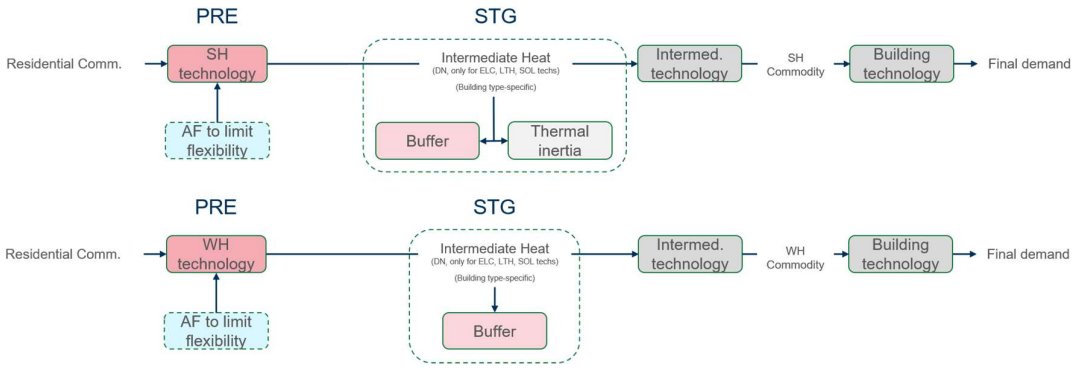


Figure 3: Design of the structure for heating flexibility in TIMES-BE

In parallel, heating demand profiles have also been revised, moving from a gas-consumption-based approach to one that better isolates the underlying heating service demand from the building envelope's thermal inertia. This separation is essential for the new flexibility structure, since inertia effects are now captured explicitly through dedicated buffer and thermal-inertia nodes rather than implicitly embedded in the demand curve itself. Comparing converged results against the original Standard Load Profiles (SLPs) confirms this shift (Figure 4): both residential and commercial curves retain the same seasonally cyclical pattern, but are visibly smoother and less peaked.

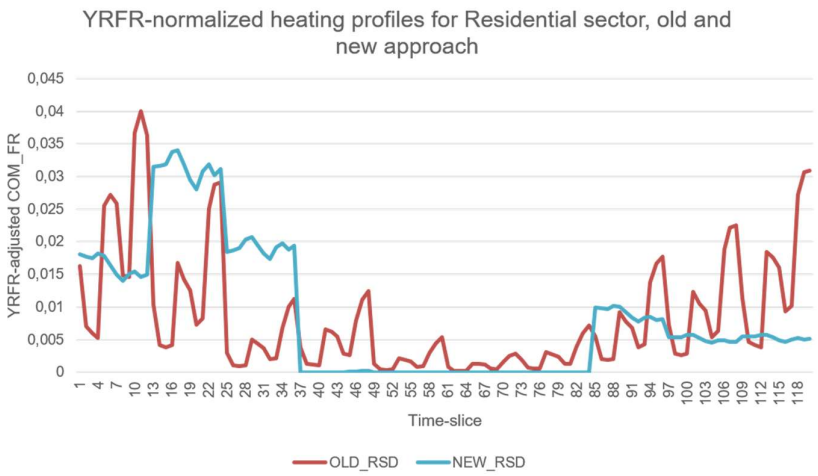


Figure 4: New heating profiles, compared with the old ones, in TIMES-BE representative hours

The water heating structure mirrors this approach but omits the thermal inertia component, reflecting that hot water demand has no equivalent building-envelope storage effect. Here, the residential commodity is converted into heat by the WH technology, similarly constrained by an availability factor, and can then be stored in an intraday, building type-specific buffer node. From there, the flow proceeds through an intermediate technology to the WH commodity and building technology to satisfy final demand.

2.1.3 Link with BUC(s) and WP4

Track A (presented here) enables an analysis of sector coupling also in relation to the demand-side flexibility which would be directly linked to BUC 7 (focused on the main other component of sector coupling individuated, i.e., power-to-X). This track is further addressed in Task 4.2, where these two dimensions converge in a final analysis.

2.1.4 Key findings and results

In order to assess the impact of flexibility options in building heating on the wider sector, nine scenarios were developed, based on the three main storylines of the 2025 PATHS study1. For each storyline, three sensitivity cases were defined: one in which full flexibility is allowed for both space and water heating technologies (labelled 50_50), one in which only water heating flexibility is allowed (labelled 50_0), and a conservative case with no flexibility allowed (labelled 0_0)2.

[1] VITO / EnergyVille, "PATHS2050: The Power of Perspective," [Online]. Available: https://perspective2050.energyville.be/. [Accessed September 2026].

[2] Note that a development branch of TIMES-BE version has been applied in ReInvent, given the project focus on heat flexibility modelling. This results in differences between the TIMES-BE main results reported under PATHS2050 Main Edition 2025 (ROTORS25, IMPORTS25 and REACTORS25) and the corresponding results under ReInvent (ROTORS26, IMPORTS26 and REACTORS26)

Table 2: Results in the nine defined scenarios, for the main KPIs regarding heating and heat flexibility.

	Heating Techs Capacity [GW]		Insul. Techs [Mm²]	Heat Flex Technologies [GW]			Heat Flex Technologies [%]		
	Total (WH)	Total (SH)	Total (SH)	Buffers (WH)	Thermal Inertia	Buffers (SH)	Buffers (WH)	Thermal Inertia (SH)	Buffers (SH)
ROTORS25*	14.1	49.9	848.9	0.0	0.0	0.0	0%	0%	0%
R50_50	9.0	46.6	316.5	8.8	15.7	0.0	98%	33.8%	0%
R50_0	8.8	62.2	666.0	8.7	0.0	0.0	99%	0%	0%
R0_0 (ROTORS26)	8.1	64.1	641.4	0.0	0.0	0.0	0%	0%	0%
IMPORTS25*	13.9	49.8	852.8	0.0	0.0	0.0	0%	0%	0%
M50_50	8.8	46.6	316.5	8.6	16.5	0.0	98%	35.5%	0%
M50_0	8.8	63.6	642.3	8.6	0.0	0.0	99%	0%	0%
M0_0 (IMPORTS26)	8.8	62.7	666.0	0.0	0.0	0.0	0%	0%	0%
REACTORS25*	10.4	49.8	854.8	0.0	0.0	0.0	0%	0%	0%
N50_50	8.5	46.4	319.0	8.4	15.6	0.0	98%	33.6%	0%
N50_0	8.8	62.2	666.0	8.7	0.0	0.0	99%	0%	0%
N0_0 (REACTORS26)	9.0	62.3	666.0	0.0	0.0	0.0	0%	0%	0%

The results are summarised in Table 2, which reports for each of the nine defined scenarios and the three PATHS2050 reference scenarios (marked '*') the main KPIs regarding heating and heat flexibility. These include both the installed capacities of heating technologies for water and space heating across the entire building stock (residential and commercial), as well as the corresponding investments in insulation technologies. In addition, the table presents the adoption of heat flexibility technologies – including WH buffers, SH buffers and thermal inertia of buildings - expressed both in absolute terms (GW installed capacity) and as relative indicators (% of total technical potential).

Several key insights emerge. Water heating buffers appear highly attractive, as their adopted capacity is close to their maximum potential (98% – 99%) in all scenarios where they are available. By contrast, building thermal inertia is exploited to around one third of the total heating potential (34%-36% when available), which implies that thermal inertia flexibility is exploited for about one third of the building stocks, with remaining buildings following the fixed heat demand profile. Space heating buffers, finally, are found to be too costly to play a significant role (0% in all scenarios).

It is also important to note that the optimal level of building insulation is significantly lower when space-heating flexibility is allowed. This can be seen from the lower levels of insulation compared to the PATHS 2050 reference scenarios (column Insul. Techs in Table 2) for increasing availability of heat flexibility options. This suggests that the increased ability to shift heating demand during critical hours reduces overall heating costs, lowering the economic incentive to invest in higher insulation levels.

2.2 Modelling Track B – Domestic Hydrogen Production under Varying DSF

2.2.1 Scope and objectives

The aim of the Modelling Track B is to assess the role of domestic onshore and offshore hydrogen production in Belgium under varying levels of demand-side flexibility, especially from building heating. The modelling framework builds on the outputs of Track A, using the resulting scenarios from the heating sector analysis in TIMES-BE, with the model's explicit treatment of electricity demand flexibility, and production pathways, also for synthetic molecules (see Figure 5). By combining these perspectives, this track aims to explore whether this flexibility alone is sufficient to trigger further sector coupling toward power-to-hydrogen.

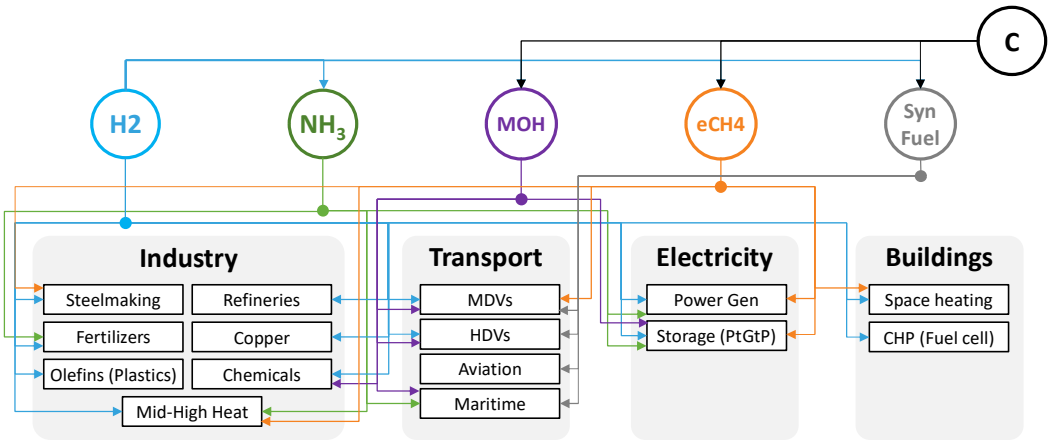


Figure 5: Synthetic molecules production and end-use options in TIMES-BE

By combining these perspectives, this track aims to identify the conditions under which domestic hydrogen production becomes competitive relative to imports, and to quantify how heating-driven demand-side flexibility influences electrolysers' economic viability when integrated with local renewable generation, and the eventual impact on system costs.

The full analysis of sector coupling, including hydrogen supply data from industry (via the Fluxys North Sea Integration Model, NSIM) and a complete impact assessment of flexibility from power-to-transport, will be carried out under Task 4.2. Moreover, this analysis could help quantify the potential of hydrogen storage, both in its molecular form and under the form of different synthetic molecules, which are already represented in the model.

2.2.2 Accomplished work and general model outline

The TIMES-BE model already includes a variety of hydrogen-based production routes, covering centralised and sector-specific electrolysis options. Recent model results show that hydrogen could be an important

energy carrier for climate-neutral industries, particularly under conditions of high renewable electricity and low carbon capture and storage availability (ROTORS scenario3).

For this track, the results generated in Track A on heating flexibility in buildings, spanning the range of scenarios from full flexibility to no flexibility, are used as an input to explore their downstream effect on domestic hydrogen production. To this end, scenario results are further analysed in terms of their impact of hydrogen supply level and origin, whether from domestic production or import, and via which specific technology. The intention is to understand how different flexibility technologies compete, as demand side flexibility, for example, would affect the hours of economically viable operation of an electrolyser plant. Current scenarios allow an initial assessment of whether flexibility originating solely from the buildings sector is material enough to influence electrolyser deployment, renewable integration, and system costs, ahead of the more detailed supply-side and cross-sectoral analysis planned for Task 4.2.

2.2.3 Link with BUC(s) and WP4

This track is directly linked to BUC 7 and to Task 4.2. Track B serves as the premise for the more advanced sector-coupling analysis performed under Task 4.2, where the focus shifts to a fuller treatment of demand-side flexibility (which includes both heating demand flexibility and EV charging flexibility), directly connecting to BUC 7 (centred on power-to-X, the main other component of sector coupling identified). These two dimensions, heating flexibility and power-to-X, will converge into a final combined analysis under that task.

2.2.4 Key findings and results

To isolate the system-wide value of heating flexibility, Figure 6 compares the fully flexible scenario (50_50, i.e., full flexibility on both space and water heating) against the no-flexibility scenario (0_0) for each storyline, expressing the difference as undiscounted annualised savings, broken down by cost component, across the 2030, 2040, and 2050 milestone years.

Flexibility on the heating side unlocks meaningful system-wide savings, ranging from 2.5 to 5 B€/year across the scenarios analysed. These savings grow over time, from roughly 1.8–2.3 B€/year in 2030 to 3.2–3.8 B€/year in 2040, reaching 5.3–6 B€/year by 2050.

Most of these savings stem from lower investment needs in insulation solutions, as flexible operation reduces the need for investing in these assets; this result is caused, however, also by the absence, in the new modelling approach for heating flexibility, of an interaction between the installed insulation technologies, and an increased thermal inertia (and resulting lower storage losses) of the building envelope. This is discarded as it would introduce a non-linearity in the problem formulation.

[3] https://perspective2050.energyville.be/results/main-edition-2025

The other major component of the cost difference, in 2030 and 2050, covering roughly half of the savings originate on the supply side instead, is the reduced imports of fossil fuels and clean molecules, and/or lower requirements for dispatchable capacity and grid investments.

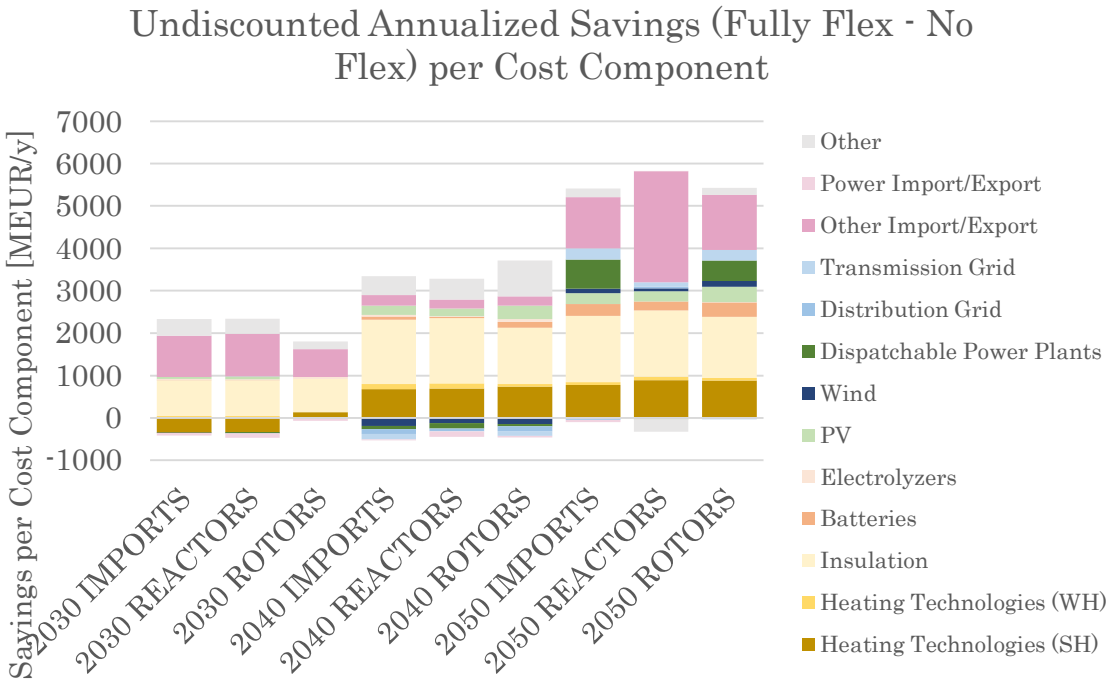


Figure 6: Undiscounted annualised savings (system cost difference between fully flexible scenario, and no flex one, for each storyline), by cost component

Despite these substantial cost benefits, the presence or absence of full heating flexibility does not appear to trigger, or hold back, investment in electrolysers, in any of the scenarios or base years considered. This is evidenced by the hydrogen production-by-route results (Figure 7), which remain essentially stable across flexibility configurations for a given storyline, and by the synthetic molecules import figures, which show consistent import volumes and mix regardless of the heating flexibility assumption applied within each storyline.

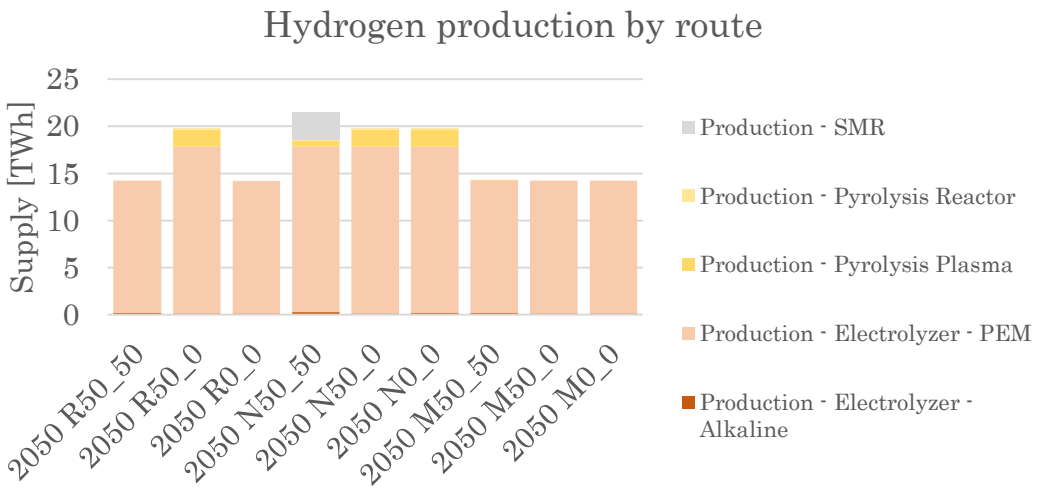


Figure 7: Hydrogen production by route, in the nine scenarios

While local hydrogen production capacity remains largely unaffected by heating flexibility, the same is not true for the import side. The synthetic molecules import results for 2050 (Figure 8) show that removing flexibility (moving from the 50_50 to the 0_0 configuration within each storyline) increases import volumes, and this additional import burden falls specifically on ammonia and eMethane, whose volumes rise in the no-flexibility cases (by 1 to 6 TWh), while eKerosene, methanol, and hydrogen imports remain comparatively stable across configurations.

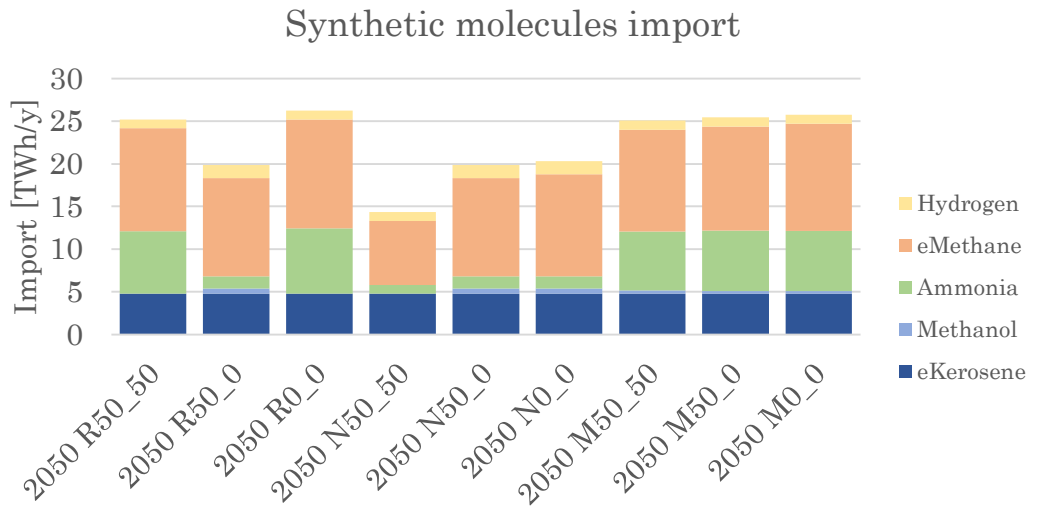


Figure 8: Synthetic molecules import, in the nine scenarios

This suggests that, while heating flexibility delivers clear economic value to the broader energy system, it does not on its own act as a decisive driver of domestic hydrogen production capacity, reinforcing the need for the more comprehensive sector-coupling analysis planned under Task 4.2, where power-to-X flexibility will be assessed alongside heating flexibility.

2.3 Modelling Track C – A European MES Model for Electricity and Hydrogen

2.3.1 Scope and objectives

Modelling Track C focuses on the development and application of a Multi-Energy System (MES) model (as depicted in Figure 9), with a specific emphasis on the electricity and hydrogen sectors.

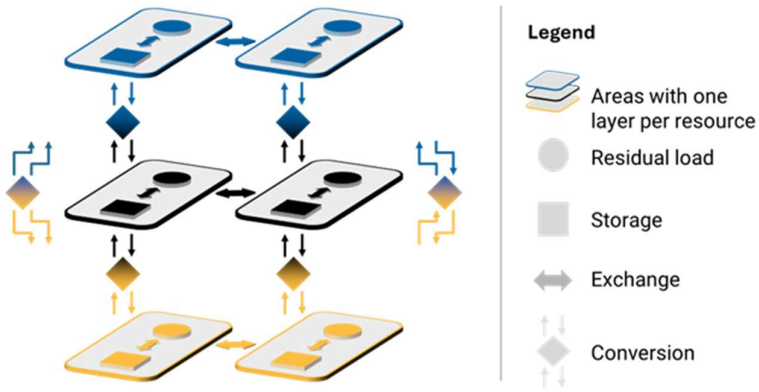


Figure 9: Principle of an energy supply-chain model | based on (Samsatli & Samsatli, 2018)[4]

The geographical scope of the modelling track is Europe, with a specific focus on Belgium in the analysis. The temporal horizon focuses on 2050, enabling the assessment of long-term investment and operational strategies in line with Belgian and European energy transition objectives.

The primary objectives of modelling track C are:

- Develop and adapt a flexible and scalable modelling framework
- Optimise cross-sectoral energy investments
- Evaluate system adequacy and security
- Evaluate the robustness of investment decisions under different hydrogen infrastructure development pathways for 2050

2.3.2 Accomplished work and general model outline

The POMMES framework

POMMES is the acronym of a recent Python framework[5] called Planning and Operation Model for Multi-Energy Systems. It was designed for multi-horizon modelling of energy systems, with the primary objective of cost minimisation, as illustrated in Figure 10.

[4] S. Samsatli and N. J. Samsatli, "A multi-objective MILP model for the design and operation of future integrated multi-vector energy networks capturing detailed spatio-temporal dependencies," Applied Energy, vol. 220, pp. 893–920, Jun. 2018.

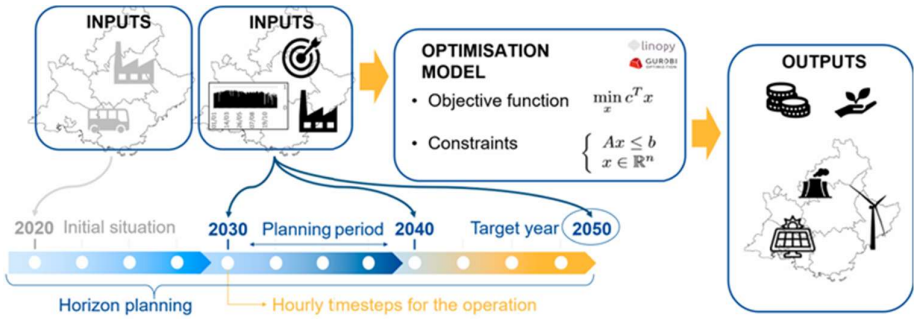


Figure 10: POMMES framework illustrative scheme

POMMES is highly modular and can be used to model both big multi-energy systems[67] and small regional systems with varying operation temporal granularity.

For this modelling track, some equations to make some demand flexible as well as including explicit demand-side response more accurately were developed and added into the framework.

The POMMES-EU model instance

Combining ERAA2024 (for the 2030–2035 period) and TYNDP2024 (for the 2040–2050 period) data, an electricity and hydrogen system model was developed. Although we further use a single horizon (2050), POMMES-EU comprises 4 investment horizons (2030–2035–2040–2050) with between each other 3 operation years (representing each a different weather scenario).

Figure 11 shows some preliminary results of hydrogen dispatch and price in Europe under different infrastructure scenarios.

[5] https://git.persee.minesparis.psl.eu/energy-alternatives/pommes

[6] Q. Raillard-Cazanove, T. Knibiehly, and R. Girard, "Decarbonisation of industry and the energy system: Exploring mutual impacts and investment planning," Journal of Cleaner Production, vol. 508, p. 145511, May 2025, doi: 10.1016/J.JCLEPRO.2025.145511.

[7] Jodry, A., Raillard–Cazanove, Q., Knibiehly, T., Affonso Nóbrega, P. & Girard, R. Resilience analysis for energy foresight scenarios: addressing the deep uncertainties of hydrogen deployment in industrial hubs. Energy Policy 214, 115258 (2026).

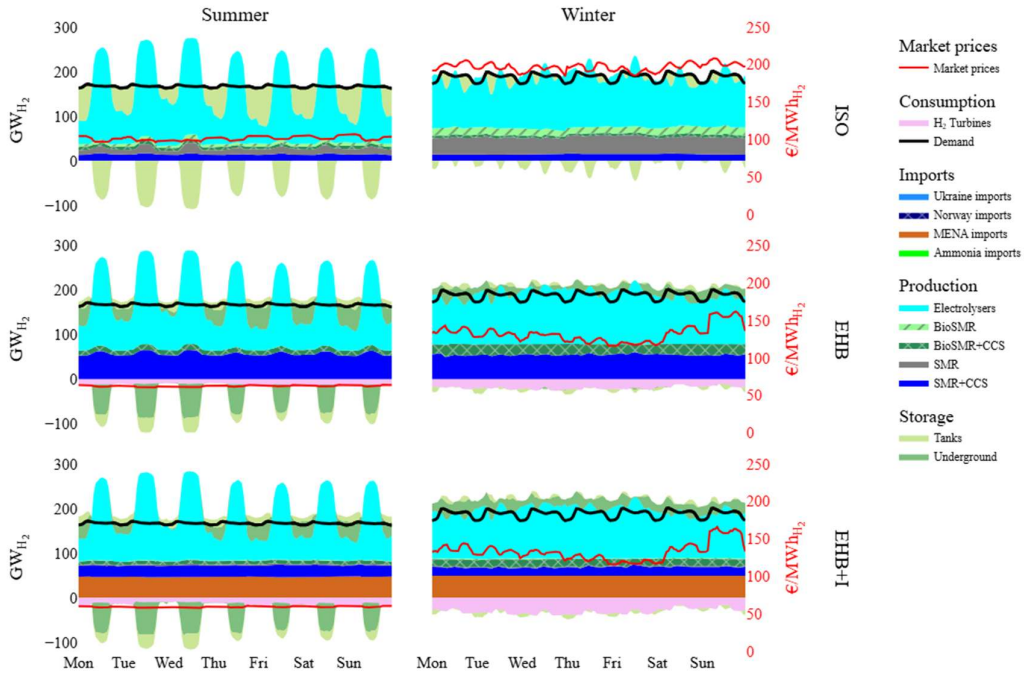


Figure 11: POMMES-EU hydrogen average dispatch and price in Europe in 2050 (summer vs winter) under different hydrogen infrastructure settings – ISO = Isolated hydrogen production in Belgium, EHB = European Hydrogen Backbone and EHB+I = EHB + Imports

2.3.3 Link with BUC(s)

This modelling track is linked to BUC 7 to answer the following research question: what are the most adequate production and storage technologies and their optimal sizing under different hydrogen infrastructure development?

2.3.4 Key findings and results

The modelling and analysis are completed. POMMES-EU was applied at European scale, covering 27 countries in a chronological hourly optimisation of the coupled electricity and hydrogen systems for the 2050 target year, in order to answer BUC 7's research question on the most adequate production and storage technologies and their optimal sizing under different hydrogen infrastructure development pathways. Three settings were compared: isolated national production without backbone access or underground storage (ISO), connection to the European Hydrogen Backbone (EHB), and the backbone complemented by extra-European imports (EHB+I). At European level, domestic electrolysis remains the backbone of supply in all three settings, providing between 56% and 67% of hydrogen, while extra-European imports capture around 25% of supply when they are allowed. Access to the backbone and to underground storage reduces total system cost by approximately 11% relative to the isolated setting, and the isolated setting also produces substantially higher combined electricity and hydrogen emissions, since greater reliance on electrolytic hydrogen raises electricity

demand while unabated steam methane reforming and methane turbines displace hydrogen-fired generation, which falls to only 1–1.5% of electricity generation.

The Belgian focus shows that infrastructure access, rather than the level of hydrogen demand, is what determines price exposure and the composition of the domestic fleet. Starting from a reference demand of 32 TWh in 2050 and scaling it up to three times that level, the isolated setting sees the Belgian hydrogen price rise from 2.9 to 3.7 €/kg and the electricity price from 75 to 95 €/MWh, as incremental demand is met almost exclusively by additional electrolysis until the solar potential cap is reached, electricity imports increase and unabated reforming is eventually mobilised as a cost relief valve, with tank storage scaling in step with electrolyser capacity. Under the backbone setting, by contrast, the hydrogen price stays close to 2.5 €/kg across the whole demand range and the electricity price remains broadly flat, because incremental demand is absorbed by reforming with carbon capture and by network imports rather than by added domestic electrolysis, and underground storage substitutes for the large tank capacity the isolated setting requires; at reference demand Belgium nevertheless remains more than 95% self-sufficient. Even with cheap extra-European imports available, a non-negligible share of domestic production stays competitive in the optimal mix at reference demand, with imports becoming dominant only as demand scales up. The full scenario definitions and detailed results are reported in Deliverable 3.4.

In conclusion, with regard to the research question formulated in Section 2.3.3, the most adequate production and storage technologies and their sizing depend primarily on the hydrogen infrastructure development pathway rather than on the level of demand. Domestic electrolysis remains the core production technology in all cases. Without infrastructure access, electrolyser capacity and tank storage must be scaled up together, with unabated reforming as a last resort, leading to higher prices and emissions. With access to the European Hydrogen Backbone, underground storage largely replaces tank storage and additional demand is met by reforming with carbon capture and network imports, keeping prices stable. Timely development of hydrogen transport and underground storage infrastructure is therefore the key enabler of a cost-efficient, low-emission hydrogen system.

2.4 Modelling Track D – Myopic investment behaviour in multi-energy markets: a case study of hydrogen investments in the steel industry

2.4.1 Scope and objectives

Modelling track D examines a central assumption in many energy system models, that market participants invest rationally and with perfect foresight. The work investigates how myopic investment behaviour, financial constraints, and policy uncertainty can affect the uptake of novel low-carbon technologies across interconnected energy markets. The analysis focuses on hydrogen-based production routes in the steel industry, reflecting the relevance of industrial hydrogen demand in Belgium.

Investment decisions in industry are often taken under imperfect foresight, with firms facing uncertainty about future carbon prices and limited ability to anticipate long-term market dynamics. We develop a partial-

equilibrium model that captures these behavioural frictions and analyse how they influence irreversible investment decisions. We investigate how myopic behaviour can delay investment in low-carbon options, lead to suboptimal technology choices, and reinforce path dependencies across multiple energy carriers.

The findings may highlight the importance of representing behavioural limitations in modelling frameworks and can help nuance results from other modelling tracks that assume fully rational actors. Moreover, understanding how investor behaviour shapes the timing and scale of hydrogen uptake is directly relevant for BUC 7. If behavioural barriers suppress early hydrogen demand, enabling policies may be required to unlock its role in Belgium's sector-coupled energy system.

2.4.2 Accomplished work and general model outline

We develop and apply a partial equilibrium model that shows investors' decision-making in emission-reduction projects, based on an imperfect carbon price. The model captures two carbon market imperfections: financial constraints and myopic foresight. A rolling horizon optimisation is implemented to capture myopic foresight, and constraints on the banking behaviour are used to represent financial constraints. The third, increased policy risk, is captured by increasing the discount rate.

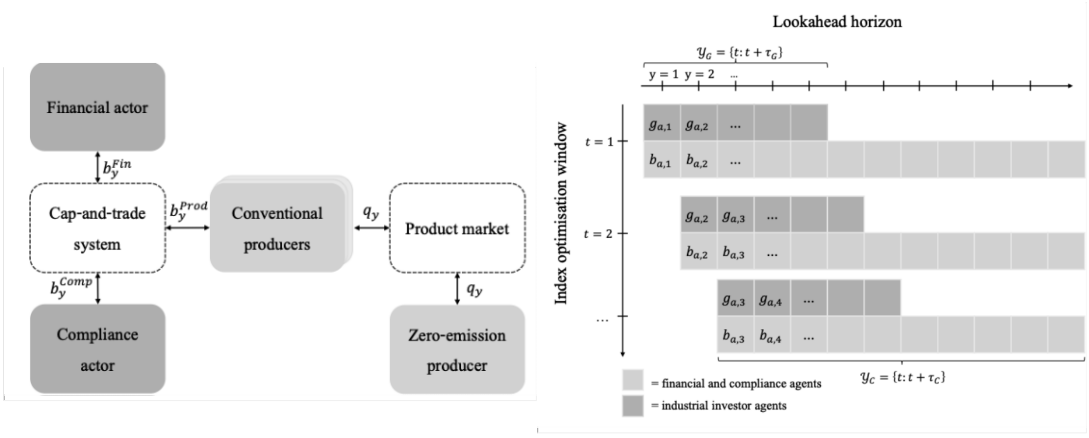


Figure 12: Model diagram showing conventional producers in competition with zero-emission producers, in a product market (left). Rolling horizon approach to model myopic behaviour (right).

An emission trading scheme is endogenously considered, consisting of one representative compliance actor and a financial actor that compete for a supply of emissions allowances that decreases linearly over the years, as illustrated in Figure 12. The model also allows for a particular sector to be explicitly modelled by considering industrial production agents that invest irreversibly in a set of technologies (we will consider a case for the steel industry). Production agents participate in the emission trading scheme, where they buy allowances for their emissions.

To model imperfect foresight, we implement a rolling horizon approach in which agents optimise their decisions over a limited forward-looking window, referred to as their lookahead horizon, which is shifted forward in time as the optimisation progresses. We use a rolling horizon approach which allows us to model

imperfect foresight, where agents do not plan over the full horizon but instead re-optimise sequentially based on updated information. Figure 12 (right) illustrates this setup, showing how decision variables are optimised over overlapping time windows that roll forward by one year per optimisation window. A full model description is available in the published paper[2].

We show a modelling result of the steel sector where we allow investment in various decarbonisation pathways: equipping blast furnaces with CCS, natural gas-based Direct Reduced Iron (DRI), hydrogen-based DRI. We consider cases where investments in the steel industry are based on an imperfect carbon price signal and where steel investors themselves may be myopic.

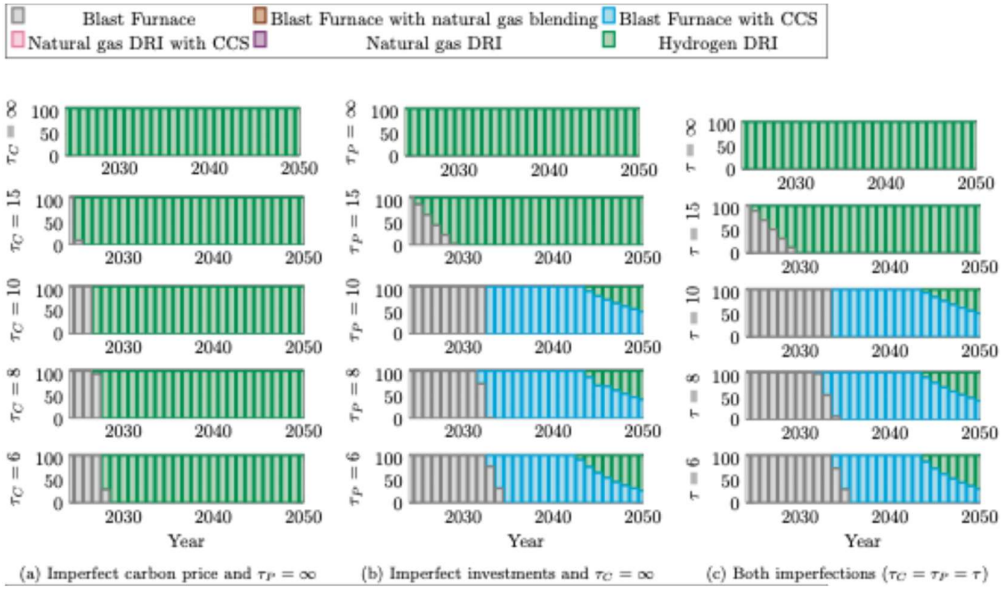


Figure 13: Steel production in Mt under (a) imperfect carbon prices, (b) myopic steel sector investments, and (c) both imperfections. Myopic investment decisions drive prolonged blast furnace use and lead to CCS adoption, which does not occur under perfect foresight

2.4.3 Link with BUC(s)

Track D links to BUC 7 by analysing why industrial hydrogen demand may fail to materialise under realistic investment behaviour. Since the steel sector is a key potential hydrogen user, understanding how myopia and policy uncertainty delay uptake helps interpret hydrogen system needs in BUC 7 and highlights where enabling policies may be required.

2.4.4 Key findings and results

We analyse (1) perfect industrial investments on an imperfect carbon price path, (2) imperfect investment behaviour, whilst foresight is perfect in the cap-and-trade system, and (3) a case with both imperfections. The top row in Figure 13 shows the reference case under perfect foresight for all actors. In this case, the model opts to invest immediately in hydrogen DRI because in such a case where banking occurs to the optimal amount, emission prices are higher. All agents have foresight over the limited availability of emission

allowances beyond 2040 and invest accordingly. In the first column, Figure 13 shows the cases where carbon prices are imperfect due to myopic behaviour by financial agents. Since this leads to lower price signals in the early years, it delays investment in low-carbon technologies. Conventional blast furnaces remain in use longer, even when cleaner alternatives would be cost-effective under perfect foresight.

Overall, we find that imperfect foresights can distort carbon price trajectories, leading to suboptimal technology choice and delayed investments in low-carbon technologies. Vice versa, imperfect behaviour of investors due to other external factors may influence the carbon price trajectory if the group of affected agents is sufficiently large to influence carbon prices. The results indicate a need for complementary policy instruments to address these carbon market imperfections. To better align model outcomes with the reality of carbon markets, we advocate that modellers use techniques that capture imperfect market behaviour.

3 Task 2.2 – Development of a Multi-Carrier Wholesale Market Model

3.1 Modelling Track A – Analysis of Integrated Multi-Energy Market Designs

3.1.1 Scope and objectives

This modelling track focuses on the quantitative assessment of novel wholesale-market designs aimed at improving the coordination of sector-coupling technologies across electricity, heat, gas and hydrogen markets. The conceptual analysis performed in Chapter 2 of Deliverable 1.2[8] identified differences in product duration and market operating days as relevant sources of temporal misalignment between energy carriers and proposed greater harmonisation of these characteristics as part of a coordinated-market design. Building on these findings, this modelling track quantitatively assesses two specific modifications: increasing the temporal granularity of day-ahead gas and hydrogen products and changing the starting time of the gas and hydrogen market day. The analysis evaluates whether these changes improve the ability of sector-coupling technologies to coordinate their positions across markets and examines their impact on asset profitability and balancing-market participation.

The assessment is performed for three representative sector-coupling technologies with different operational characteristics: a gas-fired power plant (GFPP), a combined heat and power plant (CHP), and an electrolyser. The GFPP represents the coupling between the gas and electricity systems, the CHP additionally introduces heat-production requirements, while the electrolyser represents the coupling between electricity and hydrogen. Considering these three technologies makes it possible to investigate whether the value of improved temporal market coordination depends on the type and operational flexibility of the participating asset.

Two dimensions of market design are varied systematically. First, three day-ahead gas or hydrogen product durations are assessed: 24 hours, representing the current/reference design, 12 hours and 6 hours. Second, three starting times for the gas or hydrogen day are considered: 06:00, representing the current gas-market convention, 03:00 and 00:00. Their combination results in nine market-design variants, with the 24-hour product starting at 06:00 used as the reference scenario.

The market-design variants are evaluated under different market-participation configurations for each technology, progressively considering access to day-ahead electricity, day-ahead gas or hydrogen, aFRR and within-day gas or hydrogen markets, as applicable to each technology. This allows the analysis to assess not only the direct value of changing the temporal design of gas and hydrogen markets, but also how this value interacts with the availability of alternative markets through which operational flexibility can be monetised.

[8] K. Kessels et al., “Report on improved market design, business models and financing models for sector coupling,” REINVENT Project, Deliverable D1.2, Tasks 1.2–1.5, 2026.

The assessment focuses on two main dimensions. First, the economic impact is evaluated through changes in annual profitability and the contribution of individual market components to these changes. Second, the impact on system flexibility is assessed through changes in upward and downward aFRR activation and reserved balancing capacity. The modelling therefore provides a quantitative assessment of whether greater temporal granularity and improved alignment between gas/hydrogen and electricity-market structures can increase the value of sector-coupling assets while also affecting the flexibility they make available to the power system.

3.1.2 Accomplished work and general model outline

The modelling framework and full sensitivity analysis have been implemented and executed for the three selected technologies. The work builds on VITO's market optimisation and flexibility valuation model, which determines the economically optimal operation and market-participation strategy of an asset while respecting its technical and operational constraints. Market participation is co-optimised, allowing generation, consumption and available flexibility to be allocated dynamically across the markets included in each configuration. This approach captures both the revenues and costs associated with individual markets and the opportunity costs associated with allocating flexibility between competing market opportunities. The three technologies represent different forms and degrees of operational flexibility. Table 3 presents the main technical characteristics of the technologies considered in the simulations. The GFPP is modelled as a highly flexible combined-cycle gas turbine with a large operating range and high ramping capability. The CHP is additionally subject to heat-production requirements, which constrain the extent to which its electricity production can respond exclusively to electricity and gas-market signals. The electrolyser is a flexible electricity-consuming asset whose operation determines hydrogen production. These differences are important because they determine the ability of each technology to exploit changes in the temporal structure of the markets.

Several market-participation configurations are considered for each technology. The GFPP participates in day-ahead electricity and gas markets, with additional configurations introducing aFRR and within-day gas trading. The CHP considers the same electricity and gas-market opportunities together with heat revenues. For the electrolyser, day-ahead electricity and hypothetical day-ahead hydrogen markets are considered, with additional configurations including aFRR and within-day hydrogen. Since liquid day-ahead and within-day hydrogen markets do not currently exist, their temporal structure is assumed to resemble that of the gas market.

Table 3: Main technical characteristics of the technologies considered in the market-model simulations

Characteristic	GFPP (CCGT)	CHP	Electrolyser
Main energy conversion	Gas → electricity	Gas → electricity + heat	Electricity → hydrogen
Maximum electricity production/consumption	875 MW production	320 MW production	25 MW consumption
Minimum electricity production/consumption	260 MW production	0 MW production	5 MW consumption
Minimum heat output	–	50 MW	–
Maximum heat output	–	205 MW	–
Minimum hydrogen output	–	–	3.10 MW
Maximum hydrogen output	–	–	16.63 MW
Ramp-up/down limit	3,000 MW/h	100 MW/h	40 MW/h
Can shut down	Yes	Yes	No

The simulation horizon covers one year, from September 2024 to September 2025, at a 15-minute temporal resolution. The optimisation is performed under perfect foresight, meaning that market prices and other exogenous inputs are assumed to be known in advance over the relevant optimisation horizon. Profitability should therefore be interpreted as an estimate of the maximum economic value that could be captured under the model assumptions rather than the expected profitability of a real-world bidding strategy operating under forecast uncertainty. Since this assumption is applied consistently to all scenarios, it provides a common basis for comparing the alternative market designs.

An important aspect of the framework is that the different markets retain their respective temporal structures. Day-ahead electricity trading and aFRR energy activation are represented at a 15-minute resolution, whereas aFRR capacity is reserved in fixed four-hour blocks starting at midnight. The duration and starting time of the day-ahead gas or hydrogen product are varied according to the sensitivity scenario. The model can therefore capture both the effect of increasing gas/hydrogen market granularity and the effect of changing the temporal alignment between gas or hydrogen positions and electricity and balancing-market intervals.

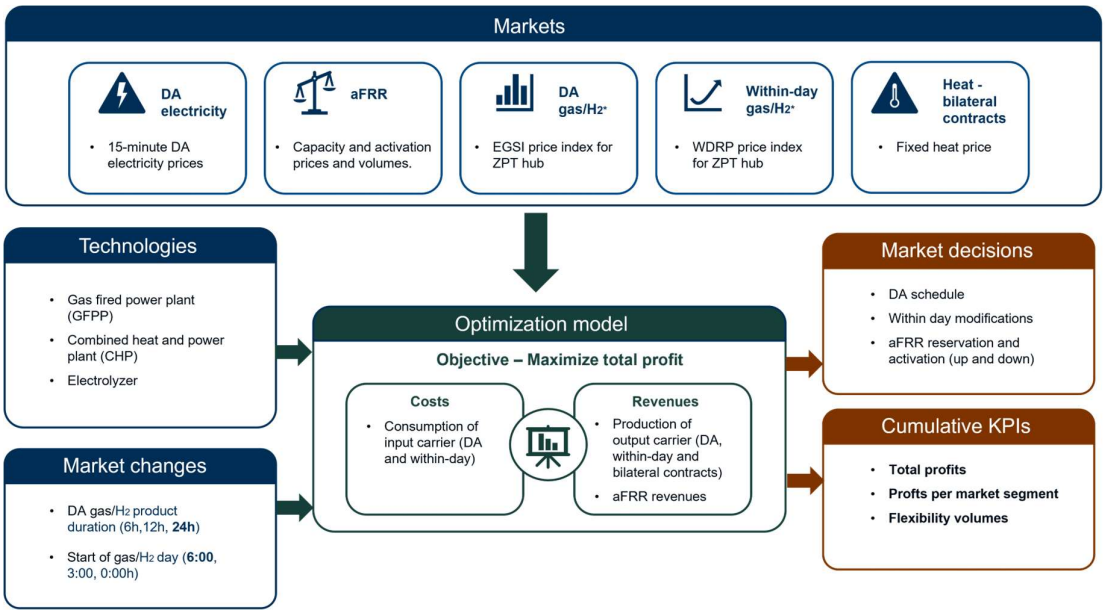


Figure 14: Overview of the market optimisation and simulation framework

Figure 14 summarises the overall modelling approach. Market information, technology characteristics and the investigated market-design changes constitute the main model inputs. For each combination, the optimisation determines day-ahead schedules, within-day adjustments and aFRR capacity-reservation and activation decisions. The resulting indicators include total profitability, profit decomposition by market segment and balancing flexibility volumes. The framework therefore establishes a direct quantitative link between the proposed market-design modifications, their economic value for individual assets and their implications for balancing-market participation.

3.1.3 Link with BUC(s)

Although there is no direct link between this modelling track and the BUCs, this modelling track will contribute to Task 4.2: Overall impact assessment for the Belgian energy system.

3.1.4 Key findings and results

The complete analyses of the results are reported in Deliverable 4.1 and are summarised as follows:

> The simulations show a consistent result across the three technologies: shortening the day-ahead gas or hydrogen product has a substantially greater impact on profitability than changing the starting hour of the market day. Across all technologies and market-participation configurations, the highest profitability is obtained when the 6-hour product is implemented. Shorter products create more frequent opportunities to adjust gas or hydrogen positions to electricity-market conditions, whereas changing the starting hour mainly shifts the boundaries of otherwise unchanged products. This explains why changing the starting time alone generally has a limited economic effect.

The magnitude of the benefit is strongly technology-dependent. The GFPP reaches a maximum profitability improvement of approximately 20.7% without aFRR, decreasing to around 14% when aFRR participation is available. The CHP is considerably less sensitive, with a maximum improvement of approximately 4.7%, reflecting the additional constraints imposed by its heat-production requirements. The electrolyser shows the strongest response, reaching approximately 45.3% without aFRR. These differences demonstrate that the value of increased gas/hydrogen market granularity depends strongly on the operational flexibility of the technology and its ability to reorganise production or consumption in response to market signals.

Access to additional markets reduces the marginal value of the proposed changes. This is particularly pronounced for the electrolyser, for which the maximum profitability improvement decreases from 45.3% without aFRR to approximately 8% with aFRR. Greater gas/hydrogen market granularity and access to balancing and short-term markets therefore provide partly alternative mechanisms for monetising flexibility. Consequently, assets with more limited access to additional markets may derive particularly large benefits from improved granularity in the gas/hydrogen market itself, while participants already able to optimise across several markets experience a smaller incremental benefit. Nevertheless, shorter products remain beneficial across the market configurations assessed.

The market-design changes also affect balancing-market participation, but the direction of this effect differs by technology. With 6-hour products, GFPP upward and downward aFRR activation decrease to approximately 92–94% and 90–91% of the reference, respectively, while the CHP remains comparatively insensitive. The electrolyser shows the opposite response, with upward activation increasing to approximately 110–111% and downward activation to around 108%. Greater market granularity therefore does not necessarily translate into greater balancing activation: depending on the technology, improved flexibility in the market can either substitute for or facilitate balancing-market participation.

A further distinction emerges between aFRR activation and capacity reservation. Activation is mainly influenced by product duration, whereas capacity reservation can also be strongly affected by the starting hour. This is related to the fixed four-hour aFRR capacity blocks starting at midnight: changing the boundaries of gas or hydrogen products changes their temporal alignment with these reservation periods. The effect is particularly visible for the GFPP and electrolyser, demonstrating that market granularity and temporal alignment are two distinct dimensions of cross-market coordination. While greater market granularity is the main driver of profitability gains, temporal alignment can materially influence how much flexibility is made available to the balancing market.

The results provide quantitative support for more granular gas and future hydrogen-market products. Among the alternatives assessed, 6-hour products are consistently the preferred option, while changing the market-day starting hour provides smaller and more context-dependent benefits. The results also demonstrate that electricity, gas, hydrogen and balancing-market design should be considered jointly: modifications in one market can alter both the economic value captured in other markets and the way flexibility is provided to the power system. In this context, further analysis of shorter aFRR capacity-reservation

periods, such as one-hour instead of four-hour blocks, would be valuable to assess whether additional alignment benefits can be achieved.

3.2 Modelling Track B – Integration of BESS for managing sourcing and imbalance costs/risks of renewable energy cooperatives' portfolios

3.2.1 Scope and objectives

This part of the REINVENT modelling environment is motivated by the case of integrating battery energy storage systems into a renewable energy cooperative portfolio. Specifically, we consider a renewable energy cooperative that provides electricity to a number of consumers belonging to the cooperative by purchasing renewable energy, e.g., from a wind farm. We suppose that this cooperative has a standard power purchasing agreement (PPA) with the producer (wind farm), i.e., the amount of power bought by the cooperative is equal to that generated by the producer.

This REC is exposed to uncertain sourcing/profiling and imbalance costs, as shown in Figure 15. As the forecasted profile of energy production from a wind farm does not necessarily match the forecasted load profile of the consumers in the cooperative (see Figure 16), the forecasted deficit of energy production must then be bought from the day-ahead wholesale electricity market (similarly, the surplus is sold to the market). This is what we consider a sourcing or profiling cost. Furthermore, the forecasts of the energy production and consumption do not always match their realisations exactly, implying that this deviation or imbalance must then be settled, incurring an imbalance cost.

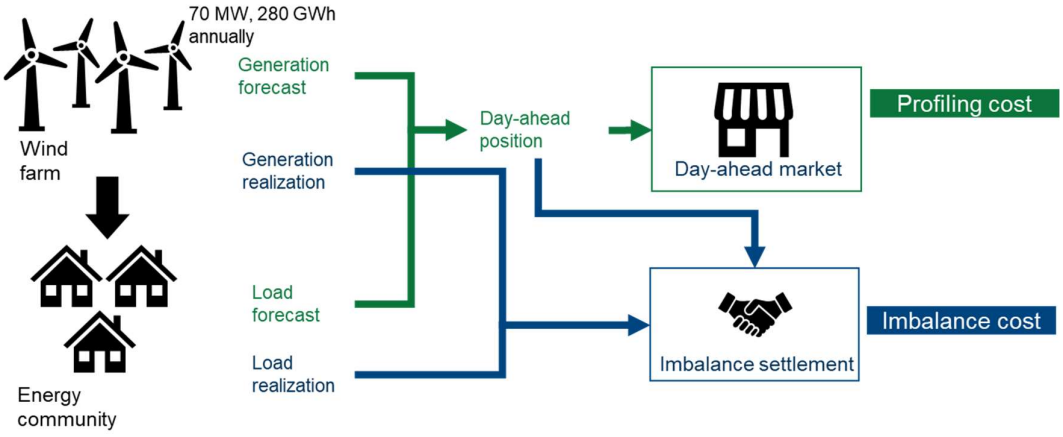


Figure 15: Risks to unmet forecasted loads and unmatched forecasts and realisations exposed by REC, i.e., profiling and imbalance costs, respectively

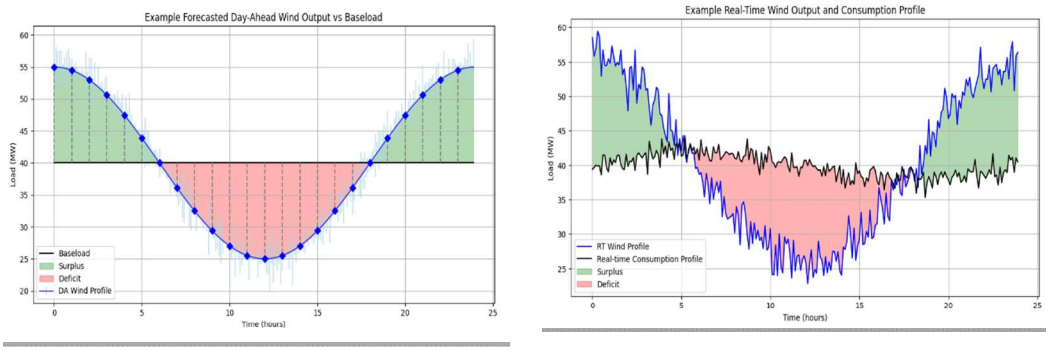


Figure 16: An example of day-ahead forecasts of generation and load (left) as compared to their realisations (right)

In order to manage these costs, the REC can consider using a battery energy storage system (BESS). Specifically, the energy deficit can be (partially) compensated by the energy stored in the BESS, and the energy surplus can be used to charge the BESS. Thus, theoretically, the energy that must be bought and/or sold as well as the imbalance are reduced, implying a potential reduction in the sourcing and imbalance costs. However, investing in a BESS induces additional investment and operational costs. Therefore, it is important to assess whether the revenue obtained by this BESS integration is worth the investment.

3.2.2 Accomplished work and general model outline

Options on how to use BESS

The BESS can be used in the imbalance settlement process. Specifically, any imbalance caused by the mismatch between the day-ahead forecasts and the realisation can be partially compensated by the BESS. To minimise the imbalance cost, the activation of the BESS must consider the imbalance price signals. In addition to activating the BESS, which helps with the imbalance cost, the REC can deviate its position in the day-ahead market from its day-ahead forecast since it has the BESS capacity that it can employ. This deviation must then be optimally chosen such that savings can be incurred as compared to simply positioning itself by using the day-ahead forecast. In this regard, both the day-ahead market position and battery activation must be optimised based on the day-ahead and imbalance price signals.

As explained, the first option (the BESS is used for imbalance settlement only) does not deal with the sourcing cost, while the second option does. In this regard, if the REC has a good forecast of the day-ahead and imbalance prices, then the second option can offer a larger reduction in the total cost, i.e., the summation of sourcing and imbalance costs. However, when the price forecast is far from reality, the second option has a higher risk of increasing this cost as compared to the first option. In other words, the first option is a more conservative strategy in using the BESS than the second one (Figure 17).

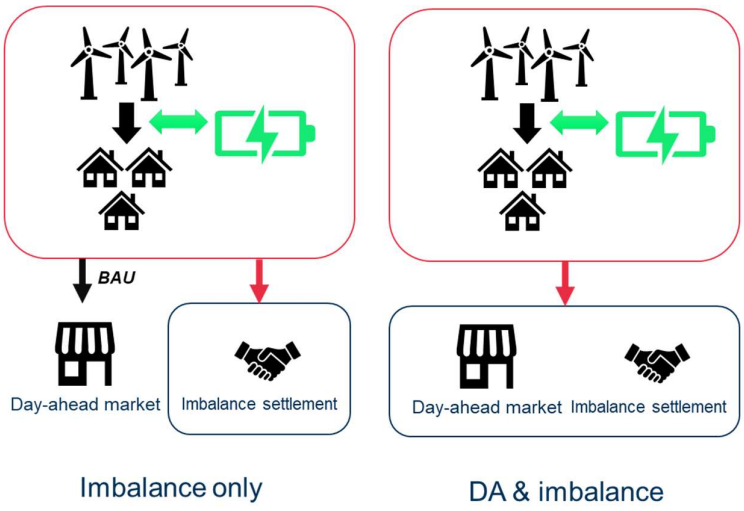


Figure 17: Two options for leveraging the battery: Option 1, for imbalance settlement only (left), and Option 2, for day-ahead market participation and imbalance settlement (right)

Modelling environment

We have developed an optimisation-based modelling environment that can simulate the two previously mentioned options of integrating a BESS into the REC's portfolio. This modelling environment is depicted in Figure 18. The components of this simulation environment include the models of a wind turbine, loads, and BESS, considered as devices (see 'Device' block). Specifically, the forecast and realisation of the wind power profile, as well as those of the load profile, are considered as inputs of the modelling environment. Furthermore, technical and operational constraints of the BESS, such as the dynamics of the state-of-charge (SoC) of the battery, maximum charging and discharging rates, as well as the maximum and minimum SoC limits, are considered. Furthermore, the REC is assumed as a price taker in the day-ahead market, i.e., its bid (day-ahead position) does not affect the price formation. This assumption is justifiable when the bid volume is relatively small. The day-ahead market and imbalance settlement belong to the 'Market' block. This market block defines the optimisation objective, which is to minimise the profiling and imbalance costs. Furthermore, this block also adds intra-market constraints, such as the balancing equation that relates the day-ahead position, realisation, and imbalance quantity, and other market constraints, such as the bid limits in the day-ahead market. As a result, for each option of BESS usage, a single-level optimisation problem, taking into account market objectives together with market and device constraints, is obtained.

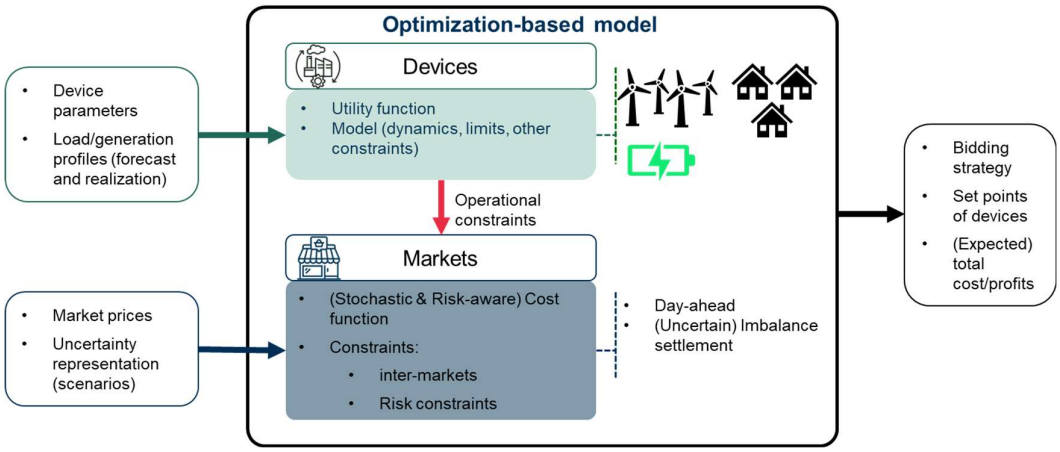


Figure 18: Modelling environment for optimal day-ahead bidding and battery use of the REC

Since the objective functions (profiling and imbalance cost functions) are parameterised by the day-ahead and imbalance prices, this model requires the forecast of these prices as well as their realisation. In this model, we assume that the day-ahead prices are perfectly forecasted, while the more volatile imbalance prices can be uncertain. As previously mentioned, this implies that the forecast quality of the imbalance prices plays a significant role in the savings evaluation. There are three price scenarios that are included in the modelling environment, namely:

1. Perfect forecast scenario (theoretical bound);
2. Stochastic and risk-neutral scenario;
3. Stochastic and risk-averse scenario.

In the perfect forecast scenario, the imbalance prices are forecasted perfectly, i.e., the forecast and realisation match. Therefore, this scenario provides a theoretical benchmark of the maximum savings that the BESS can provide. The latter two scenarios are more realistic than the first, as they consider uncertain imbalance prices and, thus, they have a stochastic optimisation formulation. In the second scenario (stochastic and risk-neutral scenario), the objective function considered is the expected value of the profiling and imbalance costs. Differently, in the third scenario (stochastic and risk-averse scenario), a risk measure is added to the objective. Specifically, we consider the conditional value at risk (CVaR) measure, which, roughly speaking, quantifies the expected loss at the tail probability or worst-case scenarios. In this regard, the REC can be risk-averse, i.e., it wants to minimise CVaR in addition to the original (expected) objective functions, and the risk-averseness level is determined by the weight given to the risk minimisation objective and the cost minimisation objective. In the latter two uncertain price scenarios, imbalance price samples are drawn based on Student's t-distribution models to form scenario-based stochastic (and risk-aware) optimisation models.

For each BESS usage option and price scenario, daily optimisation problems with a sampling time of 15 minutes and an optimisation horizon of 36 hours are solved to determine the day-ahead position and the daily set points of the battery over a certain period of simulation time. Then, the savings can be obtained by

comparing the simulation results with the business-as-usual scenario, where no BESS is involved, and the profiling and imbalance costs are simply determined by the day-ahead forecasts and realisations of the wind power generation and load.

3.2.3 Link with BUC(s)

This modelling track directly addresses BUC 4 (SeaCoop – VITO), titled "Integration of collectively owned offshore wind energy production in the electricity grid, by means of demand side management at REC level and the use of a large-scale battery". Through this modelling track, the questions posed in BUC 4 are fully addressed.

3.2.4 Key findings and results

In BUC 4, numerical simulations were carried out based on the real Belgian day-ahead and imbalance price data of 2024 while the realisation and forecast of generation and consumption profiles as well as the battery parameters were provided by SeaCoop. The complete analyses of the results are reported in Deliverable 3.4 and they are summarised as follows:

- Battery deployment reduces total costs relative to business as usual across all operating strategies (both options) and price-information scenarios.
- Jointly optimising the battery for day-ahead bidding and imbalance settlement (Option 2) increases profiling costs because the day-ahead position is deliberately reshaped to capture more valuable imbalance-market opportunities.
- Despite higher profiling costs, Option 2 generates substantially greater imbalance revenues than using the battery only for imbalance settlement.
- Battery deployment can transform imbalance settlement from a net cost under business as usual into a source of net revenue.
- Joint day-ahead and imbalance optimisation (Option 2) consistently achieves lower total costs than imbalance-only operation (Option 1) across all price scenarios.
- The battery's economic value comes not only from correcting forecast errors after the day-ahead market closes, but also from proactively shaping the day-ahead position.
- After accounting for annualised investment and operating costs, all evaluated battery strategies produce positive net savings under the modelling assumptions.
- Joint day-ahead and imbalance optimisation (Option 2) consistently delivers higher net savings than imbalance-only operation.
- Risk-neutral operation provides higher expected savings, whereas risk-averse operation sacrifices some expected value to reduce exposure to adverse price outcomes.

Results based on perfect price information represent theoretical performance limits rather than realistic profit forecasts.

Stochastic scenarios provide a more realistic basis for investment and operational decisions because they explicitly account for uncertainty in imbalance prices.

Overall, the simulations support a positive business case for a community-scale battery, particularly when battery operation is integrated into both day-ahead bidding and portfolio balancing.

Actual savings may be lower because of forecasting errors, transaction costs, battery degradation, efficiency uncertainty, and other operational constraints.

Further work should evaluate realistic forecast errors, battery ageing, alternative battery sizes, and sensitivity to market-design parameters.

4 Task 2.3 – Development of Multi-Sectoral End-Users & Energy Communities Models

4.1 Modelling Track A – Cross-Sectoral Technologies for Consumers

4.1.1 Scope and objectives

This part of REINVENT looks into the following two cases:

1. Renewable energy cooperatives (REC) in Belgium, such as Campina Energie, own renewable energy installations, e.g., PV systems in industrial, commercial, and governmental buildings. The business model of these RECs typically relies on pay-as-produced Power Purchase Agreements (PPAs) with local partners (schools, office complexes, etc.) to maximise local renewable self-consumption and injection of the excess generation into the grid. In these arrangements, the REC is connected to the grid via its partner, which makes the partner responsible for any grid injection costs. With the current trend of increasingly low or even negative injection prices, grid injection can lead to financial losses for the REC's partners. While curtailing power output is a potential strategy to limit these costs, it undermines the REC's business model, which depends on continuous energy delivery under pay-as-produced PPAs. One solution is using Battery Energy Storage Systems (BESS) to minimise this curtailment by storing excess generation and supporting financial returns through energy arbitrage.

   Based on the available historical data, this task's objective is to assess the contribution of using a BESS to the financial stability of a large-scale REC.

2. The flexibility of electric vehicles (EVs) can significantly contribute to balancing the energy system. This task within REINVENT focuses on analysing and evaluating the flexibility potential of EVs, as

well as the profitability of leveraging them for grid services, whether through implicit or explicit participation by EV owners. With the increasing penetration of EVs, their aggregated flexibility is expected to play an important role in maintaining system balance. Thus, an accurate estimation of this flexibility potential is essential for planning and operational decision-making to ensure reliable grid performance. The technical constraints of the EVs (e.g., charging rate and minimum/maximum State-of-Charge (SoC) of the EV battery), behavioural constraints imposed by the user's behaviour and preferences (such as preferred SoC before starting a journey, preferred time of charging, charging location, etc.) as well as the manufacturer's recommended usage (recommended minimum and maximum EV battery SoC) should be considered for this estimation of EV flexibility potential. Ignoring these constraints and limitations can lead to inaccurate assessments of EV flexibility, either underestimating or overestimating the available capacity and, at the same time, influencing the utilisation of other flexible assets (such as heat pumps (HPs)).

This task aims to quantify the flexibility potential of EVs while accounting for technical, user behavioural, and manufacturer constraints. It also highlights the impact of incorporating these constraints on the total cost of users' households, the self-consumption of household PV generation, and the impact on the grid in terms of peak consumption due to simultaneous EV charging.

4.1.2 Accomplished work and general model outline

Model setup. An optimisation model has been developed to support the objectives defined above. The model aims to minimise the household (or community) electricity consumption costs over a rolling horizon, optimising daily energy usage over a 36-hour window with a resolution of fifteen minutes (it is also possible to use hourly time resolution). The model incorporates household base demand, flexible asset consumption (EVs and HPs) and their technical constraints, and PV generation (if available).

The framework enables users to dynamically schedule energy offtake and injection to minimise daily electricity costs. Base demand, retail electricity pricing structures, and network tariffs drive these costs. Retail electricity pricing may follow static contracts, time-of-use (ToU) schemes with peak/off-peak rates, or dynamic pricing that reflects wholesale market conditions and incentivises responsive consumption or injection. Network tariffs can also include time-varying components and volumetric (kWh) and monthly peak capacity-based (kW) charges, as in Flanders, where the maximum power demand contributes to network charges.

The optimisation model is tailored to address the specific objectives of the two tasks outlined above and, as such, incorporates distinct sets of objectives and constraints, as detailed below.

Case 1. In this case, the above defined optimisation model is adapted to analyse the benefits of using BESS by minimising the total cost for the community and individual members. The required inputs include base load consumption data for community members, installed PV capacity and generation profiles, grid tariffs, retail prices for energy offtake and injection, and scenario-specific parameters such as the BESS parameters, PV curtailment options. The output of the optimisation toolbox includes the total cost over the considered time

period, the grid offtake schedule, the power exchange schedule within the community, and the BESS offtake and injection schedule. In the post-processing phase, KPIs include total community cost, power curtailment levels, and BESS utilisation. An overview of the adapted model is presented in Figure 19.

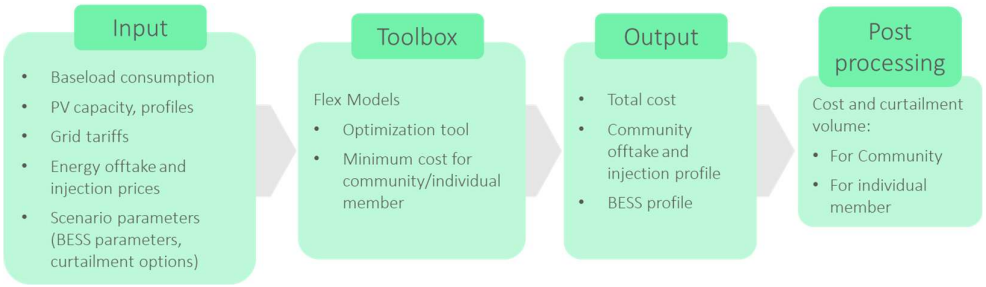


Figure 19: Overview of the optimisation tool for task 1

Case 2. This case aims to quantify the EV flexibility potential by considering the technical, user behavioural, and manufacturer constraints. An overview of the adapted optimisation tool is presented in Figure 20. The model minimises household electricity costs by taking into account the user's base consumption, the constraints of flexible assets (e.g., EVs and HPs), PV capacity and generation profile, grid tariffs (including TSO and DSO offtake/injection and monthly peak-offtake tariffs), and retail electricity offtake and injection prices. The model outputs an optimised household consumption profile, including the scheduling of flexible assets, to achieve the lowest offtake cost. Dynamic grid tariffs and retail prices serve as enablers for unlocking the EV flexibility potential by adapting EV charging schedules to price signals.

To assess this flexibility, a comparative analysis is conducted across three scenarios: (i) a base scenario with fixed offtake and injection prices, (ii) a reference scenario with dynamic prices, and (iii) a behavioural scenario that incorporates both dynamic pricing and user-specific behavioural and technical constraints. Key performance indicators (KPIs) are calculated for each scenario, including upward and downward flexibility potential, total cost, self-consumption, and consumption simultaneity.

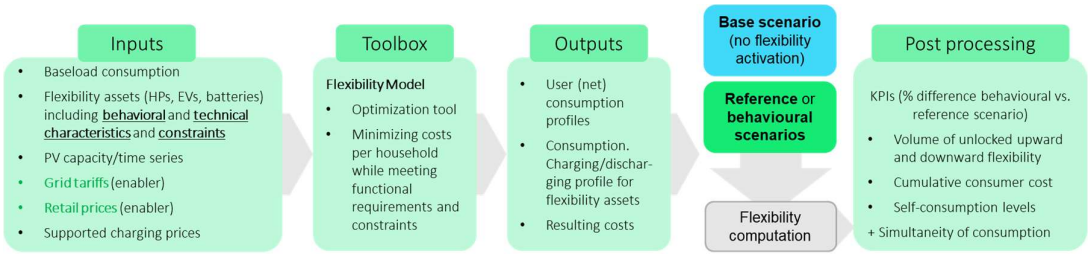


Figure 20: Optimisation tool overview for task 2

Accomplished work status

Case 1. An optimisation tool has been developed to compare community-level optimisation with individual-level optimisation and to assess the potential benefits of utilising BESS in mitigating REC PV curtailment. The tool also examines the implications of different BESS ownership and operational models on performance and cost-effectiveness.

Case 2. An optimisation framework has been developed and validated using open-source household electricity consumption profiles specific to Belgium. This framework is designed to assess the potential flexibility of EVs. The results indicate that the estimated flexibility potential is highly sensitive to the inclusion of various constraints, particularly technical, behavioural, and manufacturer-specific, which significantly influence the optimisation outcomes.

4.1.3 Link with BUC(s)

Case 1 corresponds to Campina Energie's BUC 2a: Collective, cross-sectoral business models for the integration of a BESS in a Renewable Energy Community. The analysis conducted under this task provides insights into the comparative benefits of community-level versus individual-level optimisation, demonstrating how the use of BESS can significantly reduce REC PV curtailment and lower the overall cost.

Case 2 is linked to Re.alto's BUC 10: Potential for flexibility provision with a portfolio of EVs. The analysis in this task highlights how incorporating both technical and behavioural constraints affects the overall flexibility potential of EVs and underscores the importance of realistic modelling for effective flexibility assessment.

4.1.4 Key findings and results

For Case 1, the analysis was carried out for BUC 2a using actual Belgian day-ahead electricity prices and PV generation data from 2024, together with measured power-consumption data and BESS sizing inputs provided by Campina. The complete analysis and detailed results are presented in Deliverable 3.4 and are summarised as follows:

- Community-wide optimisation generally delivers better overall economic performance than optimisation focused solely on an individual community member (school in this case).
- BESS availability reduces renewable-energy curtailment and lowers overall community energy costs.
- BESS can also mitigate the impact of negative electricity prices by storing surplus renewable energy that would otherwise be curtailed or injected into the grid at a cost.
- BESS operation and ownership arrangements significantly influence curtailment, asset utilisation, and the distribution of costs and benefits among community members.
- Tolling-type arrangements can improve BESS utilisation and support a more efficient allocation of flexibility within the community.
- Payment provisions and exposure to grid tariffs have a significant impact on the resulting community costs.
- Appropriate contractual and profit-sharing mechanisms are important to ensure a fair distribution of BESS-related benefits between the asset owner and operator.

For Case 2, the analysis was carried out for BUC 10 using actual Belgian day-ahead electricity prices and PV generation data for 2025, together with observed EV data provided by Re.alto. The EV dataset was used to

parameterise user behavioural constraints, including minimum and maximum battery SoC levels, driving times, and charging availability. The complete analysis and detailed results are presented in Deliverable 3.4 and are summarised as follows:

- Technical, behavioural, and manufacturer-imposed constraints have a significant influence on the practically achievable residential EV flexibility.
- Accurate representation of EV availability, mobility requirements, SoC preferences, charging behaviour, and manufacturer limits is therefore essential for realistic residential flexibility assessments.
- Incorporating realistic behavioural and technical constraints reduces the theoretical flexibility available under less restrictive assumptions but provides a more representative estimate of practically achievable flexibility.
- Wider admissible SoC ranges generally provide greater charging flexibility, whereas narrower SoC ranges reduce the ability to shift charging demand.
- Price-responsive charging can reduce consumer electricity costs by shifting EV charging towards more favourable price periods.
- For households with PV, optimised EV charging can improve PV self-consumption by increasing the temporal alignment between charging demand and local generation.
- Price-responsive charging can increase charging simultaneity across users and create new aggregate demand peaks.
- Manufacturer and user constraints influence both the timing and magnitude of these peaks by restricting when and how EVs can charge.
- Similar flexibility and cost trends are observed for households without PV, although PV self-consumption benefits are not applicable.

4.2 Modelling Track B – Investment Models for Multi-Sector Communities

4.2.1 Scope and objectives

With the willingness to incentivise investment in distributed energy resources (DERs) and give end-users a key role to play in the energy transition, the European Union has introduced the concept of *Energy Sharing. T*his paradigm enables individuals to exchange energy directly between them without solely relying on retailers for energy provision. One common form of energy sharing is through the creation of an Energy Community (EC) which can be defined, in its most general form[9], as:

[9] European Commission – Energy Communities: Definition and legal framework, https://energy.ec.europa.eu/topics/markets-and-consumers/energy-consumers-and-prosumers/energy-communities_en (last accessed 04.12.2025)

"A legal and autonomous entity which allows end-users to exchange any type of energy (e.g., electricity, heat, etc.) via public distribution networks. Participants can be natural persons, local authorities, municipalities, and enterprises of all sizes. The participation to the EC entity is voluntary and open to all based on non-discriminatory criteria. Finally, the primary purpose of an EC is to provide environmental, economic, or social community benefits rather than financial profits."

This legal entity is often represented by a community manager (i.e., a member or a shareholder of the EC) which is responsible for supervising the energy exchanges among members, applying the rules defined for it and centralising the exchange of information between participants and with external actors interacting with the community such as the Distribution System Operator (DSO) or traditional retailers.

Citizens are interested in ECs since they can reap benefits of different natures through the local mutualisation of resources and the coordination in decision-making (e.g., investment in renewable energy technologies, flexible resources scheduling, bundled energy contract). Advantages brought by the local entity can be economic (energy bill reduction, partial immunity to wholesale market current price spikes, lower investment costs, etc.), ecological (renewable energy promotion, greenhouse gas emissions abatement, etc.) and social (enhanced social inclusion, energy poverty decrease, etc.). In addition, participants are involved in the decision-making of the community, giving them more responsibility and control over their energy purchased and/or sold.

Before sharing energy among them, end-users must first decide which investment in DERs must be made to extract the most value out of their complementarity and the associated local exchanges. In this perspective, this modelling track aims to develop an investment model embedding the energy sharing paradigm to optimally size the production (PV, wind turbines), storage (batteries) and flexible resources (electric vehicles) facilities with the objective to minimise the cost for energy provision of the whole community. As a continuous equilibrium between production and consumption is sought for benefiting as much as possible from collective energy, (shared) electric vehicles seem to be an interesting means of flexibility as their charging control can be adapted to the community needs. In addition, potential interactions with external actors such as DSOs, and balancing responsible parties (BRPs) will be included to account for flexibility provision by the collective entity.

4.2.2 Accomplished work and general model outline

An optimisation-based methodology is proposed to optimally size the renewable electricity production resources as well as flexibility solutions under the form of a storage system and/or a fleet of electric vehicles solutions to extract the most economic value from community energy exchanges and auxiliary services provision while accounting for:

> Innovative investment strategies specific to energy communities (e.g., joint investment): If typical end-users only care about the choice of an adequate installation capacity, EC members have other degrees of freedom (i.e., dimensions in their decision set) to deal with, such as the facilities ownership (individual, collective) or the location of the assets (which member has the site with the most potential).

Flexibility potential: According to the activities carried out by the user behind-the-meter, some flexibility can be identified in the consumption profile and can be put to good use in the community.

Self-consumption objectives: Some European regulators impose balancing responsibilities to the community entity. To avoid this additional workload and associated costs, investment decisions may be taken while ensuring a minimum self-consumption threshold at the community level.

Regulation-compliant sharing mechanisms: Sharing energy is subject to regional or federal policies which have an influence on the profitability of energy mutualisation and therefore invested technologies.

Besides DERs capacity, ownership and location decisions, the proposed method also addresses the question of fair distribution of benefits by adequately designing the internal pricing structure.

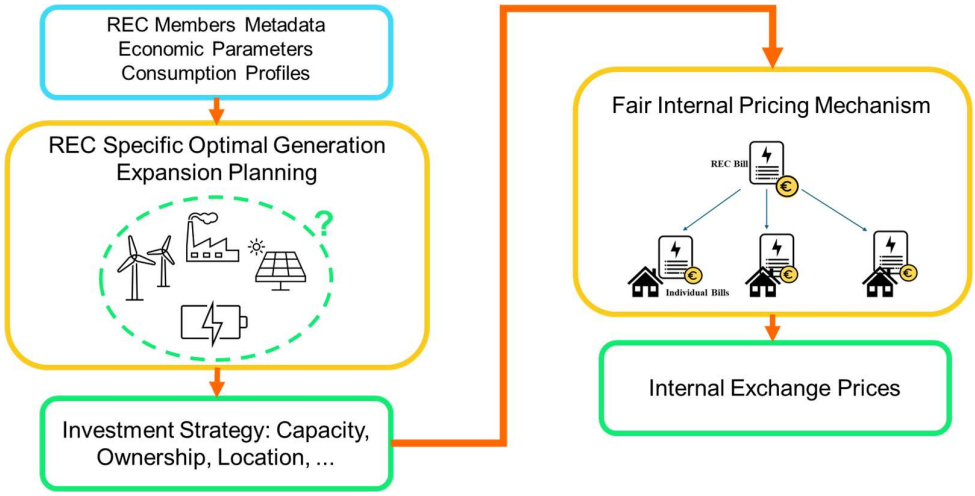


Figure 21: Block diagram of the two-stage investment model process

The whole investment process takes the form of two sequentially solved optimisation problems as depicted in Figure 21 and Figure 22. Based on end-users' metadata and expected consumption profiles, the first optimisation model solves a generation expansion planning problem including REC specific constraints described above. It minimises the total life-cycle cost of the community, accounting for investment and operational costs. The latter represents mainly the energy bill of EC members. The problem is subject to economic (budget, ownership distribution), physical (space availability, connection level to the network, etc.) and self-consumption constraints. Additionally, the mathematical formulation explicitly models the dynamic behaviour of storage systems, electric vehicles and industrial flexibility. Finally, specific constraints are considered according to the sharing mechanism applied on the case studied.

Once the first problem is solved and the optimal DERs are known, as well as the expected energy exchanges, a second problem is solved to identify the optimal internal exchange price structure for a fair distribution of the community benefits among its members. The objective function of this second problem is the minimisation of individual savings variance. In other words, it tries to get as close as possible to the equal savings situation. This problem is subject to competitiveness (collective exchanges must be incentivised with

respect to retailers) and individual return on investment (everyone must recover their investment) constraints. But more importantly, the economic balance must be met on a yearly basis (no missing money).

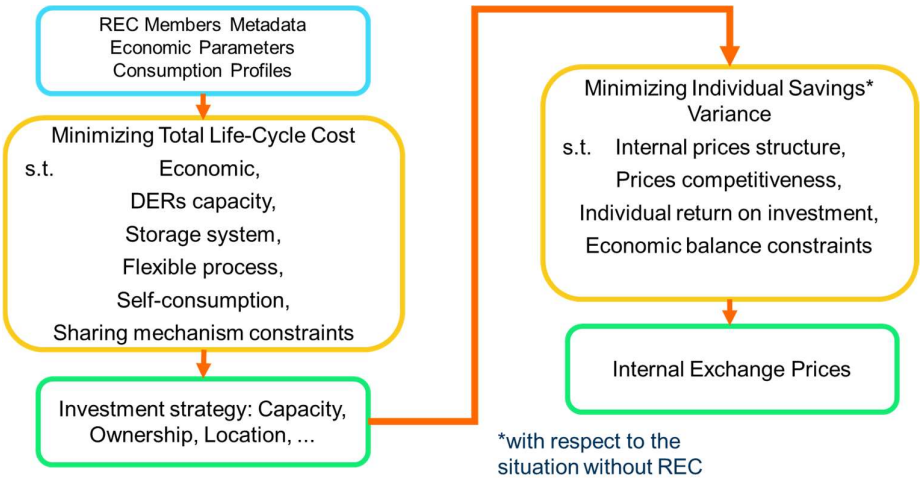


Figure 22: Optimisation problems general formulation

4.2.3 Link with BUC(s)

Models developed in this task are used to assess the performance of the following two business use cases (BUCs) involving multi-vector/multi-sector communities' concerns:

The first one is Klimaan's BUC 3a/b which focuses on the potential complementarity between electricity and mobility demand in a social district. Investment models are used to design the optimal shared EV fleet for a specific neighbourhood whose charging power may come from local PV panels to be shared in order to reduce the charging fees. Those vehicles would be made available to social tenants at an advantageous price. This BUC only required to solve the first step. The local electricity prices being already defined by existing contracts linking the PV owners and the social tenants.

The second one is IDETA's BUC 5a/b. If the former BUC is addressing multiple energy vectors sharing potential, the Wapigreen community supported by IDETA relies on the diversity of its members' business sectors (small to large enterprises, public facilities, caring facilities, etc.) to maximise the value of local wind energy. The objective is to use the investment model to assess the best energy mix and the most appropriate energy exchange conditions: the internal electricity prices and the energy sharing mechanism.

4.2.4 Key findings and results

BUC 3a:

The application of the developed model on the joint EC-SMO model demonstrated the economic and technical synergies arising from their coordinated operation. Key findings show that these benefits depend on the EV integration stage: while early-stage deployment enables flexible grid support through longer station-connected periods, the maturity stage generates greater mutual economic benefit through higher local

consumption charging volumes. These findings underscore the importance of jointly optimising operational decisions of both actors and point toward a natural extension: incorporating joint investment planning to capture long-term synergies in infrastructure sizing and tariff design. As the magnitude of the identified benefits remains highly sensitive to the local PV generation, load profiles, and mobility demand patterns, future work should assess the sensitivities of these synergies as well across a larger range of EC configurations.

BUC 5a:

The two steps investment optimisation framework has been used to identify the best investment strategy for the community and evaluate its economic and energy efficiency performance. Based on the simulation of 11 scenarios differing in terms of investments, assets and flexibility potential, the following key messages emerged:

- Special attention should be paid to the organization of internal exchanges in terms of both energy sharing rules and local tariff structure. Indeed, despite the existence of collective benefits (i.e., at the REC scale), some members may be worse off than in their initial stand-alone situation. This is a major limitation to the engagement of end-users in the energy community and therefore requires precautious consideration.
- When gathering end-users with various profiles, the community must select the appropriate production assets. As the local energy exchange relies on quarter-hourly matching of demand and production, the selected technology should have a generation profile complementary to the demand pattern. For such large-scale business energy community, relying only on solar production is not sufficient. Hence, the introduction of wind turbines considerably improved the collective economic performance of the community.
- Finally, flexibility is key to enhance the performance of the local entity from an economic and energy efficiency point of view. This flexibility may come from physical storage devices or from demand-side flexibility. Nevertheless, the benefits offered by these solutions on the local energy supply cost must be put into perspective with the direct (e.g., investment cost for deploying the solution) and indirect (e.g., loss of productivity) cost to find the best trade-off. To better valorise this flexibility, and especially storage assets, the community may envisage to extend its usage beyond energy arbitrage between local and retailer supply. It may serve to participate in flexibility services such as grid balancing or congestion management.

Future works (3b and 5b):

Another potential source of revenue that could benefit the communities and SMOs is the provision of flexibility services to other actors (TSOs, DSOs, BRPs) of the energy supply-chain which may require changes in the production and/or consumption profiles to support the network and avoid physical/economic penalties. In the investment model, this potential supplementary activity would be translated as an additional external exchange decision driven by a price signal.

4.3 Modelling Track C – Optimal Dispatch Models & Market Designs for Coupled Electricity & Heat/Cold Networks

4.3.1 Scope and objectives

This task focuses on the development and demonstration of a collective, cross-sectoral business model for a 5th-generation district heating and cooling (DHC) network at Thor Park (Genk), where four existing buildings, namely offices and research labs, will be connected to a modular DHC system that uses aquifer thermal energy storage (ATES) and building-level heat pumps powered by on-site photovoltaics or the electric power grid. Its objectives are threefold: first, to optimise the DHC network's operation so that heat and cooling (H/C) are supplied to the connected buildings as efficiently and cost-effectively as possible; second, to establish fair and transparent H/C sharing and pricing mechanisms ensuring equitable cost and revenue allocation among building owners; and third, to integrate the provision of flexibility to the electricity system while still meeting the primary goal of economical H/C provision.

4.3.2 Accomplished work and general model outline

Annual dispatch and pricing model (BUC 1a).

The core of the framework is a single-level mixed-integer linear program (MILP) that schedules every prosumer and the central supplier over a full year at hourly resolution. It captures the building assets (water-source heat pumps, chillers, direct cooling, gas-boiler backup and PV), the bidirectional warm- and cold-pipe network with its soil losses and thermal dynamics, and the supplier energy hub with its ground-source heat pump (GSHP), chiller, free-cooling exchanger, accumulator tank and ATES doublet (Figure 23). The objective minimises the net annual operating cost, grid import minus PV feed-in revenue plus gas cost, with a penalty enforcing the seasonal closure of the aquifer. The inputs are hourly time series per building (H/C demand, PV generation, tariffs, ambient and soil temperature), technology and storage parameters and aquifer characteristics, taken from the CollecThor pilot, the Belgian Royal Meteorological Institute, a Belgian two-zone retail contract and the European Environment Agency.

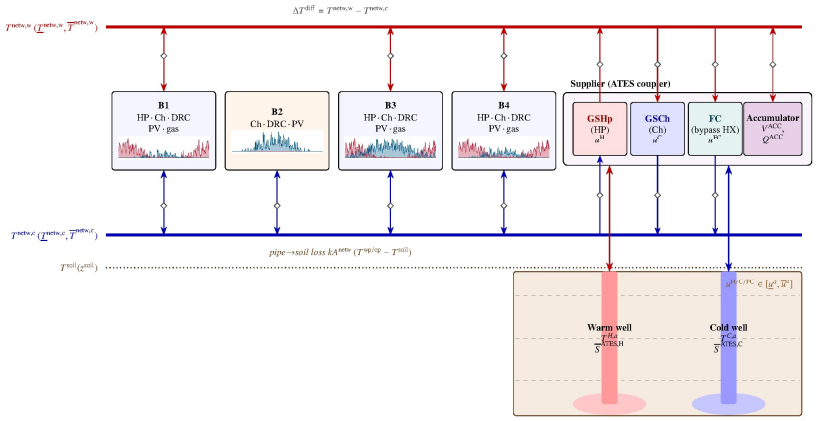


Figure 23: Integrated 5GDHC and ATES topology of the CollecThor network

On this basis, the MILP builds a network-wide energy balance across three coupled subsystems, the buildings, the pipe network and the energy hub, and returns the hourly schedule of every asset, the state trajectories of the two wells, grid import, PV self-consumption and feed-in, and the optimal pipe temperatures (Figure 24). Performance is assessed with the REINVENT KPIs: total and per-consumer cost of heat provision, primary energy, share of heat from local renewables, system coefficient of performance (SCOP), demand overlap coefficient (DOC) and specific CO_2 emissions. The model assumes perfect foresight, space heating and cooling as the only thermal demands, linear soil losses without hydraulics, and single-supplier ownership of the hub and of the ATES.

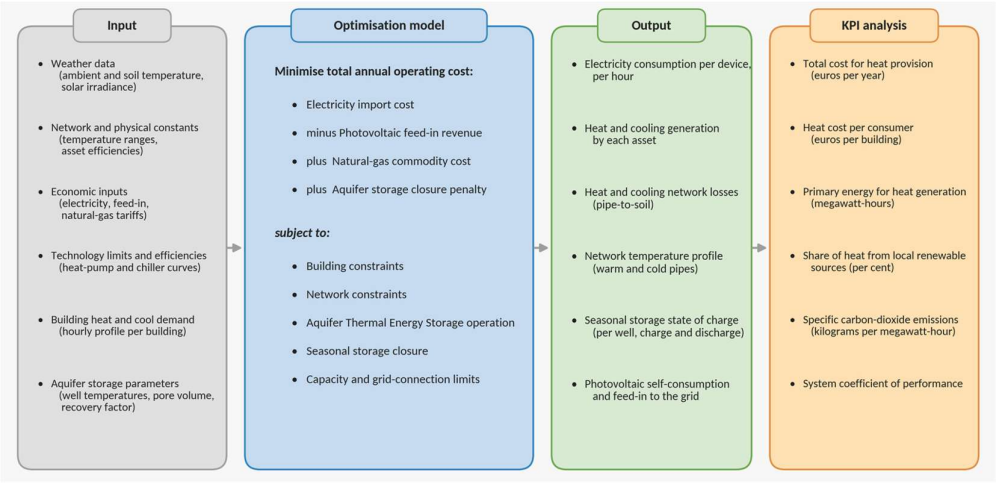


Figure 24: Heat and Cold dispatch optimisation problem formulation

A pricing layer addresses the second objective. Four arrangements are compared: Centralised, a social-welfare planner pricing at marginal value (benchmark, S0); a Revenue-Adequate Tariff (RAT, S2 Ramsey pricing) holding supplier profit at zero; a Cap-based mechanism (S1 cap), with a profit-maximising supplier under a regulated price cap; and the proposed Two-Part Tariff (TPT), where the supplier charges the marginal value of each thermal unit but takes its profit as a fixed fee bounded by the difference between outside option of each building. The last two are bilevel Stackelberg problems with the thermal supplier as a price-maker leader and buildings as price-taker followers (Figure 25).

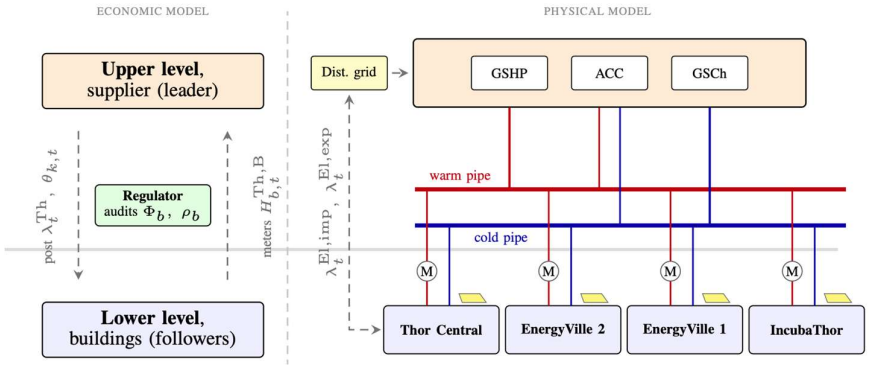


Figure 25: Schematic of the economic and physical model of the CollecThor use case

Flexibility valorisation model (BUC 1b).

The second model is a single-leader/single-follower bilevel program. The upper level is the 5GDHC operator, deciding the physical dispatch together with the quantity-price offer submitted to a DSO-run distribution local flexibility market; the lower level is the distribution system operator, clearing that market by least-cost merit order against four rival flexibility service providers under a transformer capacity constraint. For the purpose of the simulation, the thermal system is assumed to be connected at node 11 of the CIGRE European medium-voltage benchmark feeder, a standard test network used here in place of the actual distribution feeder whose PV and background loads are rescaled so that the substation experiences realistic bidirectional congestion, midday export in summer, evening import in winter.

Three representative days are simulated over a 24-hour horizon: a summer peak (8 July, cooling-dominated with high PV export), a mixed-demand day (15 April) and a winter peak (heating-dominated import). The ATES states are anchored to the annual trajectory of BUC 1a and any deviation is penalised at a shadow price, so that the operator arbitrates between market revenue and drift from its seasonal storage plan. Although demands and PV generation are fixed, five levers keep the hourly withdrawal flexible: chiller versus direct cooling and heat pump versus gas boiler at the building level, the three supplier-side channels, the accumulator thermal storage tank, and the PV self-consumption/feed-in split.

4.3.3 Link with BUC(s)

This track supports the two business use cases built on the CollecThor test case. BUC 1a, the collective business model for sharing heat and cooling in a business park, is addressed by the annual dispatch model and its pricing layer: they answer how H/C can be generated, stored and distributed to the four buildings at the lowest cost, and which pricing mechanisms reproduce that operation while allocating costs and revenues fairly. BUC 1b, the valorisation of the flexibility of the same network, is addressed by the bilevel market model, following the three steps of the use case: characterisation of the flexibility potential, mapping onto the accessible market segment, and assessment of the economic and environmental consequences.

4.3.4 Key findings and results

In this section we elaborate on the important aspects of the modelling and the results:

Cost-optimal operation

The optimal annual dispatch splits into three regimes: winter heating, in which the warm well is discharged through the supplier heat pump; summer cooling, in which condenser rejection and direct cooling charge it; and a mixed-demand-season free-cooling regime without compressor activation. Building demand is served almost entirely by the prosumer heat pumps, gas boilers being mobilised only during cold snaps, and cooling by the direct-cooling exchangers; under the current sizing, the supplier ground-source chiller is never activated, however, it is a useful asset for participation in the flexibility market.

Over the year, 231 MWh of grid electricity and 86.7 MWh of self-consumed PV deliver 878 MWh of heat and 709 MWh of cold, i.e., a system SCOP of 6.86 (3.79 for heat only) against 3.5–5 for a typical 5GDHC network; 29% of the electricity consumed by the thermal assets is locally generated and emissions reach 38 tCO_2/yr. The gross operating bill of 54.7 k€/yr corresponds to about 58 €/MWh of heat and 5 €/MWh of cold, but the 53.8 k€/yr of PV feed-in revenue brings the net unit costs down to roughly 1 €/MWh and 0.08 €/MWh, so that PV covers almost the entire campus H/C service and three of the four prosumers end the year as net sellers.

Two structural findings follow. Only about 21% of the campus heating and cooling demand overlaps day by day, well below the 40% threshold above which prosumer-to-prosumer sharing alone could close the thermal balance and make the 5GDHC network cost-effective. This makes seasonal storage a necessity. The ATES doublet, nevertheless, inherits a year-end imbalance from the geological thermal decay (about 28%/yr); the gas backup absorbs part of it, but excessive reliance on gas would compromise compliance with the Renewable Energy Directive III, so multi-year rolling balancing or an auxiliary dry cooler is required. Moreover, only about 10% of the 858 MWh of annual PV generation is self-consumed; as each kWh redirected from export to self-

consumption is worth 0.158 €/kWh, a battery shifting 50–100 MWh per year would be worth 8–16 k€/yr.

Pricing and settlement

The four designs were compared on the heating-extreme winter day (day of year 39), as reported in Table 4. The supplier also sets the loop temperature, a non-price lever that price regulation cannot observe. The centralised planner is the welfare benchmark but posts no implementable tariff. Revenue adequate Tariff (RAT, Ramsey pricing) reaches first-best welfare, yet its break-even leaves the supplier no return. The price cap-based mechanism is the costly case. The supplier does not turn its assets on, and the loop falls to its temperature floor, saving a third of its plant electricity while the buildings' heat-pump efficiency collapses and their grid purchases rise by a third. It earns 93 € by destroying 118 € of welfare, more than seven times the day's achievable surplus, pushes every building below its standalone cost, and raises emissions by 7.9%. The proposed two-part tariff reaches first best operation, posts the shadow price of the efficient dispatch, holds the efficient temperature, and takes its profit as a fixed fee bounded by each building's audited outside option, so the supplier stays solvent while every building gains. A single regulated share divides that gain at no welfare cost.

Table 4: Daily indicators of the four pricing mechanisms, simulated on a peak winter day (day of year 39)

Scenario	Social welfare (€)	Supplier profit (€)	Consumer bill (€)	Thermal price (c€/kWh)	CO_2 (kg)
Centralised	−834.87	–	–	[3.3; 3.5] — shadow price, recovered ex post	528.06
RAT	−835.00	0.00	16.50	[3.9; 5.1]	527.59
Cap-based	−952.69	93.03	−194.22	4.97(flat at cap)	569.75
TPT (proposed)	−834.87	7.21	9.43	[3.3; 3.5] Marginal price	528.06

Flexibility valorisation

Market participation changes the timing of the electricity consumption of the network, not the energy delivered to the buildings, and the aquifer drifts only marginally from its seasonal track (Table 5). On the summer day, the network absorbs the export surplus by running its chillers instead of free cooling, which gives the largest gross revenue (≈ 49 €/day) but forgoes PV feed-in and raises emissions. On the mixed-demand day, congestion is small and bidirectional and is covered with the fast levers (among the flexibility levers defined in D3.4, fast levers are those that resolve within the day without displacing the ATES from its seasonal trajectory) alone, which makes it the most profitable day in margin terms despite a modest revenue (≈ 15 €/day). On the

winter day, the network provides upward flexibility by easing off its heat pumps and drawing on stored heat, slightly improving its own thermal cost. Gross revenue therefore scales with the procurement need of the DSO, but the net benefit depends on whether the response stays within the fast-lever envelope.

Table 5: Flexibility market participation on the three representative days (without → with market)

Key performance indicator	Summer (8 Jul)	Mixed (15 Apr)	Winter (15 Jan)
Cleared flexibility (MWh/day)	0.29 (downward)	0.15 (mixed)	0.10 (upward)
Flexibility revenue (€/day)	49.4	15.5	11.1
Change in thermal cost (€/day)	36 (worse)	5 (worse)	4 (better)
Share of heat from local RES (%)	100 → 100	99.1 → 97.8	100 → 96.1
CO_2 emissions (kg/day)	21.9 → 35.9	128.8 → 141.0	114.7 → 128.1

Operationally, the downward flexibility band is set by the intra-day charge envelope of the ATES and by the accumulator rather than by the device ratings, so larger buffers would widen it; environmentally, the cheapest lever may also be the most carbon-intensive, which argues for linking remuneration to a carbon signal. The remaining steps are to extend the representative-day analysis to a full year and to test endogenous pricing scenarios inside the MILP.

4.4 Modelling Track D – Optimised DER user adoption and usage

4.4.1 Scope and objectives

Understanding the adoption and usage patterns of Distributed Energy Resources (DER) is essential for accelerating the integration of new, decentralised energy systems. While previous analyses have often emphasised economic factors, such as upfront investment costs and payback time, recent evidence suggests that intrinsic factors, including environmental awareness, lifestyle preferences, openness to innovation and community norms, can also play an important role in adoption. This modelling track therefore has two complementary objectives:

- Identify adoption clusters of DER technologies to enable more efficient and targeted policy interventions. For example, locating areas with higher current or potential EV adoption can support the optimised deployment of public charging infrastructure and other enabling services.
- Explore inclusive models of DER usage, particularly among vulnerable or resource-constrained populations. The broader modelling task examines whether groups with fewer resources may be promising target groups for shared mobility or alternative DER-access models, such as social-housing-based EV sharing schemes. This objective responds to social-equity concerns in technology diffusion, including the Matthew Effect, whereby technological benefits can accrue disproportionately to groups that are already better positioned to adopt.

4.4.2 Accomplished work and general model outline

In late 2024, a detailed data-collection effort was carried out in the Hasselt region through door-to-door surveys conducted by two students. The survey was designed to capture intrinsic factors influencing DER adoption at household level. The resulting data were processed and merged with spatial and building characteristics (Table 6) to train predictive models. The objective was to assess how behavioural, socio-demographic, building and neighbourhood variables relate to observed DER ownership and, ultimately, to establish the basis for identifying geospatial clusters with high adoption potential.

Table 6: Data layers used in the proof-of-concept modelling

Data layer	Coverage	Main variables
Household survey	n = 67	Personal values; status-quo orientation; DER ownership; socio-demographics; TAM constructs where sufficiently complete
Building data	67 surveyed dwellings	Construction year, type, protected volume, estimated EPC and related EBECS attributes
Spatial context	Building-level	Distance from each surveyed dwelling to the nearest owner of PV, EV, HP or SM
Outcomes	PV, EV, HP, SM	Binary self-reported ownership used as the prediction target

Household, behavioural and building variables

The survey measured seven value orientations on five-point Likert scales: saving energy, reducing costs, reducing CO_2 emissions, energy independence, support for innovative technologies, comfort and collaboration with others. A separate status-quo item captured resistance to purchasing new technologies. Technology Acceptance Model (TAM) constructs, perceived usefulness, perceived ease of use, attitude, behavioural intention, actual use and peer influence, were collected for the four technologies[10,11]. Because response coverage for these constructs was sufficient only for PV, TAM variables were included in PV prediction models but excluded for EV, HP and SM to avoid unstable comparisons.

Building attributes were derived from Belgian statistical data and the EnergyVille Building and Energy Characterization System (EBECS), including building type, construction year, protected volume and estimated EPC class. These variables provide proxies for technical suitability, dwelling size and energy performance.

Spatial-geographical proximity

For each technology, the nearest-neighbour distance from every surveyed building to the closest technology-owning building was calculated after projecting building centroids to Belgian Lambert 72

[10] Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13, 319–340.

[11] Venkatesh, V., Morris, M.G., Davis, G.B., & Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27, 425–478.

(EPSG:31370 - Belgian Lambert 72, official "national grid coordinate system of Belgium). Self-matches were excluded and attached buildings were assigned a minimum distance of 0.01 m. Spatial visualisations were aggregated to protect household privacy. The resulting distance variable acts as a simple indicator of local visibility and neighbourhood diffusion effects (Figure 26).

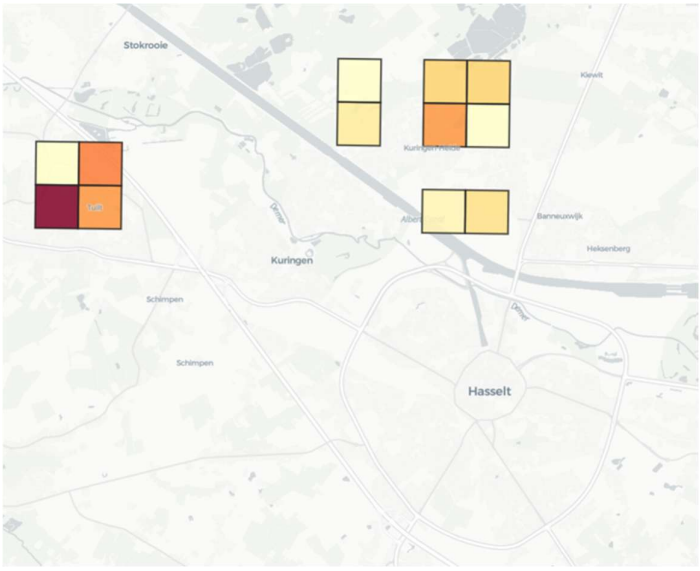


Figure 26: Aggregated spatial representation of surveyed households around Hasselt. Grid aggregation is used to reduce disclosure risk while preserving the local diffusion context.

Predictive modelling approach

Four supervised-learning specifications were compared under stratified cross-validation. Model 1 combined fold-specific univariate screening with L1-regularised logistic regression, providing a sparse and interpretable baseline. Model 2 used dimensionality reduction for mixed numerical and categorical data followed by L2-regularised logistic regression. Model 3 applied a Random Forest with nested hyperparameter tuning and class weighting, while Model 4 used Gradient-Boosted Trees with nested tuning. The non-linear models were included to capture interactions and threshold effects that simpler regressions may miss. Performance was evaluated primarily through Receiver Operating Characteristic – Area Under the Curve (ROC–AUC), supplemented by accuracy and class-level recall. Feature importance from tree models was aggregated to the parent-variable level to support interpretation.

4.4.3 Link with BUC(s)

This modelling track maps onto BUC 3. The adoption-prediction models of Case 1 identify where and among whom DER uptake is most likely, and the EV-sharing analysis of Case 2 addresses the inclusive-usage question raised by the business use case.

4.4.4 Key findings and results

Adoption, values and spatial context

Technology ownership differed markedly across the sample: 46 of 67 households owned PV (68.7%), 25 owned a smart meter (37.3%), 22 of 65 owned an EV (33.8%), and 14 of 65 owned an HP (21.5%). The sample therefore provides substantially more positive cases for PV than for HP, an imbalance that directly affects the stability of prediction models. Respondents placed the greatest importance on saving energy (mean 4.60/5), reducing costs (4.52), low CO_2 emissions (4.37) and comfort (4.36). Energy independence (3.97) and support for innovative technologies (3.85) were also rated positively, while collaboration with others was lower (2.96). The status-quo item averaged 2.37/5, indicating that resistance to new technologies varied substantially across households (Figure 37). Among TAM constructs, PV received the strongest ratings, with high perceived usefulness and favourable attitudes; EV and HP were more moderate, and SM scored lowest, consistent with its more passive and increasingly mandatory role.

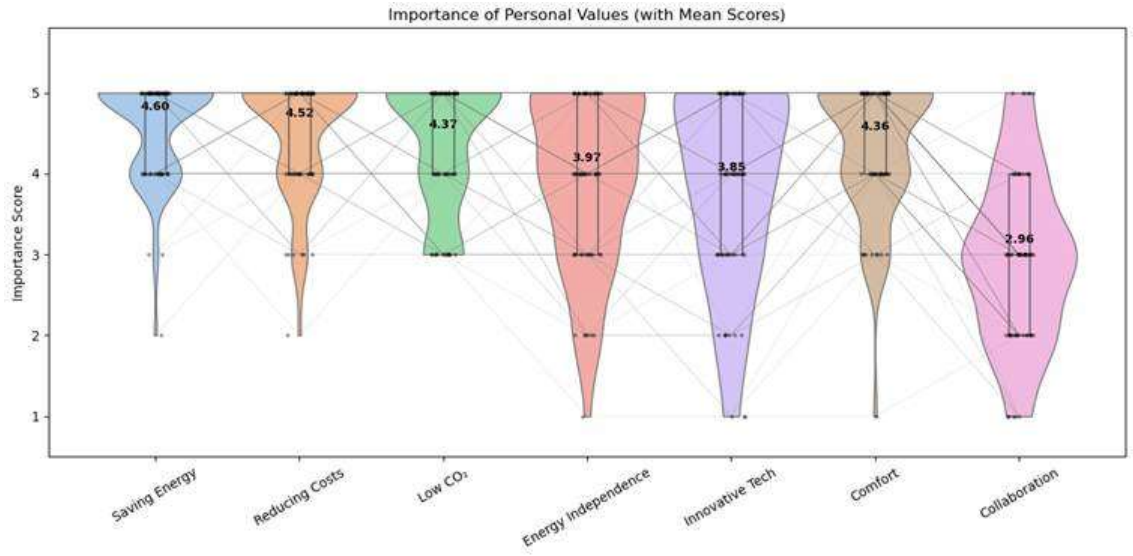


Figure 27: Violin plot showing the distribution of ratings (1–5) of personal values in energy decisions for 67 respondents. Boxes indicate medians and interquartile ranges; dots represent individual responses. Grey lines connect responses from the same individual. Mean scores are annotated above each category.

Spatial distance also varied by technology. PV adopters were the most locally concentrated, with a mean nearest-adopter distance of 61 m (median 37 m). Mean distances increased to about 110 m for SM, 145 m for EV and 223 m for HP. This ordering is consistent with the relative prevalence of the technologies, but the large variation, especially for EV and HP, also suggests heterogeneous neighbourhood exposure.

Predictive performance

Performance differed clearly by technology and model class (Table 7). PV ownership was the most predictable outcome. Tree-based models substantially outperformed the linear baselines, reaching mean ROC–AUC values of 0.871 for Random Forest and 0.881 for GBM. EV ownership showed moderate

predictability, with Random Forest performing best (0.759) and the mixed-data logistic model close behind (0.751). HP prediction remained modest (approximately 0.66–0.67 for the strongest models) and was unstable across folds because only 14 owners were observed. SM prediction was effectively at chance level across all specifications, indicating that the available behavioural and building variables do not explain its rollout well.

Table 7: Mean cross-validated ROC–AUC by technology and model. Values below 0.5 indicate no useful discrimination in this sample.

Technology	L1 logit	Mixed logit	Random Forest	GBM	Interpretation
PV	0.739	0.793	0.871	0.881	Strong
EV	0.528	0.751	0.759	0.726	Moderate
HP	0.620	0.665	0.668	0.659	Modest
SM	0.455	0.452	0.360	0.400	Near chance

Main drivers by technology

PV. Peer influence was the dominant feature in both tree-based models, followed by support for innovative technology. EPC, proximity to other PV owners, education and comfort also contributed. The combination of strong peer influence and local proximity supports the interpretation of PV adoption as a socially visible diffusion process in which direct communication and passive observation can reinforce uptake[12,13].

EV. Innovation orientation was consistently important, alongside environmental values, proximity to another EV owner and protected building volume. The latter may partly reflect practical charging conditions associated with larger dwellings and private parking. Performance remained moderate because the number of adopters was limited and EV decisions depend on mobility needs, vehicle availability and charging access that were only partly represented in the dataset.

HP. Innovation, energy-saving and comfort values contributed to Random Forest predictions; proximity, education and EPC were prominent in the GBM model. Status-quo resistance also showed a univariate relationship with ownership. However, these signals were not stable across folds, so they should be treated as hypotheses for validation rather than robust causal determinants.

SM. No model achieved useful discrimination. This is substantively plausible because smart-meter installation in Flanders is increasingly determined by regulated rollout rather than a voluntary household adoption decision. Behavioural preferences therefore have less opportunity to explain ownership.

[12] Wolske, K.S., Gillingham, K.T., & Schultz, P.W. (2020). Peer influence on household energy behaviours. Nature Energy, 5, 202–212.

[13] Müller, S., & Rode, J. (2013). The adoption of photovoltaic systems in Wiesbaden, Germany. Economics of Innovation and New Technology, 22, 519–535.

Interpretation and practical implications

The proof of concept supports the central hypothesis that DER diffusion can be modelled more effectively when household values and local social context are combined with building data. The strongest evidence comes from PV, where peer influence, openness to innovation and spatial proximity jointly provided substantial predictive signal. This is consistent with research showing that household energy technologies diffuse through both interpersonal communication and visible examples in local networks14,15. The weaker but still meaningful results for EV and HP suggest that behavioural and spatial variables remain relevant, although broader technology-specific constraints must also be represented. Three practical implications follow. First, spatial-behavioural models can complement purely technical suitability maps by indicating where households may be more receptive to a technology. This could improve targeting of information campaigns, incentives and infrastructure, for example, prioritising EV-charging investments in areas combining technical need with stronger latent adoption potential. Second, peer-based approaches such as demonstration homes, neighbourhood ambassadors or trusted local intermediaries may accelerate diffusion of visible technologies, especially PV. Third, adoption modelling should not be used only to identify likely early adopters. The broader REINVENT objective is to combine diffusion analysis with inclusive access models so that infrastructure and business-model innovation can also reach households that are less able to make individual capital investments. The technology-specific differences are equally important. A single generic adoption model is unlikely to transfer well across DERs. PV is mature, highly visible and already prevalent; EV adoption depends on mobility patterns and charging access; HP uptake is closely tied to building suitability, renovation state and heating-system replacement cycles; and SM deployment is primarily policy-driven. Future operational models should therefore retain a common behavioural-spatial framework while incorporating technology-specific decision variables and constraints.

Limitations and next steps

The principal limitation is sample size. With only 67 households, and only 14 HP owners, statistical power and generalisability are limited. Class imbalance reduced the models' ability to identify minority adopters, and cross-validation results, especially for HP, were sensitive to fold composition. The geographic concentration around Hasselt also limits representation of Belgium's socio-economic and housing diversity. In addition, TAM constructs were sufficiently complete only for PV, which weakens direct comparison across technologies. Income was not reported by a large share of respondents, and some potentially important determinants, private parking, renovation readiness, risk perception, installer access, policy awareness and technology replacement cycles, were not fully captured. The next step is therefore not to optimise the present models further on the same small dataset, but to scale and validate the approach. Priority actions are: (i) enlarge the sample across multiple municipalities and housing contexts; (ii) improve behavioural-question coverage for all

[14] Wolske, K.S., Gillingham, K.T., & Schultz, P.W. (2020). Peer influence on household energy behaviours. Nature Energy, 5, 202–212.

[15] Müller, S., & Rode, J. (2013). The adoption of photovoltaic systems in Wiesbaden, Germany. Economics of Innovation and New Technology, 22, 519–535.

technologies; (iii) add technology-specific feasibility and policy variables; (iv) use longitudinal observations where possible to distinguish diffusion from static correlation; and (v) test whether predicted adoption potential can be translated into privacy-preserving neighbourhood maps that are useful for planning. A larger dataset would also allow more robust uncertainty analysis and external validation.

From proof of concept to operational diffusion maps

The value of the present exercise is not the production of a final household-level prediction map from 67 observations, but the validation of an analytical architecture that can be scaled. An operational version would combine a larger behavioural survey with building-level technical suitability, technology-specific constraints and neighbourhood diffusion variables. The resulting adoption probabilities could then be aggregated to privacy-preserving spatial units and used as an additional planning layer alongside grid capacity, infrastructure needs and socio-economic vulnerability (Figure 28).

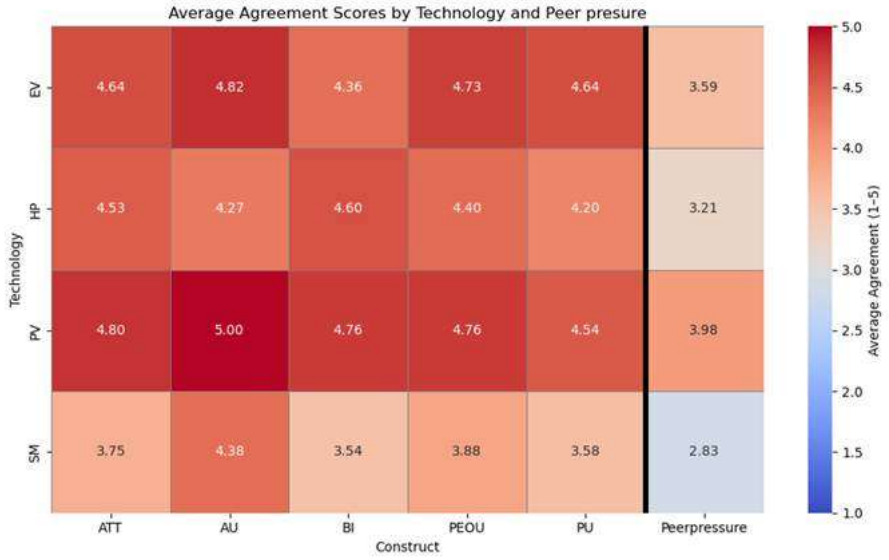


Figure 28: Heat map showing the average agreement scores (Likert scale 1–5) for each Technology Acceptance Model (TAM) construct on the x-axis across the four DER-BTM technologies investigated: photovoltaics (PV), electric vehicles (EV), heat pumps (HP), and smart meters (SM) on the y-axis, including an additional variable for peer pressure

General model development pathway

Table 8: Proposed pathway from the proof of concept to an operational planning layer

Step	Purpose
1. Enrich	Expand behavioural sampling and add technology-specific feasibility, policy and affordability variables.
2. Predict	Estimate adoption probabilities with externally validated models and uncertainty bounds.
3. Spatialise	Aggregate household predictions into privacy-preserving neighbourhood diffusion maps.
4. Act	Combine adoption potential with grid, infrastructure and vulnerability layers to select targeted or shared-access interventions.

A central design principle should be to report uncertainty and avoid deterministic labelling of individual households. The planning value lies in identifying probabilistic patterns at an aggregated level, not in classifying specific residents. This is also important for fairness: adoption-potential maps should be interpreted jointly with affordability and vulnerability information so that lower predicted individual ownership does not become a reason to deprioritise neighbourhood investment.

Conclusion

This proof of concept demonstrates the feasibility of combining behavioural, spatial and building-level information to model household DER adoption. PV ownership was predicted with strong discrimination, while EV and HP showed moderate or modest predictive potential and SM remained largely unexplained by household-level variables. Across the voluntary technologies, openness to innovation, environmental and comfort-related values, local proximity and building characteristics repeatedly emerged as useful signals. The results should not yet be interpreted as deployment-ready forecasts, but they establish a credible methodological foundation for a larger spatial-behavioural adoption model. Scaling the dataset and explicitly integrating inclusion and access considerations would allow the approach to support more targeted, equitable and system-aware energy-transition planning within REINVENT.

4.5 Modelling Track E – Hidden flexibility in vulnerable households

4.5.1 Scope and objectives

Introduction and problem scope

The Klimaan case investigates household electricity-use patterns in a social housing district in Mechelen-Noord, Belgium. Its wider research motivation is to understand how vulnerable households could participate in renewable-aligned electric vehicle (EV) charging and shared mobility. This section presents the electricity data as the empirical starting point: when households consume electricity, how seasonal patterns differ, and how demand relates to local photovoltaic (PV) generation. A single average household profile can conceal distinct morning and evening consumption patterns. This analysis therefore groups households by normalised load shape and compares peak concentration, consumption volume and PV flows. The aim is to explore whether these patterns reveal opportunities for EV charging schemes that could reduce charging costs for vulnerable households and increase the use of locally generated PV electricity. These indicators describe observed electricity use; they do not directly measure residents' ability to shift demand or the availability of shared vehicles. Vulnerability refers to the case-study context rather than a verified household-level classification of energy poverty.

4.5.2 Accomplished work and general model outline

Data preparation

Hourly household electricity consumption from the Klimaan/Fluvius dataset was reconstructed as grid import + PV production − grid injection, with negative values set to zero, thereby accounting for directly consumed PV electricity that is not captured by grid import alone. Days with fewer than 24 hourly observations were excluded. Four households lacking autumn data were removed from the seasonal clustering analysis, resulting in a final sample of 43 households. Most retained households had at least 353 complete days of data, with three exceptions containing 292, 303 and 303 complete days, respectively. To ensure that clustering reflected load-shape characteristics rather than absolute consumption volume, each daily 24-hour profile was normalized by dividing each hourly value by that day's total electricity consumption. Normalized daily profiles were then averaged for each household. Annual clustering was based on 24 hourly features, whereas seasonal clustering combined four seasonal 24-hour profiles into a 96-feature vector per household.

K-means clustering was applied to identify groups of households with similar temporal consumption patterns. Candidate solutions were evaluated using silhouette scores, within-cluster sums of squares and substantive interpretability. For the annual analysis, solutions with k = 2 and k = 5 were examined. For the seasonal analysis, the k = 3 solution was retained as the most interpretable clustering structure.

4.5.3 Link with BUC(s)

This modelling track maps onto BUC 3.

4.5.4 Key findings and results

Overview of the results

The three seasonal groups are "evening peak" (11 households), "balanced" (23) and "morning peak" (9). The evening group has the highest typical peak-to-average ratio (PAR) and annual consumption. The balanced group contains the largest consumption outliers. Summer has lower PAR in all three groups. PV generation and injection show broadly similar midday patterns, while PV self-consumption differs more visibly between clusters.

Seasonal household load profiles

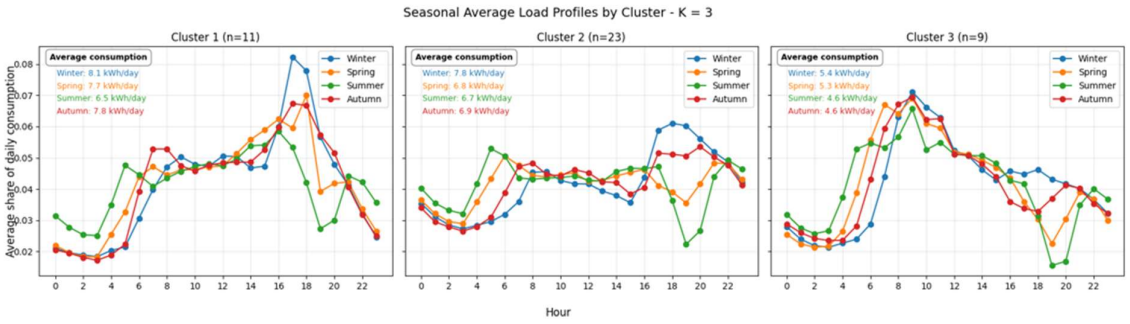


Figure 29: Original seasonal average load profiles and daily consumption annotations. Curves show average hourly shares of daily consumption; cluster sizes are 11, 23 and 9.

Cluster 1 is the evening-peak group. In winter, the hourly share rises to approximately 0.082 around 17:00; spring and autumn also show pronounced late-afternoon or evening demand. In summer, the profile is less concentrated, with a marked decline around 18:00–20:00. The evening peak is therefore a seasonal characteristic rather than a fixed year-round pattern. Cluster 2 is the balanced group and accounts for 53.5% of the sample. Daytime shares are relatively even, although winter still has an evening increase around 16:00–18:00. Summer includes a morning rise and a pronounced dip around 19:00. Individual profiles vary within this cluster, so the average should not be interpreted as uniformly flat behaviour. Cluster 3 is the morning-peak group. Consumption increases between approximately 06:00 and 10:00, with the highest shares around 08:00–10:00. Shares then decline through the afternoon, without a comparable evening peak. The summer evening dip is also visible in this group.

Daily consumption complements normalised shape

Table 9: Average consumption in kWh/day, transcribed from Figure 29. Seasonal means should not be confused with the household annual-consumption medians in Figure 32 (see below).

Cluster	Winter	Spring	Summer	Autumn
1 Evening peak	8.1	7.7	6.5	7.8
2 Balanced	7.8	6.8	6.7	6.9
3 Morning peak	5.4	5.3	4.6	4.6

The morning group has the lowest daily average in every season. The evening group is highest in winter, spring and autumn. The balanced group is slightly higher in summer. Summer consumption is below winter consumption in all three groups. Because the curves are normalised, an hourly-share decline should be assessed alongside absolute demand before assigning an energy reduction to that hour.

Peak concentration across clusters and seasons

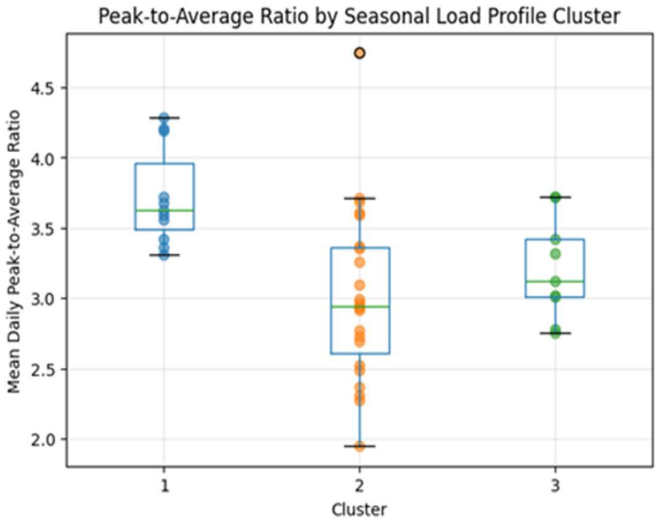


Figure 30: Original distribution of mean daily PAR by seasonal cluster. Points show household observations; boxes summarise their distributions.

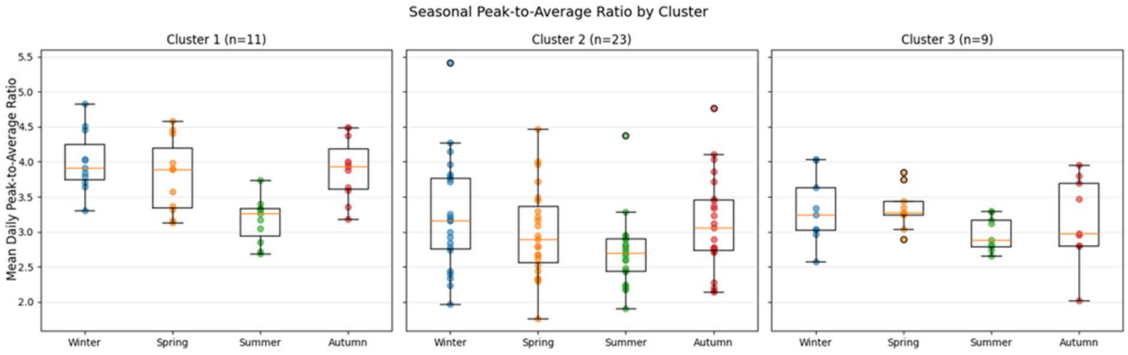


Figure 31: Original seasonal distributions of household mean daily PAR. Colours indicate winter, spring, summer and autumn. Values discussed below are approximate visual readings.

The typical mean daily PAR is highest in Cluster 1, around 3.6, compared with roughly 2.9 in Cluster 2 and 3.1 in Cluster 3. Cluster 2 spans the widest range, from about 2.0 to an outlier near 4.7. The balanced average therefore coexists with some strongly peaked individual households. For Cluster 1, seasonal medians are approximately 3.9 in winter and autumn, 3.8 in spring and 3.3 in summer. Cluster 2 has medians around 3.2, 2.9, 2.7 and 3.1 respectively. Cluster 3 is around 3.2 in winter, 3.3 in spring, 2.9 in summer and 3.0 in autumn, with substantial autumn dispersion. Summer has the lowest median PAR in all three groups. The seasonal boxplots reinforce the distinction between peak timing and peak concentration. A recognisable morning peak does not produce PAR as high as the evening group's. These are descriptive differences; the charts do not provide significance tests or uncertainty estimates for comparisons between clusters.

Annual consumption and household variation

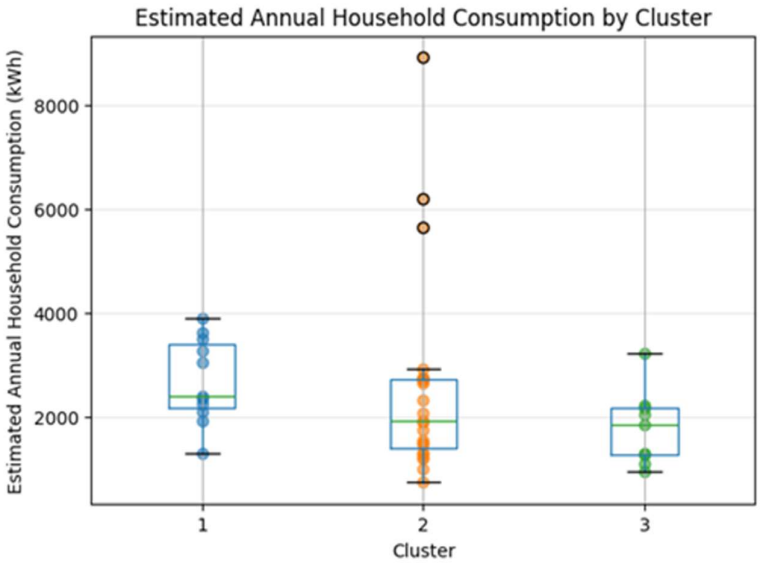


Figure 32: Original estimated annual household consumption by cluster. Each point represents a household. Values are in kWh; annual totals were extrapolated for incomplete coverage.

Cluster 1 has the highest approximate median annual consumption, around 2400 kWh. Its central box spans roughly 2200–3400 kWh, and the plotted observations extend from about 1300 to 3900 kWh. This combines a relatively high typical annual volume with the strong evening concentration observed in the load profiles. Cluster 2 has a lower median, around 1900 kWh, but the widest overall spread. The central box is approximately 1400–2800 kWh. Three high observations are visible near 5600, 6200 and 8900 kWh. These households demonstrate why a balanced average load shape should not be treated as a proxy for low electricity use. Cluster 3 has a median around 1800 kWh and a central box spanning approximately 1300–2200 kWh. Most observations are below those of the evening group, with one higher observation around 3200 kWh. Its relatively low annual consumption is consistent with its lower daily averages in Figure 29.

Estimation and contextual characteristics

Annual consumption was estimated by multiplying consumption on complete days by 365 divided by the number of complete days. This assumes that observed days represent missing days; uneven seasonal coverage can affect the estimate. Exact observation dates and coverage should accompany any subsequent numerical analysis. Social-tariff status was assigned if a household received the tariff at any point during the period. The accompanying analysis reported no clear differentiation across clusters, so this characteristic contributed little to their description. No corresponding statistical test or original tariff chart was supplied.

PV production and grid injection

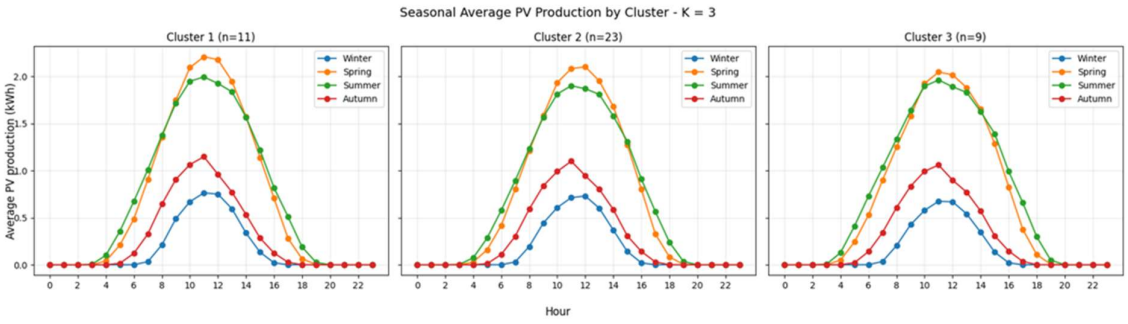


Figure 33: Original seasonal average PV production by cluster. The vertical axis shows average energy per hourly interval in kWh.

PV production is broadly similar across clusters: a midday maximum, much lower winter generation, and higher spring and summer generation. Spring peaks are approximately 2.1–2.2 kWh per hourly interval, summer peaks about 1.9–2.0 kWh, autumn peaks around 1.0–1.1 kWh and winter peaks around 0.7 kWh. These values describe the observed sample and period, rather than a general seasonal yield rule.

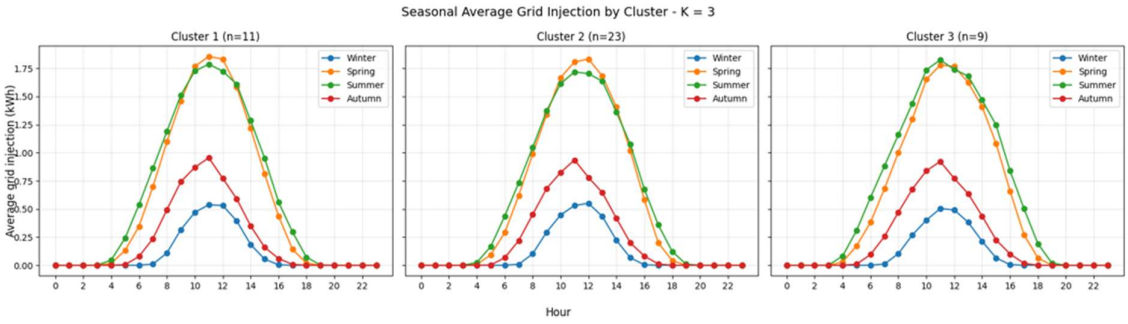


Figure 34: Original seasonal average grid injection by cluster. Export follows the daytime production window, with broadly similar profiles across clusters.

Spring peaks are approximately 2.1–2.2 kWh per hourly interval, summer peaks about 1.9–2.0 kWh, autumn peaks around 1.0–1.1 kWh and winter peaks around 0.7 kWh. These values describe the observed sample and period, rather than a general seasonal yield rule. Spring and summer injection peaks are around 1.7–1.9 kWh per hourly interval, compared with roughly 0.9–1.0 kWh in autumn and 0.5–0.6 kWh in winter. Summer exports continue later into the afternoon than spring exports. The large midday export relative to production indicates that much of the generated electricity is not retained on site at those hours.

Relationship to the evening load profile

PV production and injection have already declined sharply by 18:00 and approach zero around 19:00. This does not support PV generation alone as an explanation for the decline in household consumption shares around 18:00–20:00. Moreover, the household profiles incorporate PV use through the reconstruction formula. Seasonal routines, normalisation and any storage operation remain relevant to interpreting the evening pattern. Injection identifies candidate periods of solar surplus for a charging assessment. It does not

establish that a vehicle is present or that network capacity is available. A proposed comparison with Fluvius Open Data would also require compatible PV characteristics, metering definitions and seasons.

PV self-consumption and integrated findings

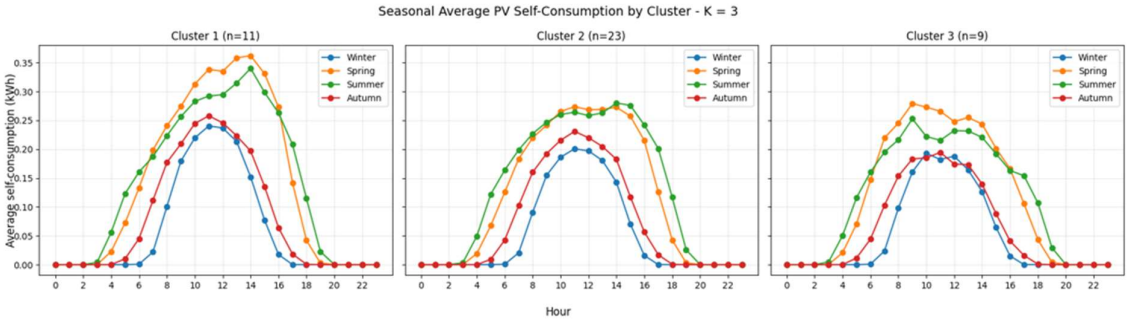


Figure 35: Original seasonal average PV self-consumption by cluster, calculated as PV production minus grid injection. The plotted quantity is energy in kWh, not a self-consumption percentage.

Cluster 1 has the highest visible midday self-consumption, reaching roughly 0.36 kWh per hourly interval in spring and 0.34 kWh in summer. Cluster 2 has a broader daytime plateau around 0.25–0.28 kWh in those seasons. Cluster 3 has an earlier spring maximum near 0.28 kWh and lower summer values, mostly around 0.21–0.25 kWh during the central daytime period. The profiles therefore reveal differences in on-site PV use despite broadly similar generation patterns. Winter and autumn self-consumption are lower and occur over shorter windows. Summer extends later into the afternoon across all clusters. The absolute differences are consistent with differing household demand patterns, but self-consumption rates or annual solar shares cannot be calculated from the displayed peaks. Storage, if present, would also need to be distinguished from immediate household use.Overall, The Klimaan analysis identifies three distinct household electricity-use patterns. Evening-oriented households have the highest typical peak concentration, annual consumption median and midday PV self-consumption peaks. The balanced group is the largest and most diverse in annual consumption, while morning-oriented households have the lowest seasonal daily averages. Across all three groups, peak concentration is lower in summer, and substantial daytime PV exports indicate opportunities to investigate charging with locally generated electricity. These findings provide a basis for tailoring EV charging strategies to household demand patterns and seasonal solar availability, with the potential to reduce charging costs and increase PV use. Realising these benefits depends on whether vehicles are available during suitable charging windows and whether charging can meet mobility needs within local network limits. The study therefore identifies promising conditions for further assessment, rather than demonstrating demand flexibility or shared-fleet feasibility.

5 Task 2.4 – Efficient Incorporation of Sector-Integrated End-Users

5.1 Modelling Track A – Revenue Stacking for End-Users Participating in Local & System-Level Flexibility Markets

5.1.1 Scope and objectives

The main goal of Task 2.4 is to quantify whether cross-sector integrated end-user models (Task 2.3) can increase the provision of flexibility (implicit or explicit) services to the grid, thus supporting balancing and operation (Task 2.2), and security of supply (Task 2.1).

This modelling track A focuses on the development of a customer-centred investment model to determine whether the provision of demand-side flexibility by cross-sector end-users can improve the business case in investing in cross-sectoral technologies, by stacking revenues arising from implicit flexibility remuneration and local arbitrage on prices.

The focus being on end-users, the general scope of the modelled energy system is the local generation and management of energy to supply demands of energy in one or several forms, given an objective (generally the least cost over the system's lifetime). This investment model is therefore multi-energy as it involves multiple energy vectors, which are fully coupled by means of converting technologies, allowing to switch from one energy vector to another. Local imports or exports of energy through transmission or distribution network infrastructures as well as storage technologies are also involved to manage the different streams of energy in a fully integrated way by a centralised energy management system.

On top of that, additional revenue streams can be generated through flexibility mechanisms. In this case, the energy management system will adapt the global behaviour of the energy system in response to price signals (implicit flexibility, capacity tariff), while in modelling track B explicit patterns required by the grid operator (explicit flexibility services such as FCR) are studied.

Therefore, from a customer-centred perspective, this investment model helps quantify the impact of cross-sectoral integration on improving (or not) the business models, while empowering the delivery of flexibility services to the grid.

5.1.2 Accomplished work and general model outline

The framework presented in Figure 36 was developed for a decentralised, grid-connected end-user producing renewable power, and consuming energy (i.e., electricity, heat or hydrogen); conversion and storage technologies being added to allow the convenient switching and storage between energy carriers.

This modelling environment is optimising the selection and installed capacities of several competing conversion and storage technologies, such that energy demands are supplied while maximising the revenues

over the project lifetime. It can also simulate the best behaviour of each unit of a given multi-energy system such that the annual costs are minimised.

To do so, based on historical data for climate and on-site energy consumption, the energy production and demand profiles are simulated over one year with a 1-hour timestep (called "i", can be lower than 1 hour) and entered as input of the model, representing a perfect forecast scenario. Dynamic tariffs are similarly elaborated based on EPEX historical time-series. Then, technical and operational constraints of the involved conversion technologies are described as linear input–output relationships, considering their conversion efficiency and their maximum output capacity. Similarly, storage technologies such as are described using storage efficiency, maximum and minimum SoC, self-discharge, and charging and discharging rates.

In addition to that, the investment model comprises a dataset of unit costs for each technology: the unit capex, and the unit OPEX, divided into a fixed annual cost component and a variable cost component per kWh. Grid costs, energy prices and regional tariffication schemes are also included to accurately compute the energy bill of the end-user as a function of the on-site economics.

The implicit flexibility is modelled through the value of the commodity component of the electricity price: it can either be fixed over the year, following a Time-of-Use scheme (day/night, peak/off-peak, or other more specific ToU), or variable (dynamic tariff). The addition of a battery energy storage system (BESS) to perform daily energy arbitrage is also considered. Likewise, the model is allowed to increase the hydrogen storage capacity whenever seasonal energy storage is found to be economically beneficial.

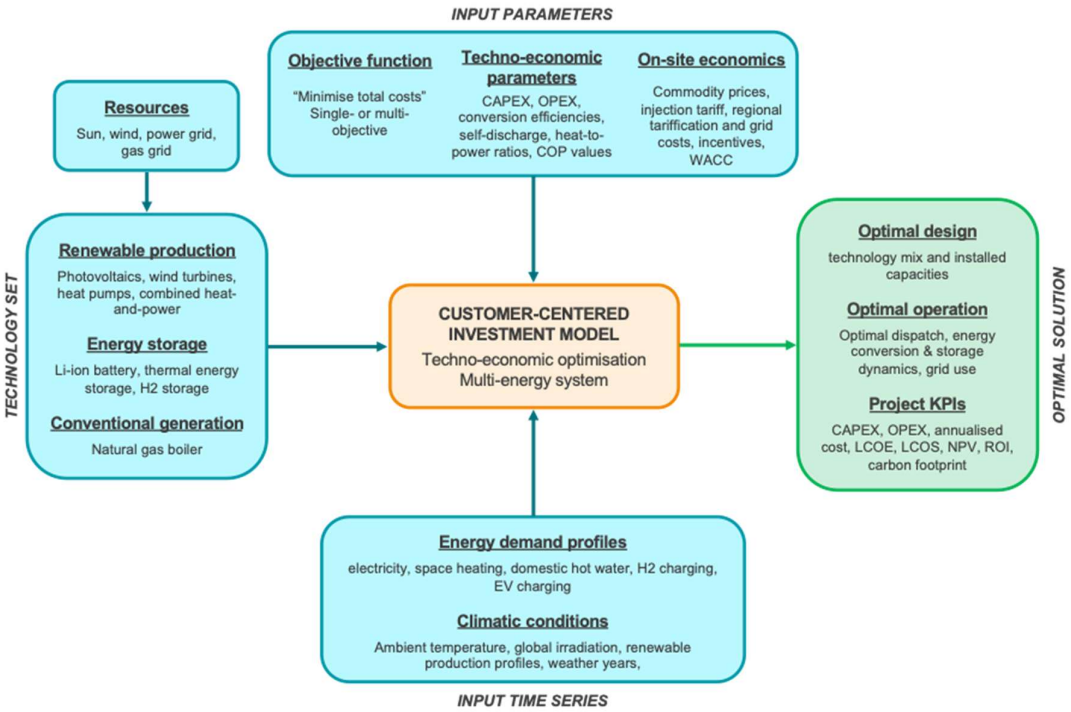


Figure 36: Schematic of the inputs and outputs of the optimisation model for Task 2.4 A

A stochastic formulation is implemented to explicitly account for the impact of interannual uncertainty on climatic conditions and dynamic prices. The optimisation therefore relies on the time series associated with several years. The stochastic design is expressed as:

$$x^{st} = \underset{x}{\operatorname{argmin}} \left\{ CAPEX(x) + \sum_{\omega \in \Omega} p_\omega \, Q(x, \omega) \right\}$$

Where x^{st} represents the design variables, $CAPEX(x)$ represents the annualised investment cost, and $OPEX(x, y_\omega, \omega)$, embedded in the recourse function $Q(x, \omega)$, represents the annual operating cost associated with the considered deterministic year. Each scenario ω represents one historical year and p_ω denotes its probability of occurrence. The recourse function is defined as follows:

$$Q(x, \omega) = \min_{y_\omega} OPEX(x, y_\omega, \omega)$$

Where y_ω represents the operation decisions associated with the scenario ω.

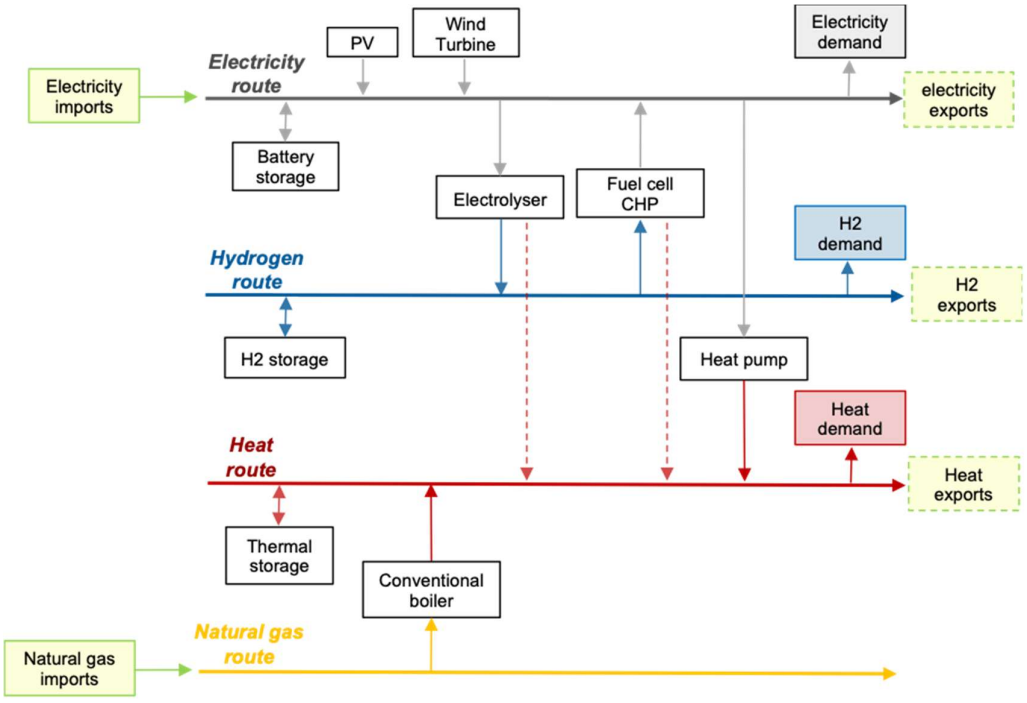


Figure 37: Interactions between energy vectors and technologies involved in the developed multi-energy system in its full form

Figure 37 illustrates how the different energy vectors of the system, in its full form, are coupled through conversion and storage technologies in order to supply respective energy demands, enabling flexibility to be transferred across electricity, hydrogen and heat. Technologies such as electrolysers, fuel cells, heat pumps and hybrid energy storage act as flexibility enablers by allowing energy production, conversion and consumption to be shifted across vectors and time in response to local system conditions and price signals.

5.1.3 Link with BUC(s)

This framework is adaptable to address BUC 6a (IDETA – ULB) on long-haul mobility, entitled “Wind to trucks: green hydrogen for heavy-duty vehicles”. The objective is to develop a techno-economic model to determine whether the whole value chain to run heavy duty vehicles on hydrogen produced from local green electricity can be considered a cost-efficient investment over time. A second BUC 6b is elaborated as a variant of the initial test case for a fully electric long-haul truck fleet as a low-carbon alternative. The final objective is to analyse and compare the most efficient option to provide road heavy-duty transport services from local green power.

The hydrogen consumption profile was also created based on the needs of the truck operator. If activated, the heat recovery part of the electrolyser model can evaluate the part of waste heat that can be valorised during the electrolysis process. Any surplus hydrogen production not consumed by the transport fleet operator can also, if activated, be valorised through other hydrogen-based applications via tube trailer supply (Figure 38).

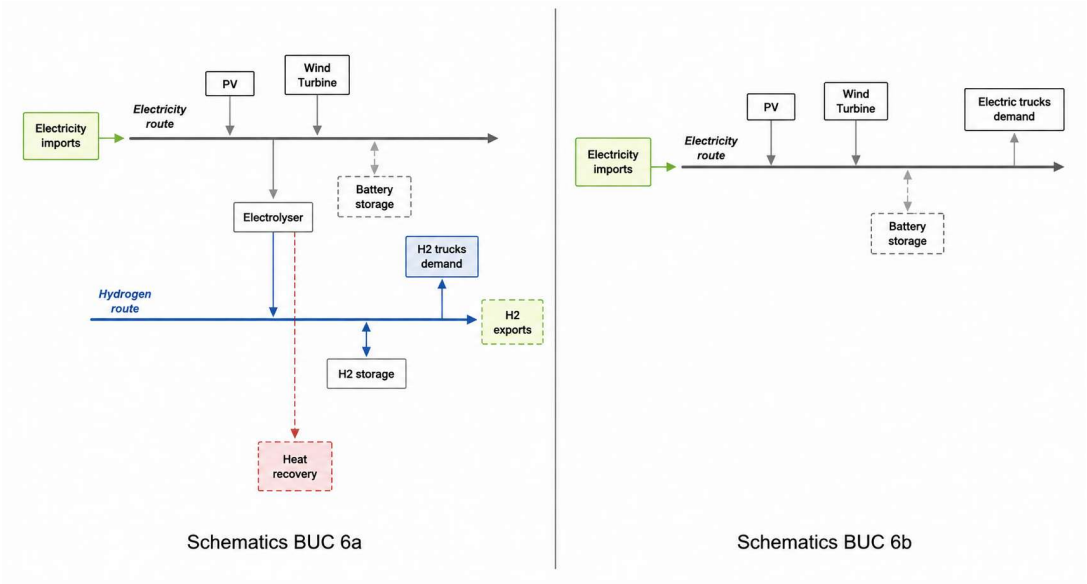


Figure 38: Interactions between vectors and technologies involved in BUC 6a (left) and BUC 6b (right)

Data requirement is an important part of elaborating the case study, and a data-sharing agreement with the BUC owner allowed us to build most of the case study’s input dataset.

This adapted investment model is able to compute the following KPIs:

- Optimal capacity of PV panels, electrolyser, BESS and H_2 storage units
- Share of electricity sources in H_2 production
- Grid injection volume, self-consumed volume, volume imported from grid
- Compressed H_2 net production cost (depending on on-site energy prices)

Total CAPEX and annual OPEX of assets

Economic performance indicators such as LCOE, ROI, NPV (depending on on-site economics)

The model is also capable of assessing the impact of investing in a BESS for daily energy arbitrage, as well as expanding the hydrogen storage capacity to enable seasonal energy storage.

Finally, different truck refuelling patterns can be investigated, allowing the impact of various operational strategies, such as uniform refuelling throughout the day or clustered refuelling during predefined time windows, on the optimal system design and operation to be quantified.

5.1.4 Key findings and results

This illustrative case study investigates the optimal design and operation of a decentralised hydrogen production system supplying a hydrogen refuelling station under different flexibility options and hydrogen demand profiles. In contrast to BUC 6a, technology capacities are optimised, allowing the model to identify the most cost-effective combination of PV, electrolyser, hydrogen storage and battery capacity.

Table 10: Comparison of optimal system sizing for incremental scenarios unlocking implicit flexibility

Scenario	Sizing PV [MWc]		Sizing Electrolyser [MW]		Sizing H_2 storage [kg]		Sizing Battery [MWh]	
	Capacity tariff	No capacity tariff	Capacity tariff	No capacity tariff	Capacity tariff	No capacity tariff	Capacity tariff	No capacity tariff
(1) No dynamic prices – No battery – Uniform	2.38	2.30	1.21	1.19	385.84	341.94	-	-
(2) No dynamic prices – Battery – Uniform	2.38	2.30	1.21	1.19	385.84	341.94	0.00	0.00
(3) Dynamic prices – No battery – Uniform	2.07	1.93	1.34	1.38	549.07	535.99	-	-
(4) Dynamic prices – Battery – Uniform	2.07	1.93	1.34	1.38	549.07	535.99	0.00	0.00
(5) Dynamic prices – Battery – BATCH	2.10	1.94	1.36	1.41	680.38	652.75	0.00	0.00
(6) Dynamic prices – No battery – BATCH	2.10	1.94	1.36	1.41	680.38	652.75	-	-

The incremental scenarios (Table 10) show that dynamic electricity prices provide the main economic benefit, reducing the $LCOH_2$ from 9.00 to 8.73 €/kg H_2 with the capacity tariff, and from 8.56 to 8.06 €/kg H_2 without it. Interestingly, although battery investment is allowed, no BESS is selected in the optimal design: operational flexibility of the PEM electrolyser combined with hydrogen storage is sufficient to exploit electricity-price variations. Dynamic pricing consequently leads to slightly larger electrolyser and hydrogen storage capacities, while reducing the PV capacity. Also, relying on local renewable energy production seems highly beneficial to limit grid dependence and the associated, penalising capacity tariff.

Table 11: Expected CAPEX, $LCOH_2$, grid-electricity share and peak grid power for incremental scenarios unlocking implicit flexibility

Scenario	Total CAPEX [M€]		$LCOH_2$ [€/kg H_2]		Share grid electricity [%]		Annual peak power from grid [MW]	
	Capacity tariff	No capacity tariff	Capacity tariff	No capacity tariff	Capacity tariff	No capacity tariff	Capacity tariff	No capacity tariff
(1) No dynamic prices – No battery – Uniform	2.89	2.77	9.00	8.56	18.76	20.29	0.58	1.19
(2) No dynamic prices – Battery – Uniform	2.89	2.77	9.00	8.56	18.76	20.29	0.58	1.19
(3) Dynamic prices – No battery – Uniform	2.92	2.84	8.73	8.06	19.73	22.29	0.61	1.38
(4) Dynamic prices – Battery – Uniform	2.92	2.84	8.73	8.06	19.73	22.29	0.61	1.38
(5) Dynamic prices – Battery – BATCH	3.07	2.98	8.89	8.21	19.45	22.35	0.62	1.41
(6) Dynamic prices – No battery – BATCH	3.07	2.98	8.89	8.21	19.45	22.35	0.62	1.41

Analysing Table 11, the capacity tariff clearly provides an additional incentive to limit peak grid withdrawals, approximately halving annual peak power compared with the corresponding cases without the tariff, although at the expense of slightly higher CAPEX and $LCOH_2$. Overall, these results show that implicit flexibility signals affect not only system operation but also its optimal investment structure.

It is interesting to note that, comparing scenarios (4) and (5), the refuelling pattern does not significantly impact the expected costs (and sizing) of the system, with an observed $LCOH_2$ increase of only 0.12 €/kg H_2. Note that the expected optimal share of grid electricity in the H_2 production mix hardly goes lower than 20%, possibly meaning that only optimising around an economic objective may not lead to the production of H_2 defined as "clean" or renewable; therefore decreasing the financial benefits associated with CO_2 removal objectives.

Additional constraints might therefore be required, and a sensitivity analysis is performed in Table 12 to illustrate the impact on system's design and economics for scenario (4). It is observed that constraining the maximum allowed grid share from 20% to 5% quickly increases PV capacity to its maximum allowed 2.5 MWp capacity; then electrolyser and storage requirements increase substantially, with hydrogen storage rising from 372 to almost 5000 kg and total CAPEX from 3.47 to 13.57 M€.

In this case, investing in battery storage appears to be an optimal solution to maximise self-consumption, although it does not seem a priority compared to increasing the capacity of the other system components. Consequently, the $LCOH_2$ almost doubles from 8.82 to 17.75 €/kg H_2, illustrating the economic trade-off between grid dependence and local self-sufficiency and cleaner hydrogen production.

Table 12: Sensitivity of optimal system sizing and economic KPIs to the maximum grid electricity share

Uniform H_2 demand · No H_2 exports							
Maximum grid share [%]	**PV sizing [MWc]**	**Electrolyser sizing [MW]**	**H_2 storage sizing [kg]**	**Battery sizing [MWh]**	**Total CAPEX [M€]**	**Electricity bill [k€/year]**	**$LCOH_2$ [€/kg H_2]**
20.00	2.07	1.34	549.07	0.00	2.92	424.77	8.27
15.00	2.50	1.57	571.91	0.04	4.06	373.47	9.02
10.00	2.50	1.97	1286.22	0.11	5.84	308.64	10.36
5.00	2.50	2.08	4963.87	0.71	13.57	233.98	17.75

Returning to the impact of price signals on promoting more grid-friendly system behaviour, Figure 39 illustrates the resulting operational response for scenarios (1) and (4), respectively. Scenario (1) represents the reference case without implicit flexibility signals, whereas scenario (4) fully unlocks implicit flexibility. The figures highlight the interactions between hydrogen production, renewable generation and electricity market signals for 4 typical days of the year, one per season. The electrolyser consumption, shown in blue, indicates when hydrogen is actively produced. The photovoltaic production, shown in green, captures the local renewable generation profile available to the system. The orange markers indicate the refuelling events, while the grey dashed curve represents the dynamic electricity price.

The comparison further illustrates how implicit flexibility modifies electrolyser operation in a grid-friendly way. When dynamic electricity prices and the capacity tariff are introduced, hydrogen production is increasingly shifted towards periods associated with favourable price signals, which frequently coincide with periods of abundant renewable generation. Conversely, it avoids consuming grid electricity in periods of scarcity. The resulting dispatch is therefore not only more economically responsive, but also more grid-friendly, as the electrolyser adapts its consumption to broader system conditions rather than following a purely demand-driven operating pattern.



Figure 39: Comparison of electrolyser operation without implicit flexibility signals (Scenario 1, left) and with fully unlocked implicit flexibility (Scenario 4, right) across representative seasonal days

Finally, Table 13 presents the interannual variability of the electricity-bill components obtained across the different historical years considered in the stochastic formulation and computes the associated expected value.

Table 13: Breakdown of annual electricity-bill components per year for the optimal system design

Uniform demand · No H_2 exports								
Year uniform demand	**Grid electricity [k€]**	**Prop. grid costs [k€]**	**Capacity tariff [k€]**	**PV electricity [k€]**	**Wind electricity [k€]**	**GOO [k€]**	**H_2 export revenues [k€]**	**Total [k€]**
2023	163.54	28.21	44.77	153.35	206.19	10.27	-0.00	452.97
2024	126.43	39.78	42.76	71.10	154.21	10.17	-0.00	373.35
2025	179.98	44.86	46.73	78.65	167.03	9.39	-0.00	447.99
Expected value	**156.65**	**37.62**	**44.75**	**101.03**	**175.81**	**9.94**	**0.00**	**424.77**

These results confirm the relevance of the stochastic formulation for investment planning. Although a single optimal system design is selected across the considered years, its annual operating performance remains strongly dependent on the joint evolution of renewable availability and electricity-market conditions. To confirm this, the presented electricity-bill breakdown varies from k€373.35 in 2024 to k€452.97 in 2023, with substantial variations in grid purchases and locally sourced PV and wind electricity. Since climatic conditions, renewable production and dynamic electricity prices are intrinsically interrelated, evaluating the investment from a single historical year (deterministic optimisation) could significantly bias annual cash flows and derived indicators such as the $LCOH_2$. Considering several consistent yearly time series within a stochastic formulation therefore provides a more robust representation of the expected techno-economic performance under interannual uncertainty.

5.2 Modelling Track B – Operation of an electrolyser system participating in the Belgian aFRR down flexibility market

5.2.1 Scope and objectives

Modelling track B's main objective is to address Task 2.4's aim to investigate end-users' integration within flexibility procurement mechanisms (focusing on electrolysis). Thus, the following sections present an **optimisation** model developed for strategic operation of an electrolyser system participating in the Belgian aFRR down flexibility market while maintaining RFNBO compliance for green hydrogen production.

5.2.2 Accomplished work and general model outline

The model is a non-convex Mixed-Integer Quadratic Program (MIQP), implemented in Python using the Pyomo modelling framework and solved with a commercial MILP/MIQP solver (Gurobi, with SCIP available as an open-source fallback). It optimises the hourly operation of an electrolyser that simultaneously produces green or grey hydrogen, sells excess renewable electricity on the day-ahead market, and offers aFRR down-regulation capacity to the Belgian TSO (Elia), all while maintaining compliance with the RFNBO (Renewable Fuels of Non-Biological Origin) regulation.

The optimisation horizon can span one or more calendar months. Because no state variable crosses a month's boundary, the problem decomposes naturally month by month: one MIQP is built and solved per calendar month, and results are concatenated to form the full time series. The model outputs a CSV file with

one row per hour covering all decision variable values, revenue and cost components, RFNBO certification details, and hydrogen routing.

Use case setup

The modelling setup considers the Virya electrolyser facility in Zeebrugge. The electrolyser can source electricity from two channels: a Power Purchase Agreement (PPA) tied to an offshore wind asset, providing low-cost renewable power at variable output, and the day-ahead market (grid electricity at a price that includes a fixed network tariff). Hydrogen can be delivered via two routes: tube trailers (TT) serving industrial customers, and direct injection into the gas grid (GG). The electrolyser can additionally offer aFRR down-regulation capacity to Elia, earning capacity and activation revenues.

Model formulation

The model maximises total profit over the simulation horizon, defined as hydrogen revenues from both delivery routes (with a green price premium for RFNBO-certified production), revenues from selling surplus PPA electricity on the day-ahead market, and aFRR activation revenues, net of grid electricity costs. The key structural elements of the formulation are described below (Figure 40).

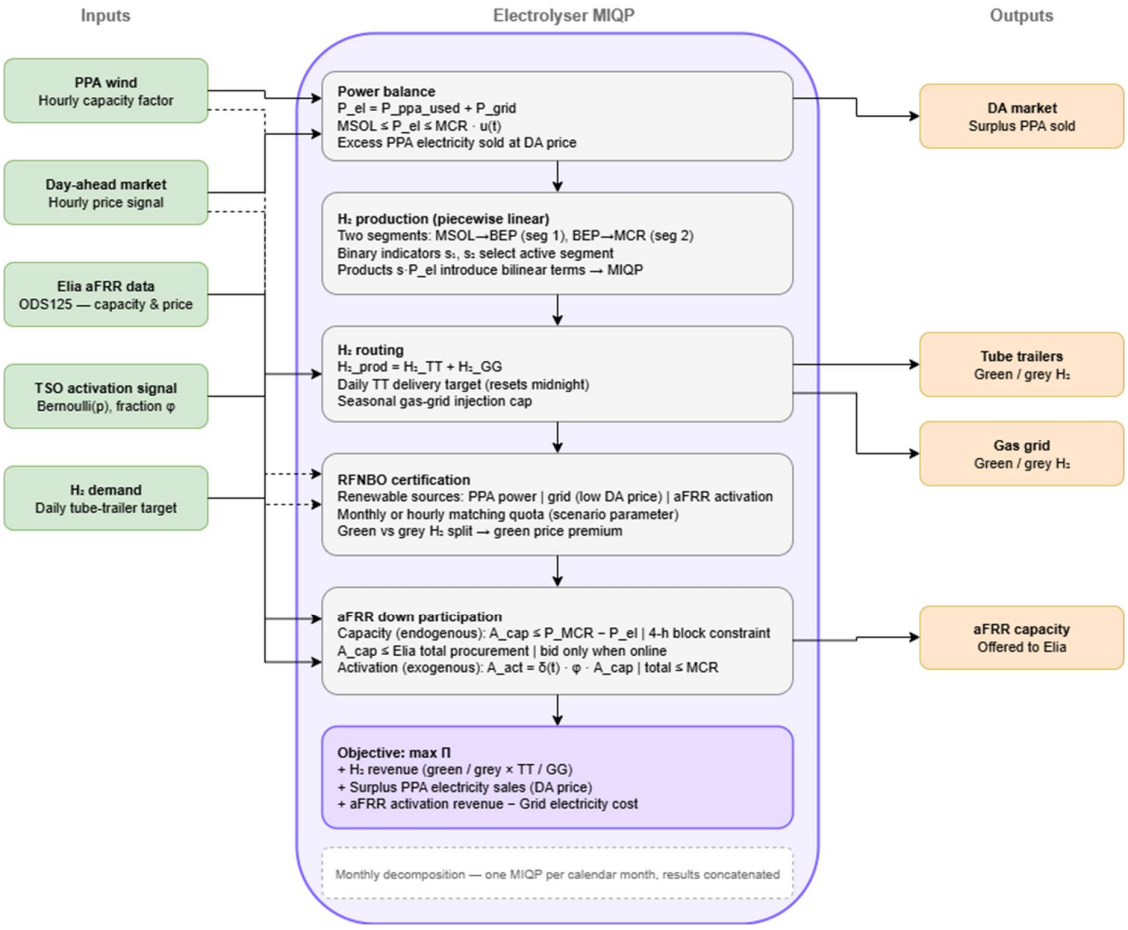


Figure 40: Model formulation of the electrolyser MIQP optimisation

Piecewise linear H_2 production

The piecewise linear hydrogen production approach uses data points from actual electrolyser performance curves to create accurate production relationships between power input and hydrogen output. The model divides the operating range into two distinct segments. Segment one spans the MSOL (Minimum Stable Operation Load) to the BEP (Best Efficiency Point) and captures the lower efficiency region. Segment two covers the BEP to MCR (Maximum Continuous Rating) and reflects the high efficiency plateau. The model selects the appropriate segment through binary variables that activate based on the instantaneous power consumption level, ensuring accurate hydrogen production calculations across the entire operating range.

Tube trailer filling

The dynamic routing and arrival times of the tube trailers are not considered. Instead, a constant hydrogen daily demand is set. The model keeps track of the TT demand fulfilment throughout each 24-hour period. Once the daily TT demand is met, the spillover is injected in the GG. Since delivery in TT gets compensated at a higher H_2 price, the model ensures that the higher-value tube trailer market is always served first while maintaining operational flexibility to utilise the gas grid as an outlet when contractual obligations are satisfied or when production exceeds TT capacity (either during normal operation times or during aFRR down activation periods).

aFRR down market representation

The aFRR market is modelled in two parts. The capacity dimension is endogenously optimised: the model decides how much down-regulation headroom to offer to Elia in each hour, subject to the physical headroom between the current operating point and MCR, the total aFRR down capacity procured by Elia (which was obtained from Elia's Open Data platform[16]), and a 4-hour block constraint reflecting the actual Belgian market rule under which bids must be constant within each procurement slot. The electrolyser can only bid when it is online and above MSOL.

The activation dimension is exogenous: it is not a decision variable but an input signal imposed by the TSO. Activation timing is drawn from a Bernoulli process with a configurable probability parameter, and activation magnitude is set as a fixed fraction of the offered capacity. When activated, the electrolyser ramps up consumption toward MCR, producing additional hydrogen that is routed according to the delivery logic described above. Total power during activation is capped at MCR. The two-part revenue structure, capacity payments per MW for availability, and activation payments per MWh for actual delivery, reflects the real Belgian aFRR payment mechanism, though the capacity revenue term can be toggled independently in the scenario configuration.

[16] https://opendata.elia.be/explore/dataset/ods125/information/

Main data inputs

Table 14: Main data inputs for BUC 9

Parameter	Description	Units
P_{MSOL}, η_{MSOL}	Minimum stable operating point (power and efficiency)	(MW, %)
P_{BEP}, η_{BEP}	Best efficiency point (power and efficiency)	(MW, %)
P_{MCR}, η_{MCR}	Maximum continuous rating (power and efficiency)	(MW, %)
$H_2(P)$	Hydrogen production rate as a function of power input	(Nm³/h)
$InjRateLimit_{GG}$	Maximum allowed H_2 injection rate into the gas grid (seasonal)	(Nm³/h)
$R_{aFRR,cap}\ (t)$	Revenue per MW from supplying aFRR down capacity	(€/MW/h)
$P_{aFRR,cap,awarded}(t)$	Total aFRR down capacity awarded by Elia across all market participants	(MW)
$\beta_{aFRR,cap}(t)$	Binary flag indicating whether Elia has procured aFRR down capacity in a given hour	(–)
$R_{aFRR,act}(t)$	Revenue per MWh from aFRR down activation	(€/MWh)
p_{act}	Bernoulli probability governing the frequency of TSO activation	(–)
φ	Fraction of offered capacity activated by the TSO in each activated hour	(–)
$\pi_{DA}(t)$	Hourly day-ahead electricity price	(€/MWh)
$c_{network}$	Fixed network tariff add-on to the grid price	(€/MWh)
$CF_{wind}(t)$	Hourly wind capacity factor from the PPA asset	(–)
$E_{PPA,month}$	Monthly renewable energy quota derived from the annual H_2 target and average electrolyser efficiency	(MWh/month)
α_{RFNBO}	Minimum renewable electricity share required for H_2 to qualify as RFNBO-compliant	(%)
$D_{TT,day}$	Daily hydrogen delivery target to tube trailers	(kg/day)
π_{H_2} (green/grey × TT/GG)	Hydrogen selling prices by quality (green/grey) and delivery route (tube trailer/gas grid)	(€/kg)

5.2.3 Link with BUC(s)

Modelling track B was developed to directly address BUC 9.

5.2.4 Key findings and results

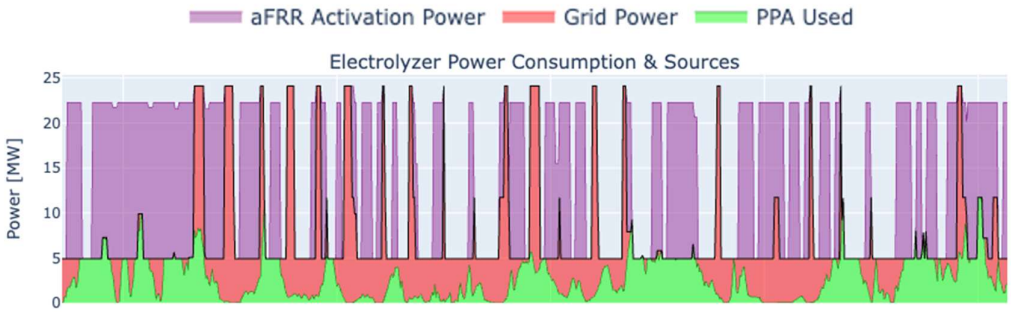


Figure 41: Results example of hourly operation across a representative aFRR-down activation episode. Purple shading shows aFRR activation power, green is PPA, red is day-ahead grid. Activation events appear as upward steps in absorbed power coinciding with downward TSO signals.

The model described above was applied to the Virya electrolyser use case in Zeebrugge as part of BUC 9, whose full setup, scenario definitions and detailed results are reported in Deliverable 3.4. The runs covered a full calendar year of hourly operation, decomposed month by month, and compared the electrolyser's baseline operation, sourcing from the offshore wind PPA and the day-ahead market and serving tube trailer and gas grid demand, against operation in which aFRR down-regulation capacity is additionally offered to Elia (Figure 41).

The main findings from this modelling are:

- Offering aFRR down capacity is profitable for the electrolyser: participation increases total profit relative to the baseline without eroding hydrogen delivery obligations, since down-regulation activation raises consumption and therefore hydrogen output rather than curtailing it.
- The 4-hour block constraint on aFRR bids, combined with the requirement to stay online and above MSOL, is the binding limitation on how much capacity can be offered, headroom to MCR is rarely the active constraint.
- RFNBO compliance is maintained across the horizon, with the monthly renewable quota from the PPA rather than instantaneous renewable availability determining the share of production that can be certified green.
- The value of participation is concentrated in hours of low day-ahead prices, where the opportunity cost of increasing consumption is smallest and the electrolyser can absorb activation at near-zero or negative energy cost.
- Hydrogen produced during activation is absorbed predominantly by the gas grid route, since the daily tube trailer target is typically met earlier in the day; gas grid injection rate limits therefore set the practical ceiling on activation volumes in some months.

6 Conclusion and Outlook

This deliverable presents the final evaluation of the REINVENT WP2 modelling environment. For each of the thirteen modelling tracks distributed across the four WP2 tasks, it documents the scope and objectives, the modelling approach, the data and assumptions used, and the results obtained. Together, the tracks form a coherent multi-scale, multi-horizon simulation environment linking electricity, thermal energy, hydrogen, and mobility, from the individual end-user and the energy community up to the European wholesale system, and from short-term dispatch to long-term investment planning. WP2 therefore delivers what it set out to build, an operational modelling environment on which the quantitative evaluation of the WP3 Business Use Cases and the impact assessment of WP4 can rely. The following tasks have been evaluated and reported in this deliverable:

- Task 2.1 – Integrated multi-energy system models (planning & system perspective)
- Task 2.2 – Multi-carrier wholesale markets (operation & markets)
- Task 2.3 – End-users & energy communities (local perspective)
- Task 2.4 – Efficient incorporation of sector-integrated end-users (user-centric investment & flexibility)

Beyond the track-specific findings summarised at the beginning of this document, the thirteen tracks converge on a consistent message. Sector coupling creates value at every scale, but that value is unlocked by design choices rather than by technology alone: by the (i) temporal and structural design of the markets in which coupled assets operate, (ii) tariffs and pricing mechanisms that govern local exchanges, (iii) regulatory conditions under which aggregated end-users can access flexibility markets, and (iv) foresight that investors actually exercise. On the other hand, flexibility that is technically available is not automatically mobilised, and the economically optimal operation is not necessarily the most grid-friendly or the least carbon-intensive one. Coordination, and the price signals which carry the flexibility product, is where most of the remaining benefit lies.

7 Related publications

Task 2.1, Modelling Track C (KUL)

[1] A. Hoogsteyn, Q. Raillard-Cazanove, K. Bruninx, and E. Delarue, “When hydrogen is not fully flexible: Implications for sector-coupled energy models,” SSRN preprint, 2026. [Online]. Available: https://ssrn.com/abstract=7177068

Task 2.1, Modelling Track D (KUL)

[2] A. Hoogsteyn, J. Meus, K. Bruninx, and E. Delarue, “Barriers to efficient carbon pricing: policy risk, myopic behaviour, and financial constraints,” Environ. Res.: Energy, vol. 3, no. 2, Art. no. 025018, May 2026, doi: 10.1088/2753-3751/ae6b8e.

Task 2.3, Modelling Track B (UMONS)

[3] J. Allard, N. Diffels, F. Vallée, B. Cornélusse, and Z. De Grève, “On the Complementarity of Shared Electric Mobility and Renewable Energy Communities,” preprint (to be submitted).

Task 2.3, Modelling Track C (UMONS, VITO)

[4] H. Hesamzadeh, W. Ananduta, E. Dumont, and Z. De Grève, “Incentive-Based and Welfare-Maximizing Regulatory Mechanism for Monopoly Utilities: An Application to District Heating and Cooling,” preprint.