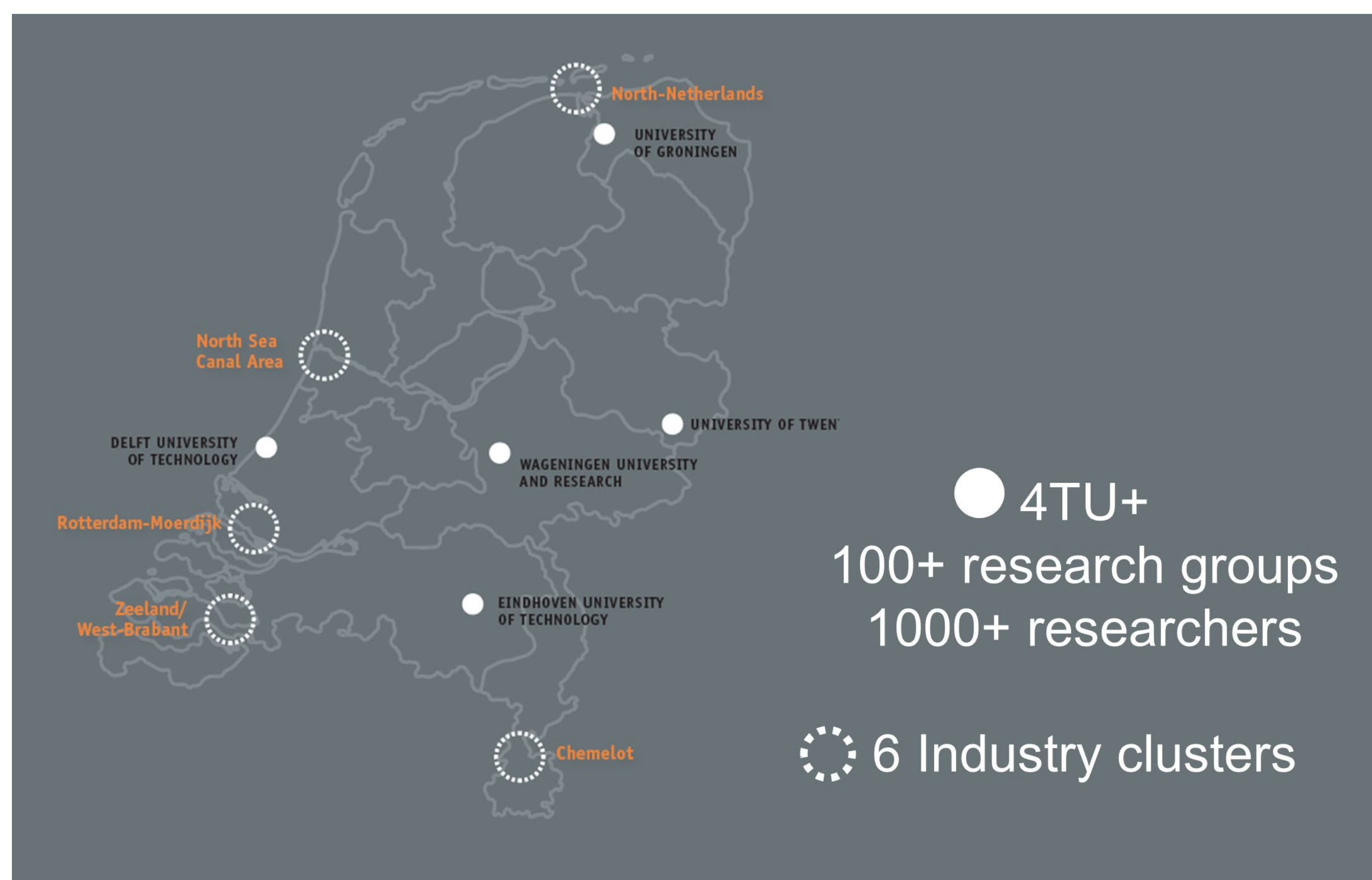


4TU. Energy

4TU.Energy is one of the Research networks under 4TU. Federation (joint effort of TUDelft, TU/e, Utwente, and WUR), with the mission to accelerate the energy transition through connecting, representing, and strengthening research and education. 4TU.Energy positions itself as a structural interface between research, industry, and public stakeholders.



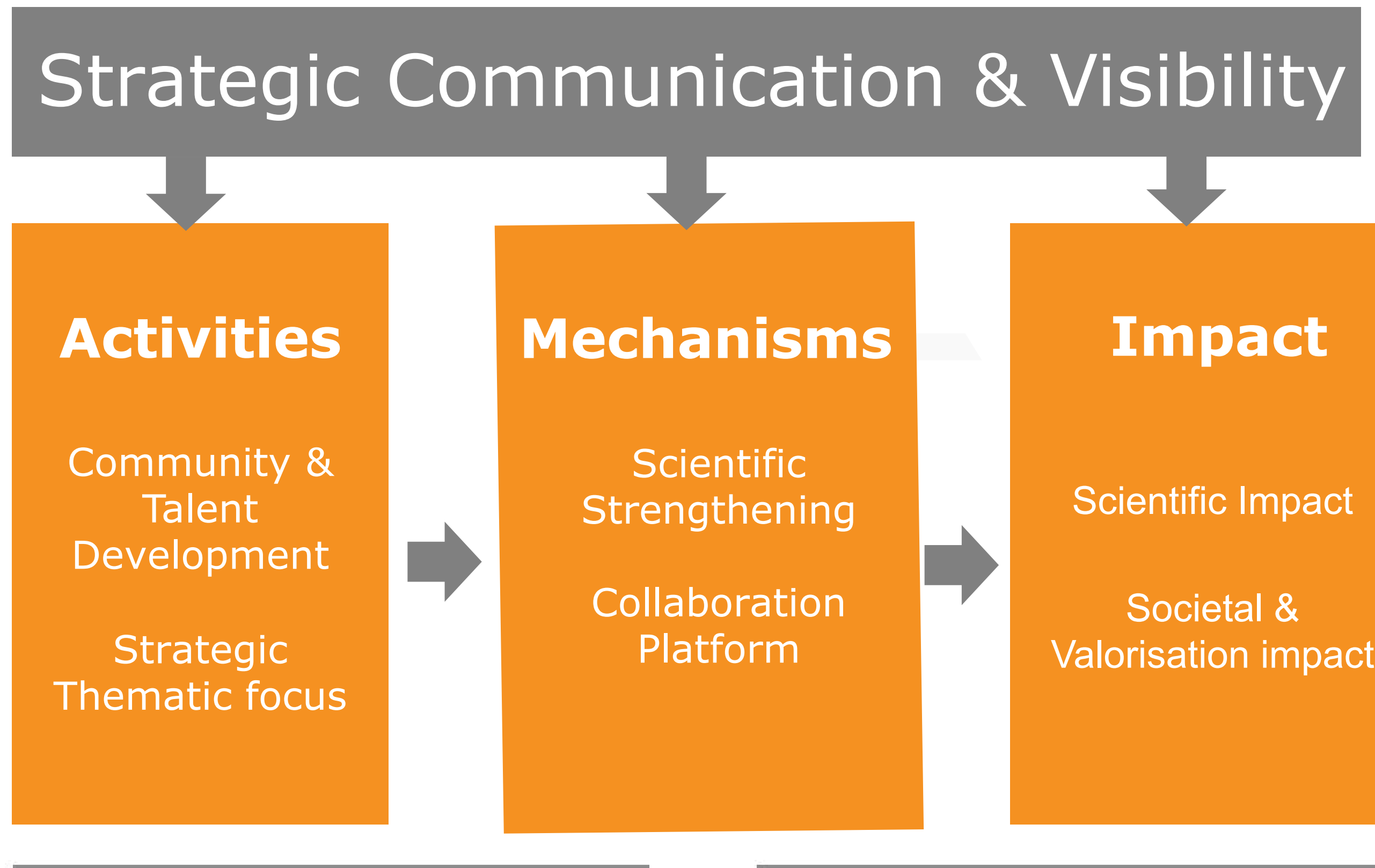
Accelerating the energy transition through connecting, representing, and strengthening research and education



4 Themes:

-  **From Ideas to Large-Scale Consortia**
-  **From Expertise to a Connected Energy Ecosystem**
-  **From Individual Researchers to a Visible, Vibrant Community**
-  **From Education to Coordinated Energy Talent Development**

- Facilitate cross-disciplinary research that integrates technical, digital, economic and societal perspectives.
- Enable the formation of competitive, large-scale national and EU consortia.
- Contribute to long-term research programming aligned with Dutch and European strategic priorities.
- Strengthen the visibility and coherence of the Dutch energy research landscape.



CityLearn: Occupant-Centric Grid Congestion Management



www.citylearn.net

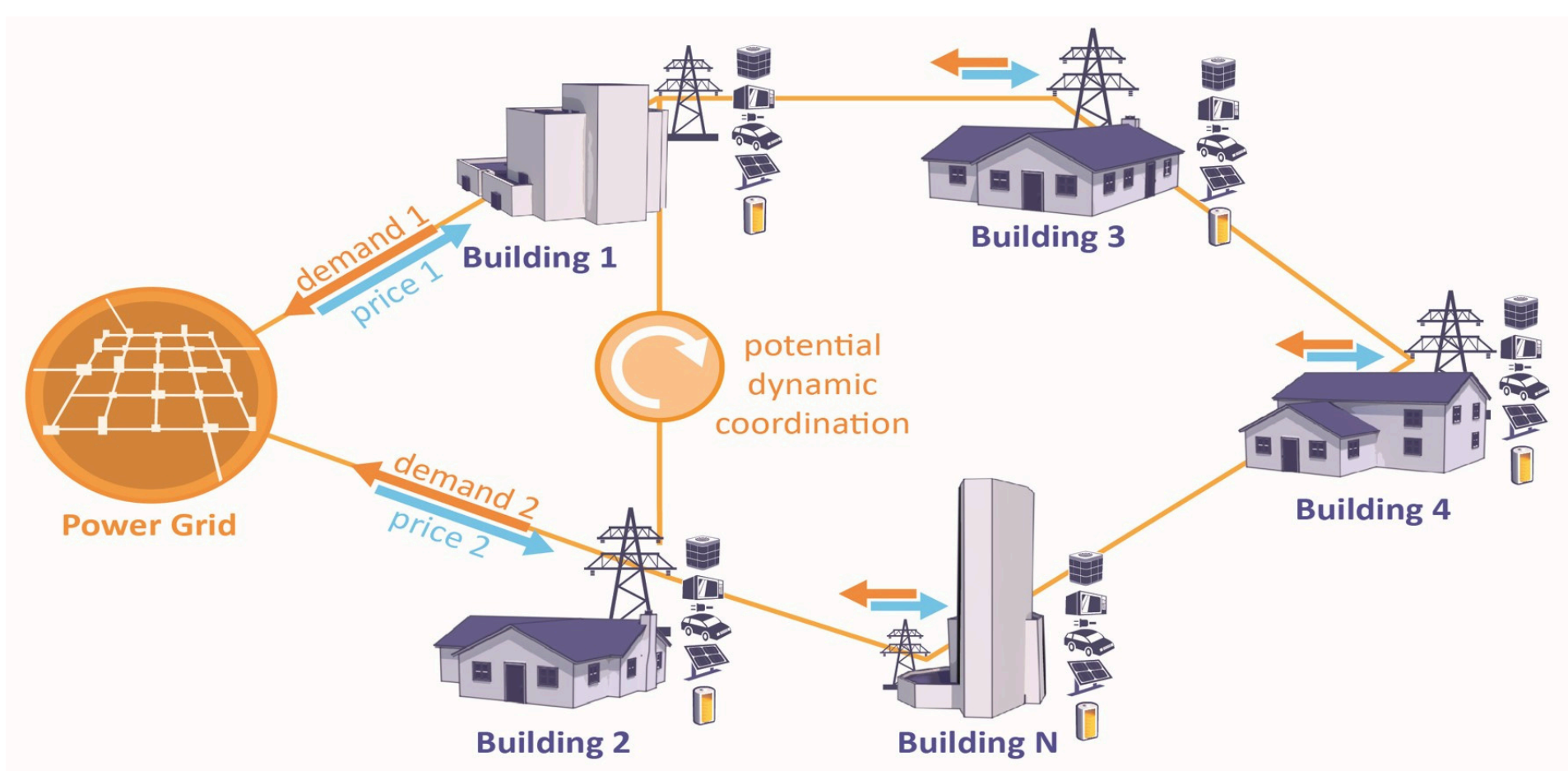


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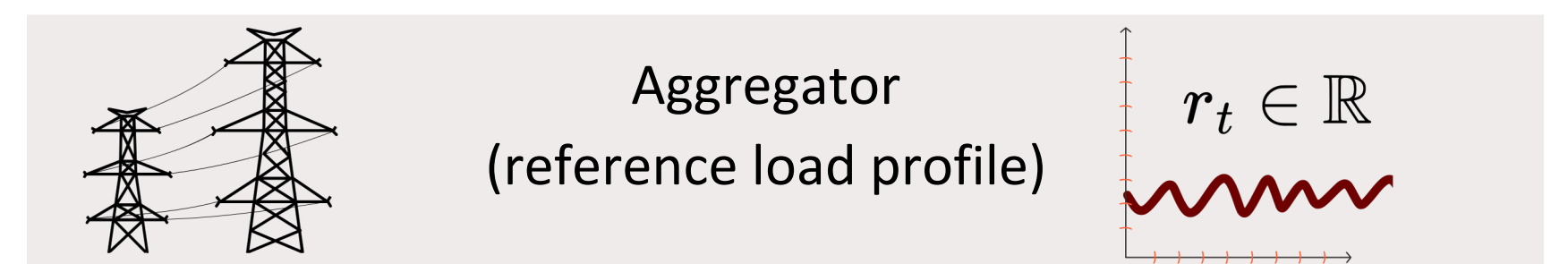
Ava Mohammadi, Zoltan Nagy

Chair of Building Services, Eindhoven University of Technology (TU/e)

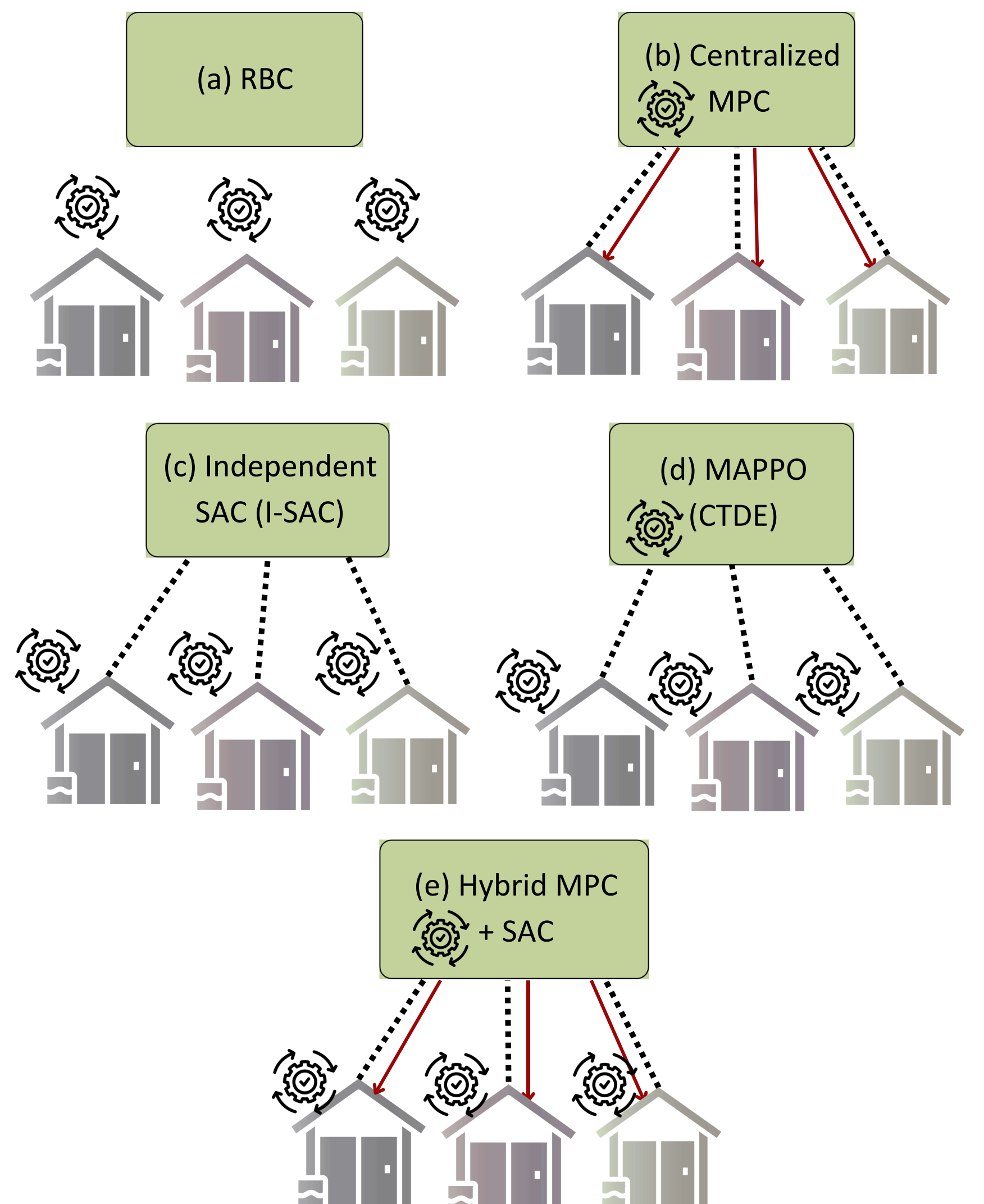
Email : a.mohammadi@tue.nl , z.nagy@tue.nl



Can Aggregated Buildings' Flexibility act as a virtual power plant?



Control Communication ———— Decision Making



Digital Public Goods Alliance



Buildings as Virtual Power Plants

Aggregating residential buildings to provide coordinated flexibility services to the grid.

Coordinating Heat Pumps, PV, and Battery Storage

Using distributed energy resources together instead of as isolated devices.

Grid-Interactive and Congestion-Aware Buildings

Enabling buildings to actively support future distribution grids and DSOs.

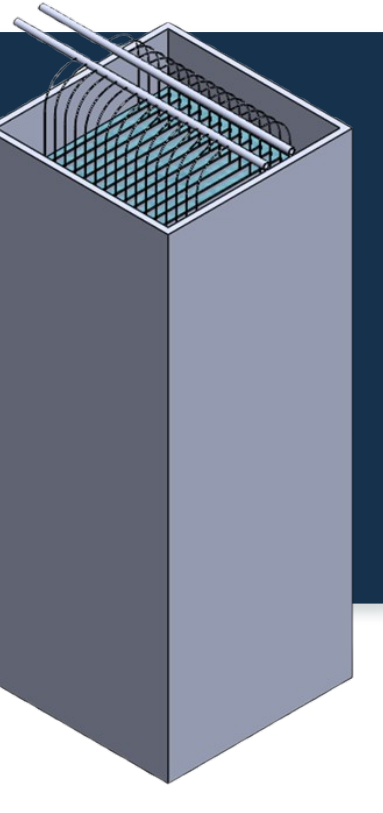
Occupant-Centric Energy Flexibility

Balancing grid objectives while maintaining indoor comfort and occupant preferences

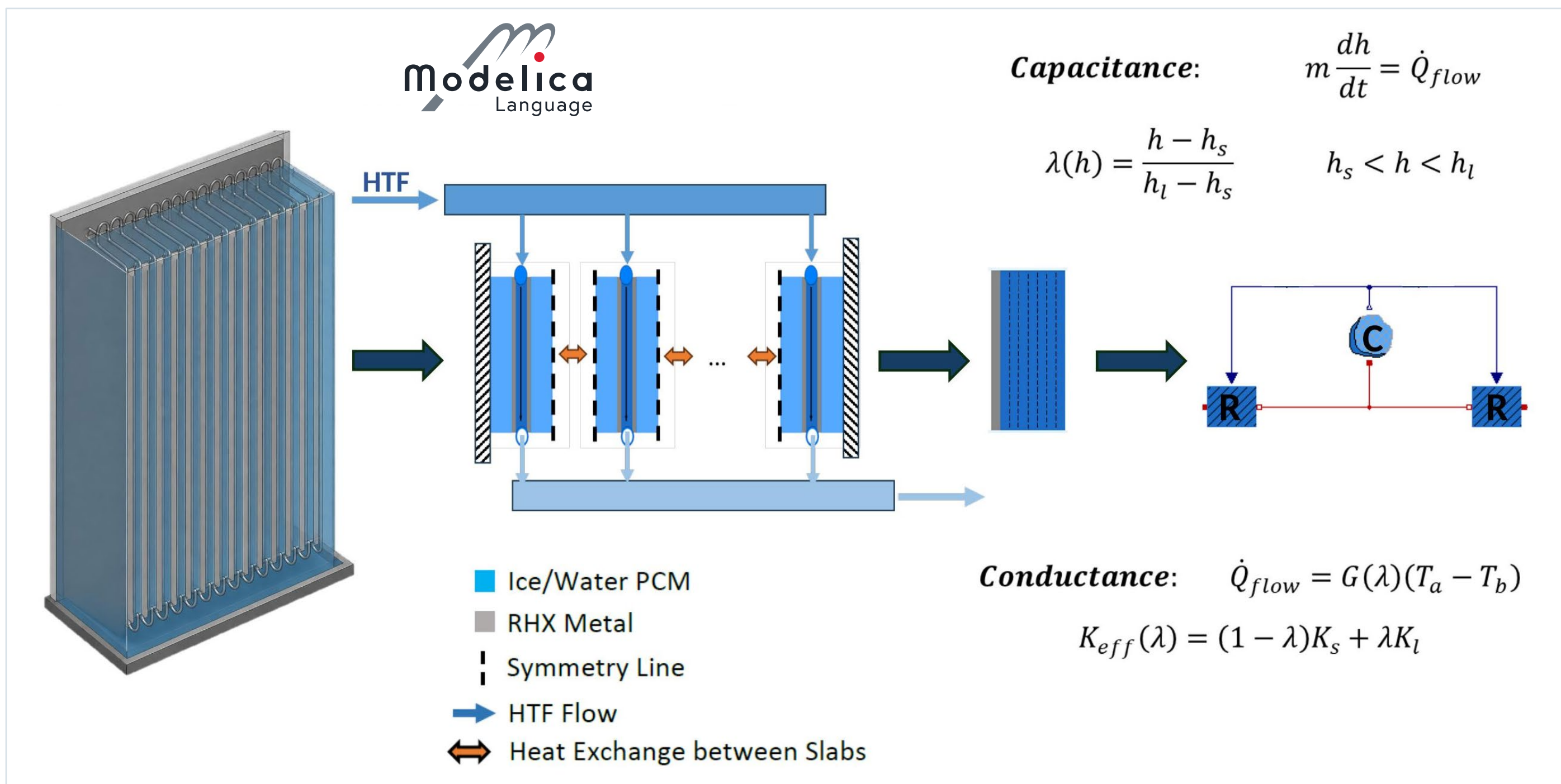
The idea:

An ice-based Latent Thermal Energy Storage (LTES) turns rigid cooling into a flexible, shiftable load.

Run the chiller on cheap, clean or off-peak power; deliver cold when needed. Our validated model quantifies the flexibility.

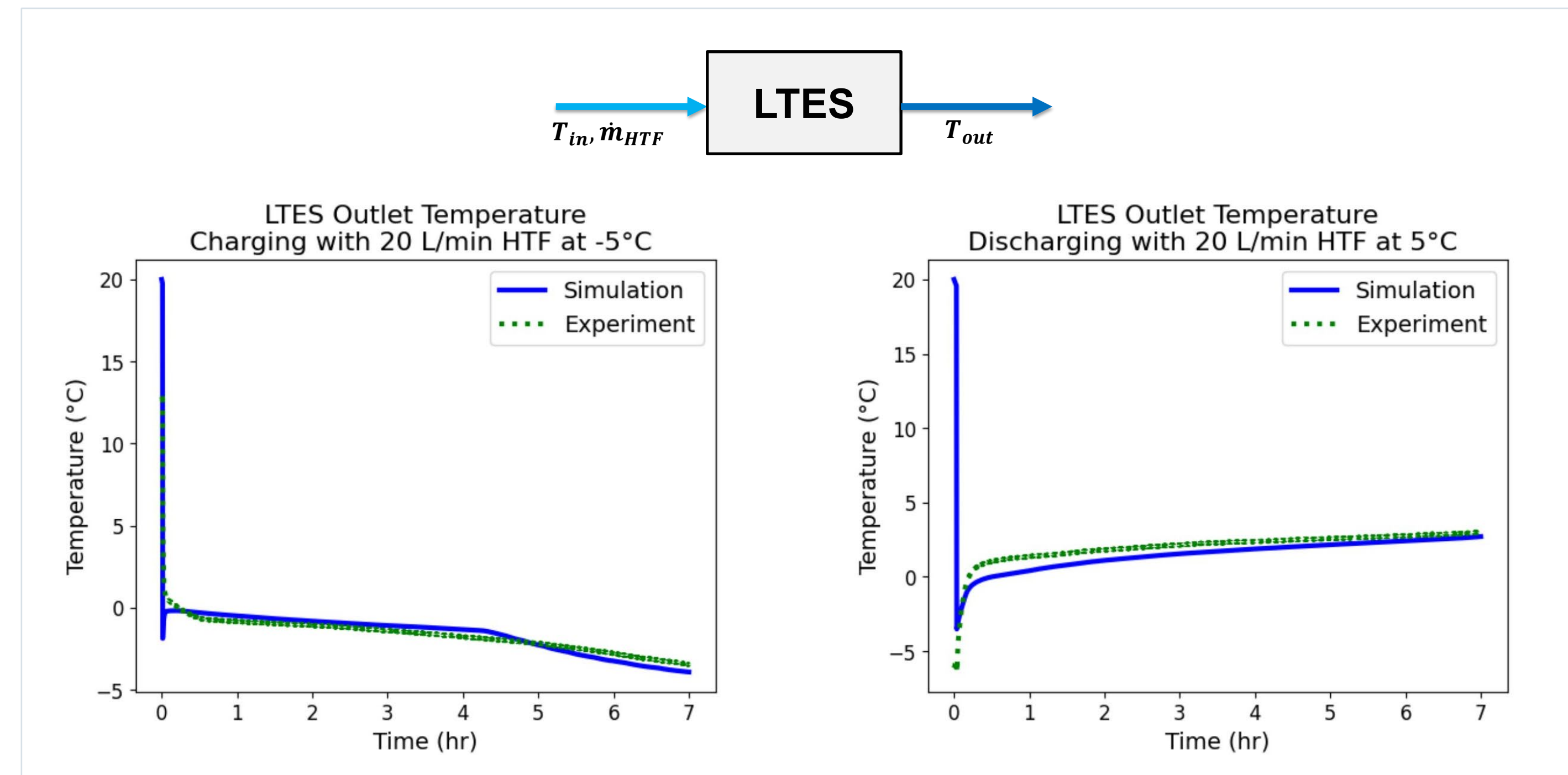


1 Numerical model of the LTES in Modelica



Enthalpy-based R-C-R network; modular, scalable, fast. Capacity scales by adding heat-exchanger units.

2 Validation against experiment



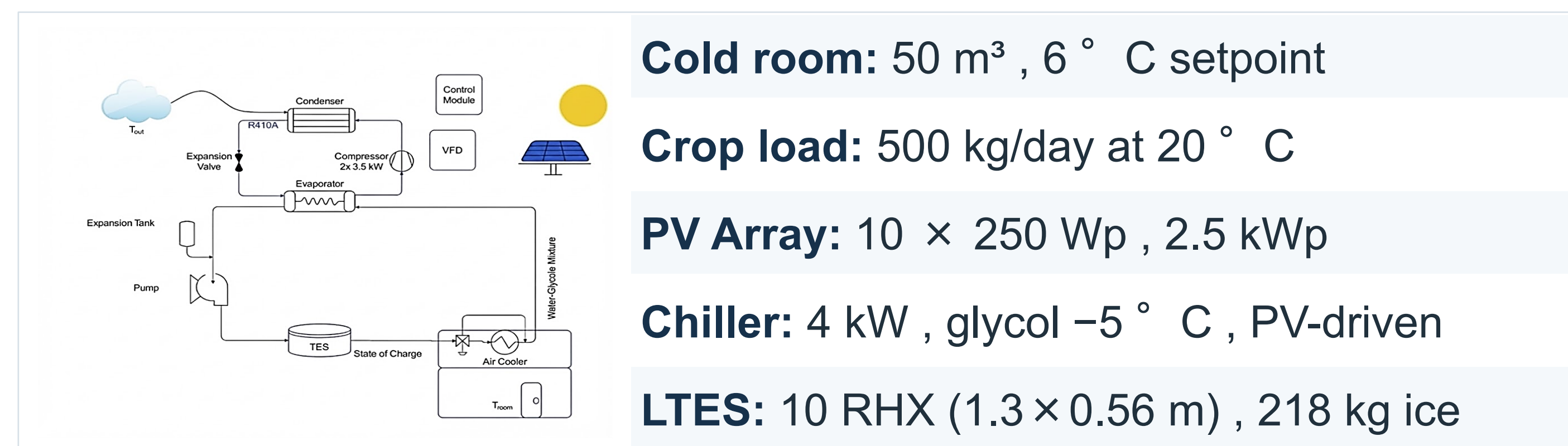
Outlet temperature matches measurements through charge and discharge.

3 Use case & demonstrator

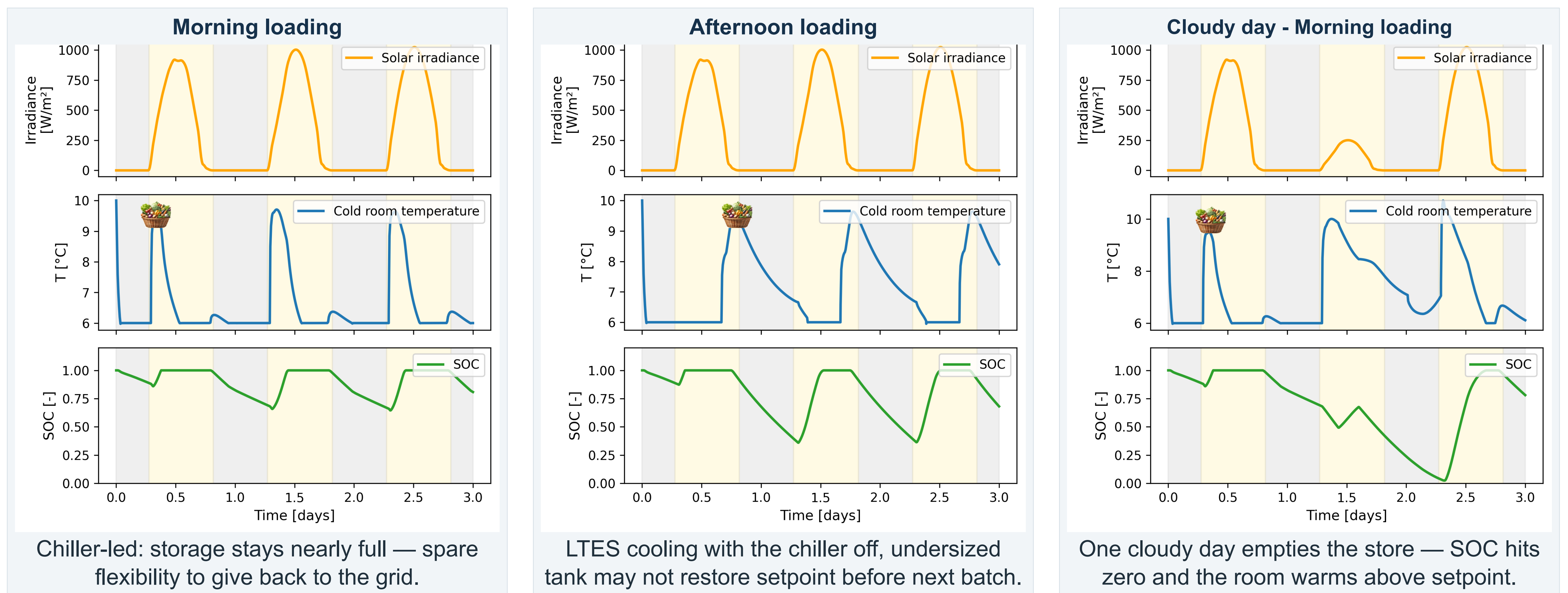
Post-harvest losses reach 30–50% where electricity is scarce or unreliable; the usual fix, diesel or grid-tied vapor-compression cooling, is carbon-intensive and supply-constrained.

Sustainable Alternative: Off-grid PV Powered Cold Rooms. The chiller runs only when the sun is up, cooling the room and charging the LTES; at night, the storage discharges to hold setpoint, the same load-shifting a grid storage gives during congestion or peak hours.

4 System & sizing



5 What the model shows — cooling that follows the supply



Conclusions

- Load timing vs. supply sets the regime. sizing and control must be co-designed.
- The model quantifies the flexibility: hours of cooling shiftable, and when the store runs out.
- Steady-state methods cannot capture this charge–discharge behaviour.

Why it matters for DSOs

- Battery-free flexibility, lower material use and lifecycle impact.
- Shifts cooling load away from congested / peak hours.
- A dispatchable thermal asset for local energy hubs.



Machine Learning-Based Prediction of Photovoltaic Power Generation: A Case Study Using Two-year Time Series Amsterdam Weather Data and SAM Simulations

Guang Hu ¹, Roel Loonen ², Angèle Reinders ¹

1. Energy Technology Group, Department of Mechanical Engineering, Eindhoven University of Technology, 5600MB Eindhoven, The Netherlands

2. Building Performance Group, Department of Built Environment, Eindhoven University of Technology, 5600MB Eindhoven, The Netherlands

Email address for correspondence: g.hu@tue.nl

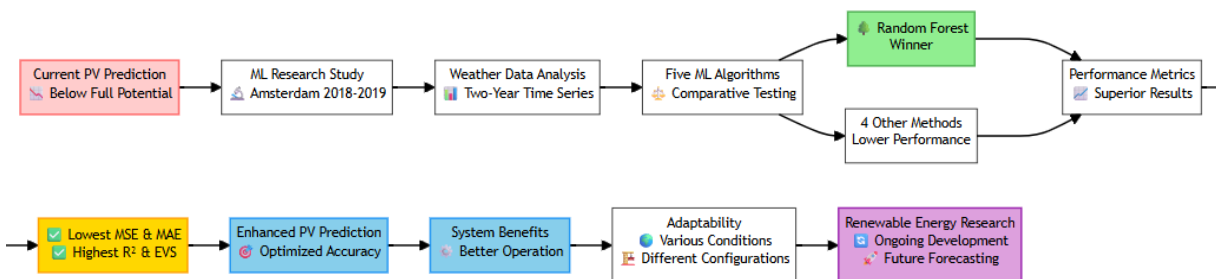
How can we improve the accuracy and reliability of photovoltaic (PV) power generation predictions using machine learning (ML) approaches to optimize system operation and maintenance?

The potential for accurate PV power prediction using ML algorithms is significant and can be quantified through weather data analysis.

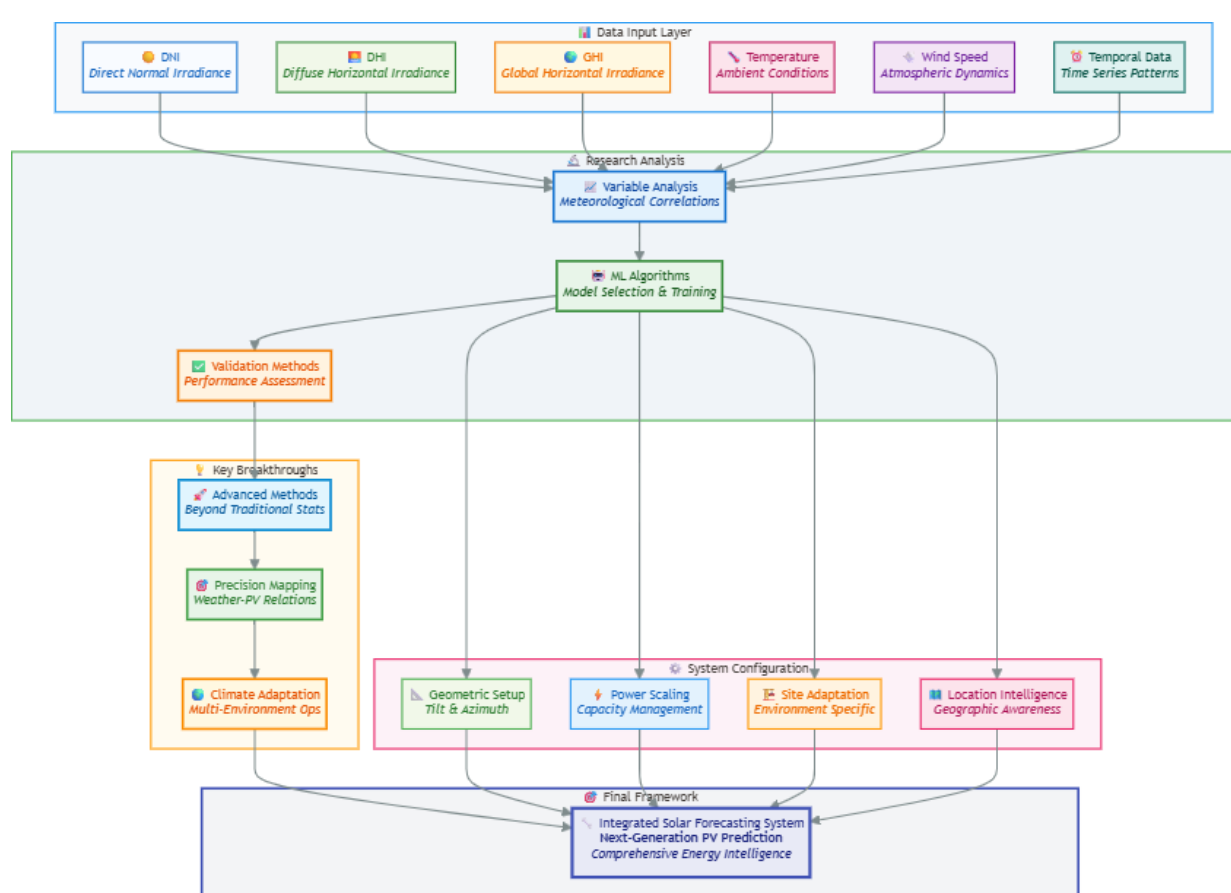
This poster is focused of such an analysis for PV systems in the Netherlands, using weather data from Amsterdam (temperate oceanic climate zone), as shown in Figure 1. We evaluate:

- (1) algorithm performance and computational efficiency,
- (2) weather data integration and temporal modeling,
- (3) enabling technologies for high-resolution forecasting, and
- (4) validation approaches using SAM simulations, see Figure 2.

ML-based PV Prediction



Required research for ML-based PV prediction



Leading to following technological advancement

- Increased accuracy and reliability of PV power generation predictions across various environmental conditions by both system operators, energy managers, and grid operators.
- A framework for effective PV system operation and maintenance with a focus on machine learning-enhanced forecasting capabilities.

Reference

Hu G., Loonen R. C., Reinders A. H. Analyzing the Influence of Weather Conditions and Solar Irradiance on Photovoltaic Power Generation: A Case Study in Amsterdam[C]. ICUC12, Rotterdam, 2025.

Acknowledgement

This research is funded by 4TU program HERITAGE (HEat Robustness In relation To AGEing cities) in the Netherlands.

Table 1: Options for machine learning algorithms in PV power prediction and specific types of possible forecasting applications.

Specific Method	Application Type	Key Characteristics	Optimal Use Cases
Random Forest (RF)	High-accuracy prediction	Lowest MSE/MAE, highest R ² /EVS	Primary forecasting, grid integration planning
Gradient Boosting (GB)	Moderate-accuracy prediction	Sequential learning approach	Secondary forecasting, backup systems
k-Nearest Neighbors (kNN)	Pattern recognition prediction	Excellent for non-linear patterns	Variable weather conditions, seasonal forecasting
Neural Networks (NN)	Complex pattern prediction	Powerful but computationally intensive	Research applications, high-performance computing
Linear Regression (LR)	Basic prediction baseline	Simple, interpretable, lower accuracy	Preliminary analysis, educational purposes
Weather Data Integration	DNI, DHI, GHI integration	High-resolution meteorological data	Real-time forecasting, operational planning
SAM simulation-based	Standardized PV parameters	Tilt 20°, azimuth 180°, 1kW peak	System design validation, performance benchmarking

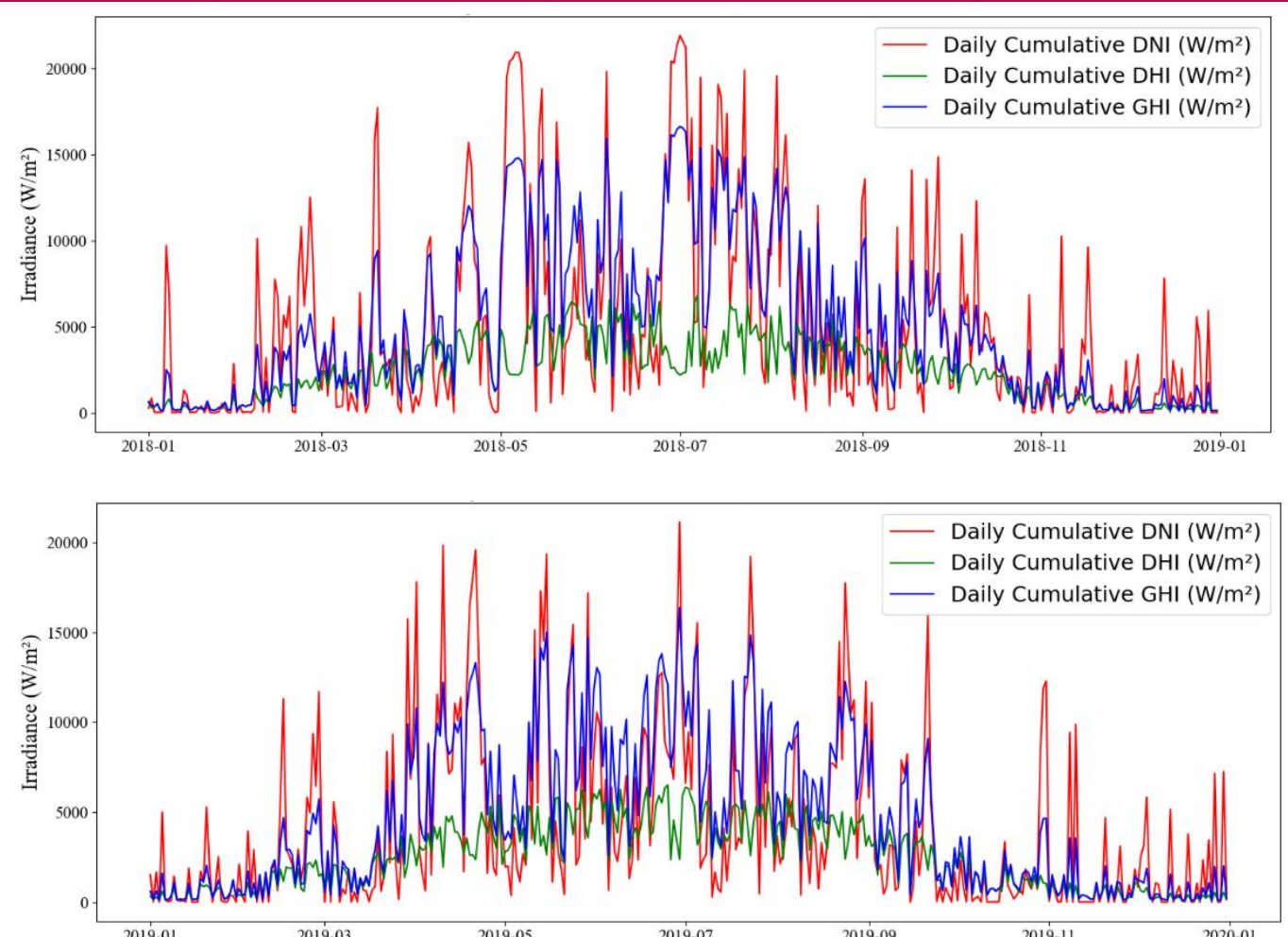


Figure 1: Weather data files for Amsterdam, was used by SAM software with PV power simulation, including as Direct Normal Irradiance (DNI), Diffuse Horizontal Irradiance (DHI), Global Horizontal Irradiance (GHI), ambient temperature, and wind speed; top: Daily cumulative variation of solar irradiance (DNI, DHI, GHI) of weather data of Amsterdam in year 2018; bottom: Daily cumulative variation of solar irradiance (DNI, DHI, GHI) of weather data of Amsterdam in year 2019.

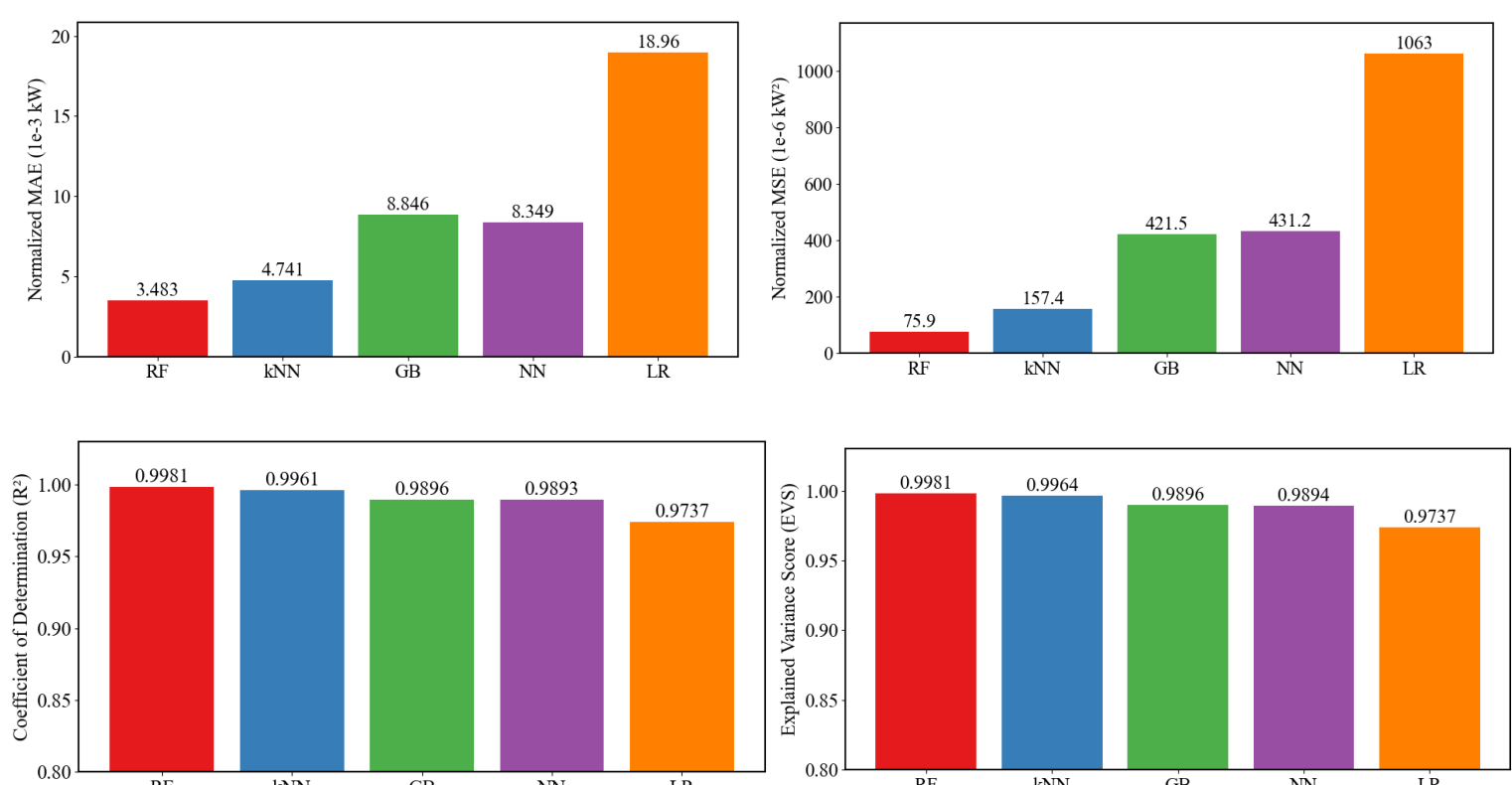


Figure 2: Performance comparison matrix showing accuracy metrics (MSE, MAE, R², EVS) for five machine learning algorithms applied to PV power prediction using two-year Amsterdam weather data, with Random Forest achieving optimal results for 1 kW normalized peak power system. The dataset has been split into training (50%) and testing (50%) sets based on the year of data collection to ensure a temporal separation between the training and evaluation phases. Specifically, all data points from the year 2018 are used for training the mode; all data points from the year 2019 are used for testing and validation

Managing the net zero transition: co-optimized planning of coal retrofits, renewables, and transmission

Herian Atma^{1,2}, Franco Ruzzenenti¹, Machteld van den Broek³

¹Energy Sustainability Research Institute Groningen (ESRIG), University of Groningen, Groningen, The Netherlands; ²PT PLN (Persero), Jakarta Selatan, Indonesia; ³Faculty of Technology, Policy and Management (TPM), Delft University of Technology, Delft, The Netherlands

Introduction

Electrification and VRE growth create **spatial mismatches** between generation and load, while grid congestion limits power transfer from resource-rich areas to demand centers. Meanwhile, existing thermal assets face a critical question: **retire or retrofit?** What is the value of flexibility options (asset retrofits, grid expansion, storage) when decarbonizing a spatially constrained system?

Most decarbonization studies treat **asset retirement** as fixed and exogenous [1], **brownfield retrofits** are rarely modeled as system-level choices [2], and **transmission constraints** are frequently ignored or simplified [3]. No or limited existing framework co-optimizes all three simultaneously. This study builds a co-optimization framework for **asset fate x grid constraints x new capacity expansion** to identify least-cost decarbonization pathways under a net-zero target.

Context

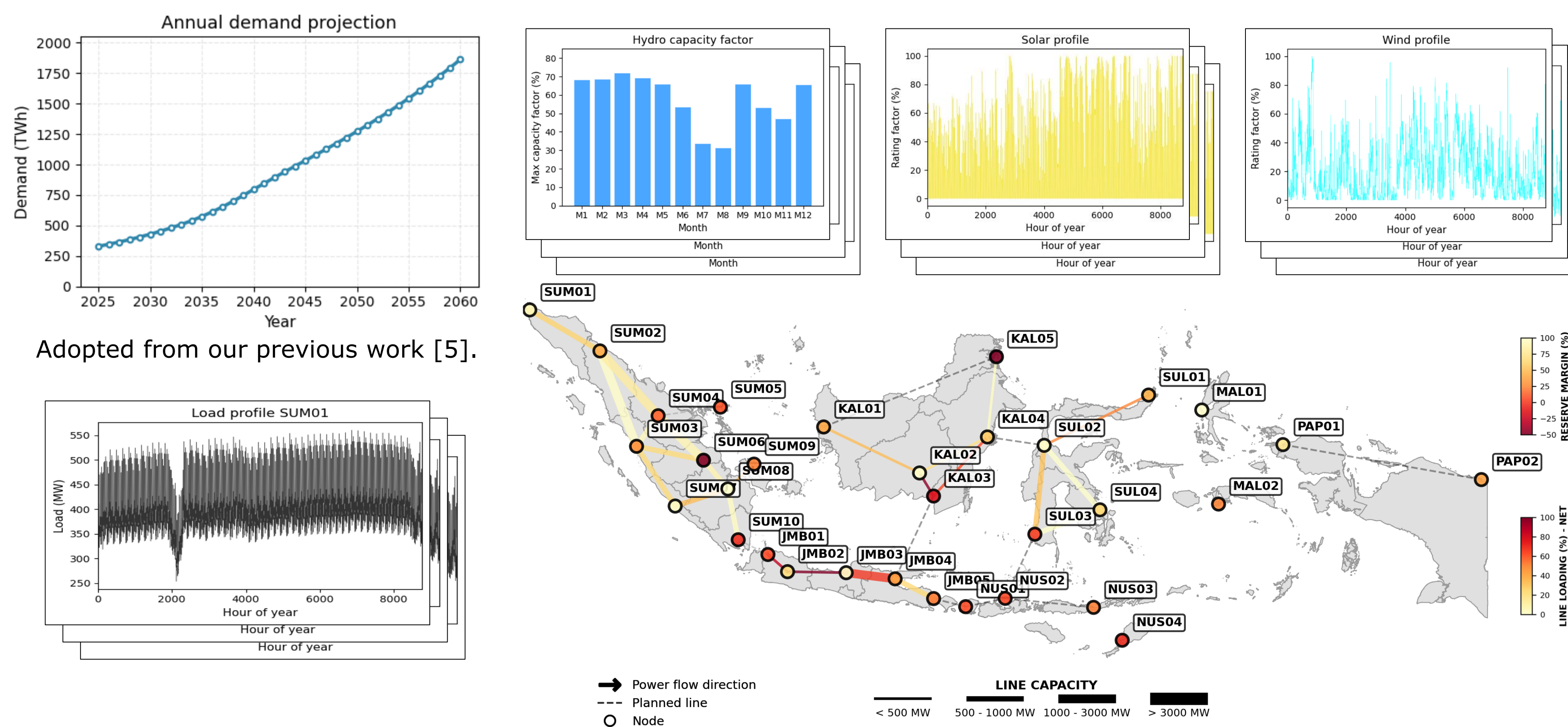
Highlights on the Indonesia's power sector:

- ~60% coal-dependent; young fleet (10–12 years).
- Net Zero Emission (NZE) target: 2060.
- 70% of demand on Java-Madura-Bali.
- Abundant renewables, but far from load centers.
- 17,000+ islands → transmission is critical and costly.

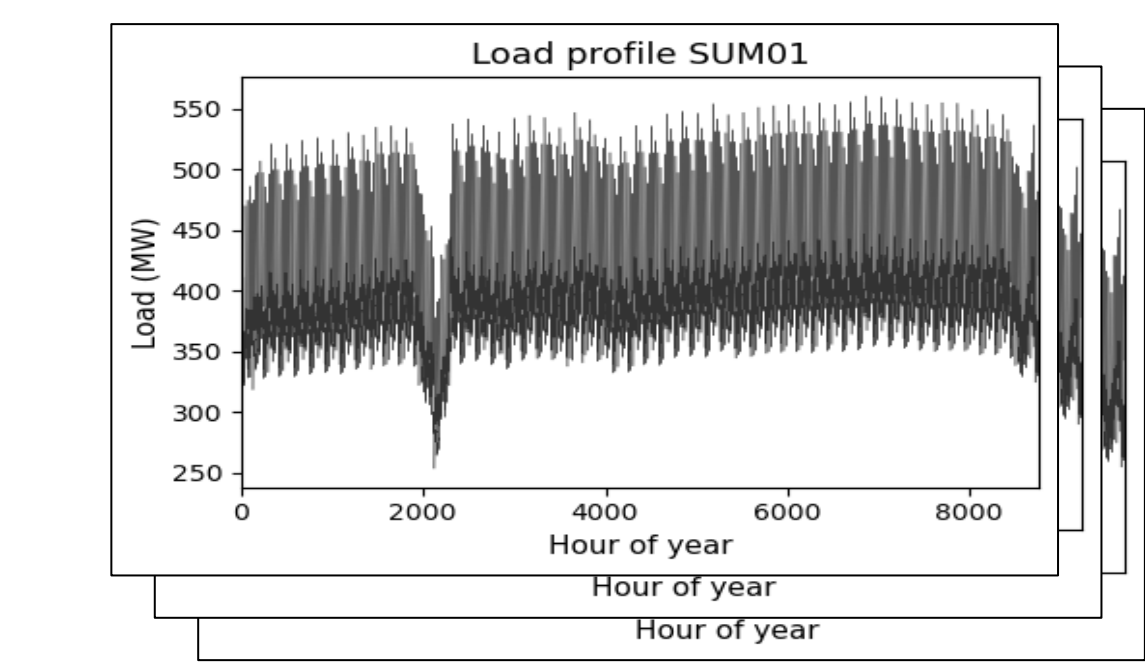
Methodology

We use PLEXOS (version 12.0) capacity expansion modeling framework [4]:

- Mixed-integer linear programming, minimizes total system cost, planning horizon: 2025–2060.
- Spatial resolution: 32 nodes, distributed in 7 regions of Indonesia.
- Temporal resolution: 48 time blocks per year.
- 14 new generation and storage technologies and 6 retrofit options (for 197 individual units of coal-fired power plants).
- Endogenous transmission expansion: HVAC and HVDC candidate intra- and inter-island transmission links.



Adopted from our previous work [5].



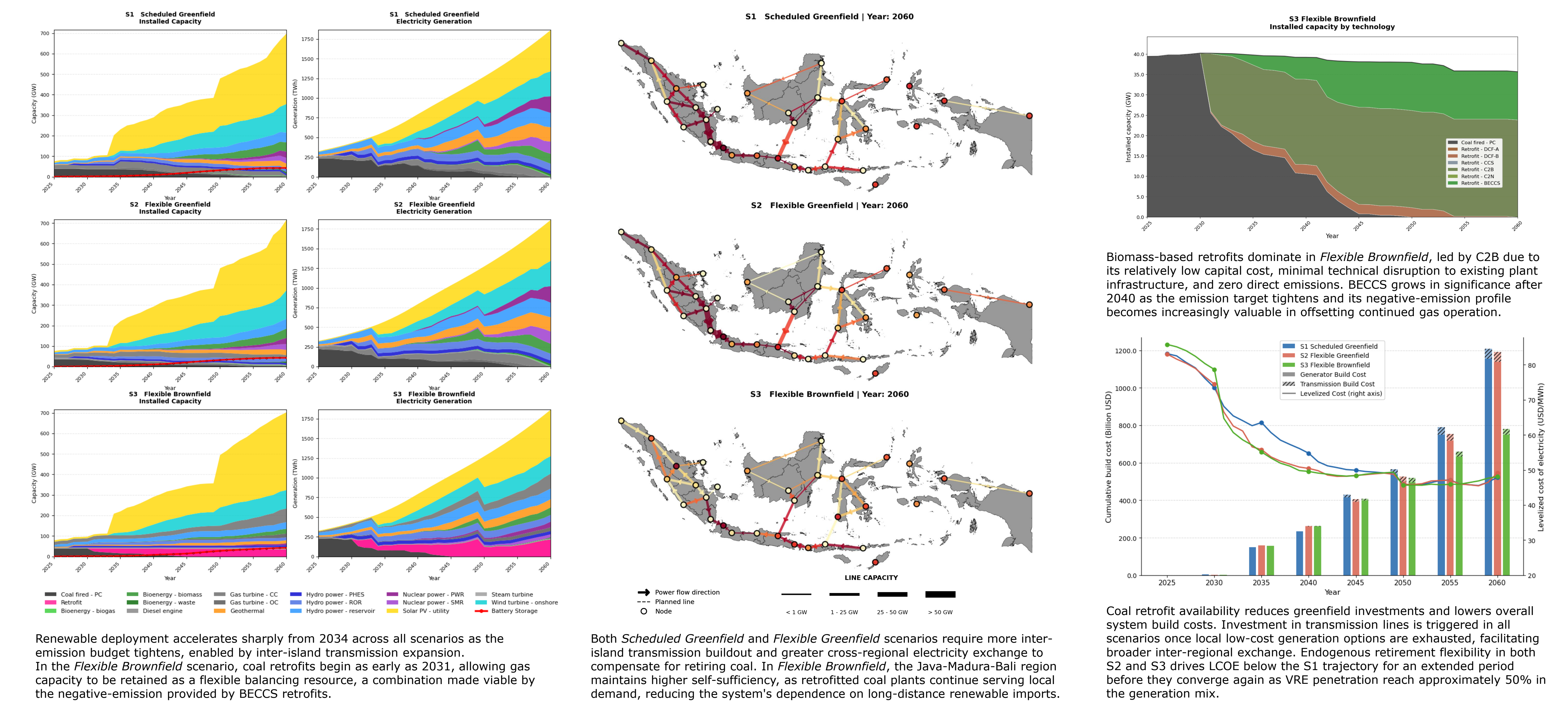
Each existing coal plant can receive one of six retrofit interventions. Techno-economic parameters are taken from our plant-level analysis [6].

Retrofit	Intervention	Key characteristic
DCF-A	20% ammonia co-firing	Proportional CO ₂ reduction; burner modification cost
DCF-B	20% biomass co-firing	Similar to DCF-A; different fuel cost/availability
PC-CCS	Post-combustion CCS	Higher CAPEX; up to 90% emission capture
C2B	Coal-to-biomass repowering	Zero direct emissions; retains steam turbine
C2N	Coal-to-nuclear (SMR)	Replaces boiler; retains turbine and grid connection
BECCS	C2B + post-combustion CCS	Net-negative emissions

Three scenarios are developed to highlight the system-level value of endogenous coal retirements and retrofits.

Scenario	Coal retirement	Coal retrofit	Purpose
Scheduled Greenfield	Exogenous (fixed at 30 years)	None	Baseline: what does NZE cost if retrofit is off the table and retirement is mandated?
Flexible Greenfield	Endogenous (system-optimal)	None	Isolates the value of retirement flexibility alone
Flexible Brownfield	Endogenous (system-optimal)	Full (six options)	Full optionality: reveals whether and how the system uses retrofits

Results



Renewable deployment accelerates sharply from 2034 across all scenarios as the emission budget tightens, enabled by inter-island transmission expansion. In the *Flexible Brownfield* scenario, coal retrofits begin as early as 2031, allowing gas capacity to be retained as a flexible balancing resource, a combination made viable by the negative-emission provided by BECCS retrofits.

Both *Scheduled Greenfield* and *Flexible Greenfield* scenarios require more inter-island transmission buildout and greater cross-regional electricity exchange to compensate for retiring coal. In *Flexible Brownfield*, the Java-Madura-Bali region maintains higher self-sufficiency, as retrofitted coal plants continue serving local demand, reducing the system's dependence on long-distance renewable imports.

Biomass-based retrofits dominate in *Flexible Brownfield*, led by C2B due to its relatively low capital cost, minimal technical disruption to existing plant infrastructure, and zero direct emissions. BECCS grows in significance after 2040 as the emission target tightens and its negative-emission profile becomes increasingly valuable in offsetting continued gas operation.

Coal retrofit availability reduces greenfield investments and lowers overall system build costs. Investment in transmission lines is triggered in all scenarios once local low-cost generation options are exhausted, facilitating broader inter-regional exchange. Endogenous retirement flexibility in both S2 and S3 drives LCOE below the S1 trajectory for an extended period before they converge again as VRE penetration reach approximately 50% in the generation mix.

Conclusions

- Retrofits (esp. biomass-based) **lower system cost** and enable a **more flexible** NZE transition.
- Endogenous retirement + retrofits **reduce LCOE** vs. forced phase-out pathways.
- Transmission expansion complements retrofits, while constrained grids increase **reliance on repurposed coal**.
- Integrated planning of the existing coal assets, renewables, and transmission delivers the **cheapest net-zero pathway**.

References

- [1] Langer et al., *Environ. Res.: Energy*, 1(2), 2024. doi:10.1088/2753-3751/ad53cb
- [2] Cormos & Dinca, *Energy*, 220, 2021. doi:10.1016/j.energy.2020.119734
- [3] Reyseliani et al., *J. Clean. Prod.*, 454, 2024. doi:10.1016/j.jclepro.2024.142202
- [4] Energy Exemplar, PLEXOS® Software. energyexemplar.com/plexos
- [5] Atma et al., *Energy Strategy Rev.*, 60, 2025. doi:10.1016/j.esr.2025.101805
- [6] Atma et al., SSRN:6619354, 2026. doi:10.2139/ssrn.6619354

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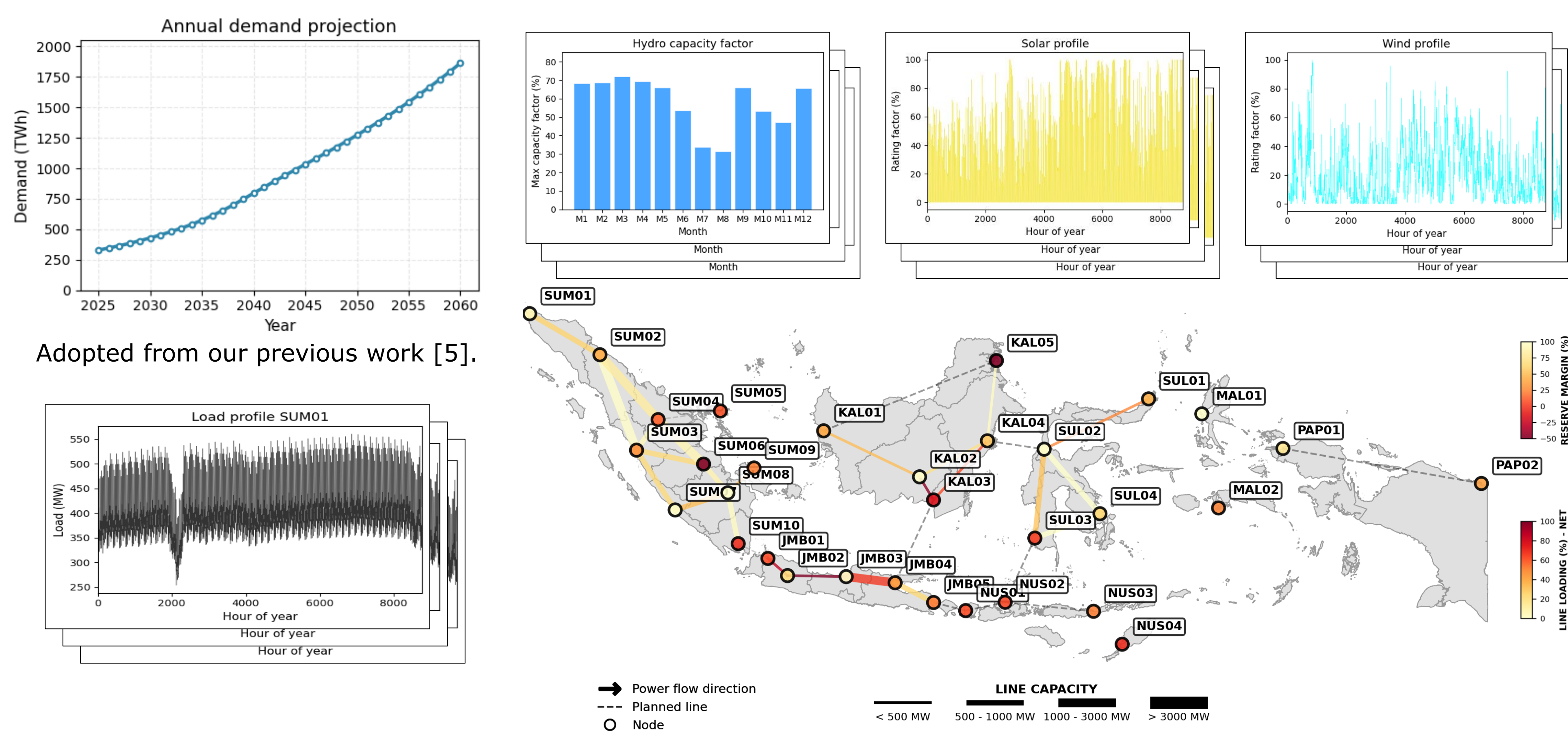
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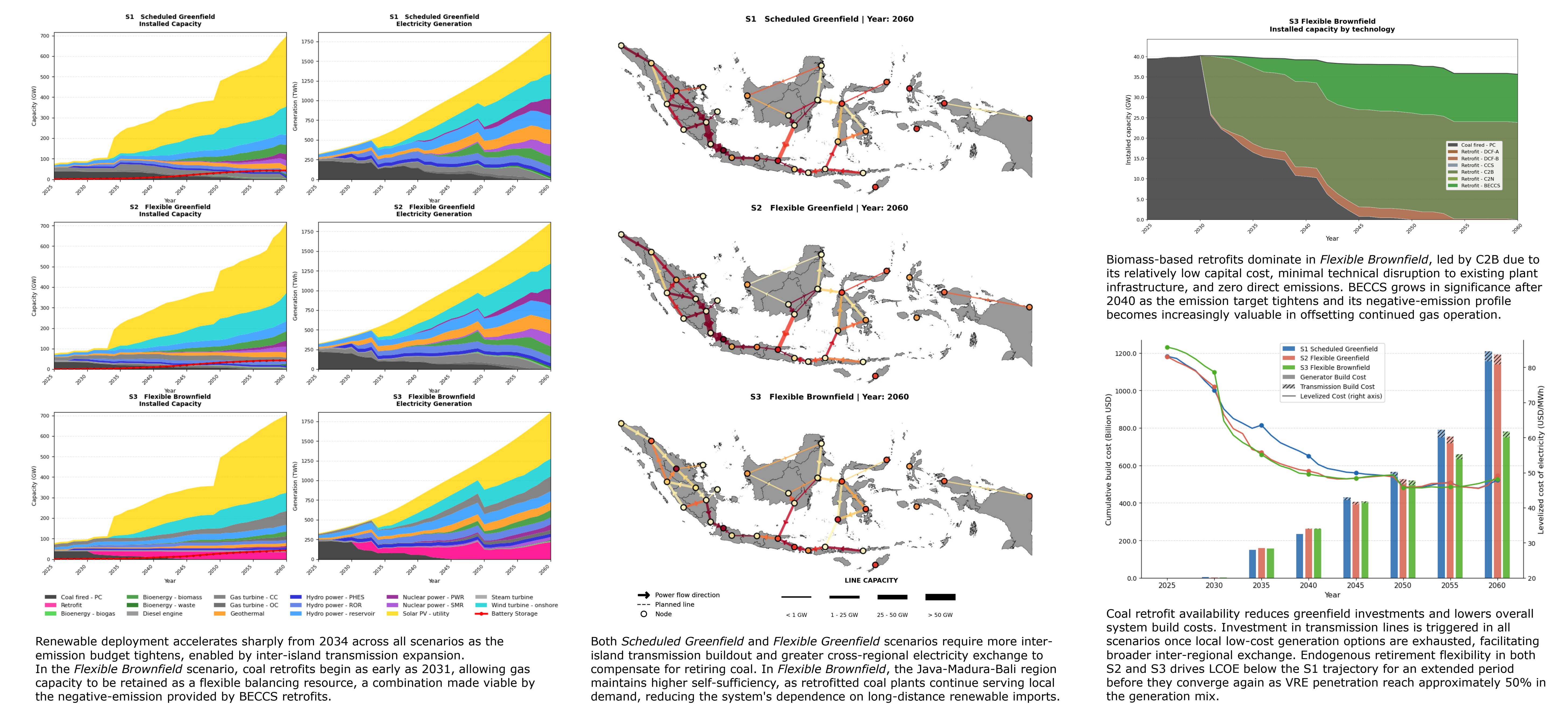
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Results



Conclusions

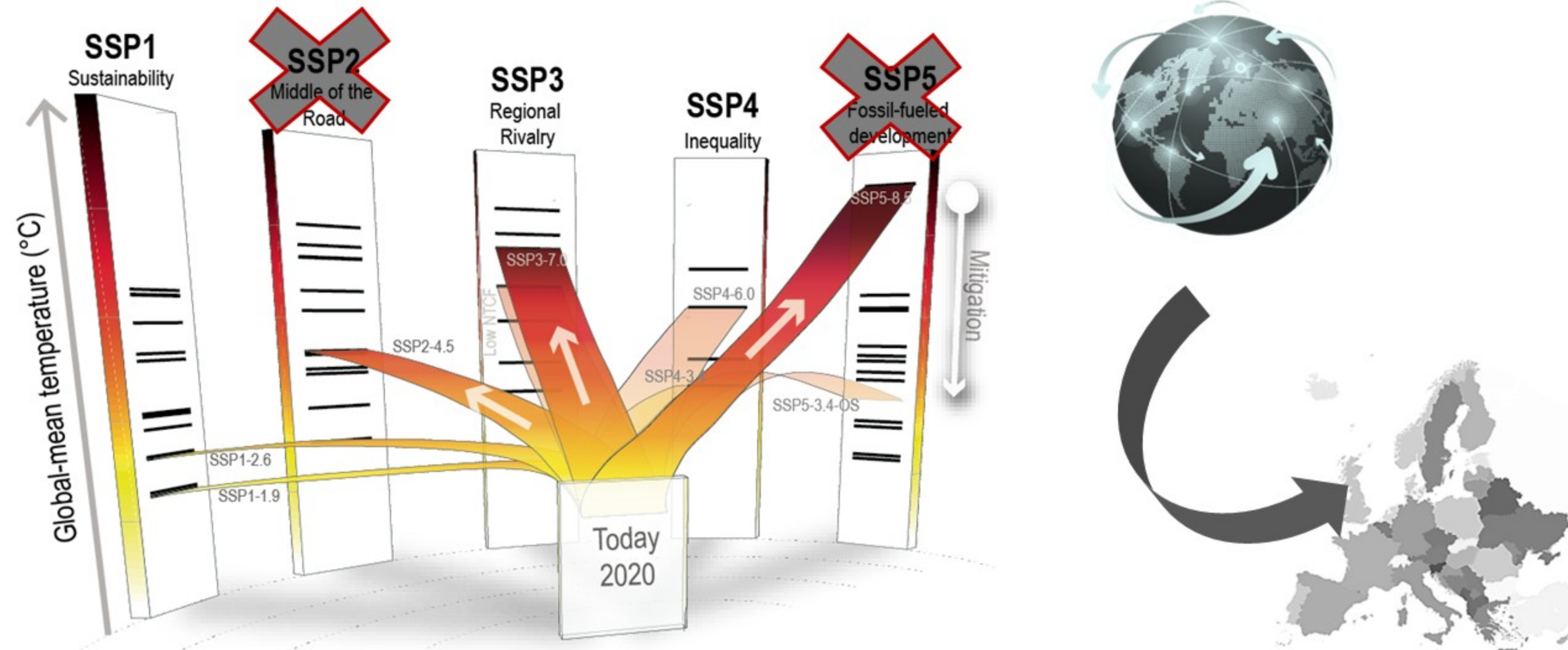
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Strategic planning for the future energy grid: exploring possible configurations of the future energy infrastructure in the Dutch North Sea

From 3 selected Global IPCC pathways



We selected and analysed 3 plausible coherent and holistic narratives formulated at the global level (IPCC) to identify key drivers of change that could shape the future of the European and Dutch Energy systems in 2050. The 3 global pathways were aligned to European narratives and operationalised at the local Dutch level.

DUTCH energy sector objectives and ENERGY SYSTEM CONFIGURATION

Based on stakeholder input, we identified 5 key objectives for the future energy system:

- Grid availability and connection at low prices.
- Diverse and secure generation of energy offshore.
- Improved flexibility of the energy system.
- Cross-sectoral coordination and market readiness.
- Adaptive and strategic planning of the North Sea.

BUT reaching those objectives is met with many **UNCERTAINTIES** on how to tap into opportunities and how to avoid risks:

Under what **scenario conditions** can the **North Sea Offshore Grid** become technically, environmentally and economically feasible?

Can **technological innovations** reduce the **environmental footprint** of the energy infrastructure?

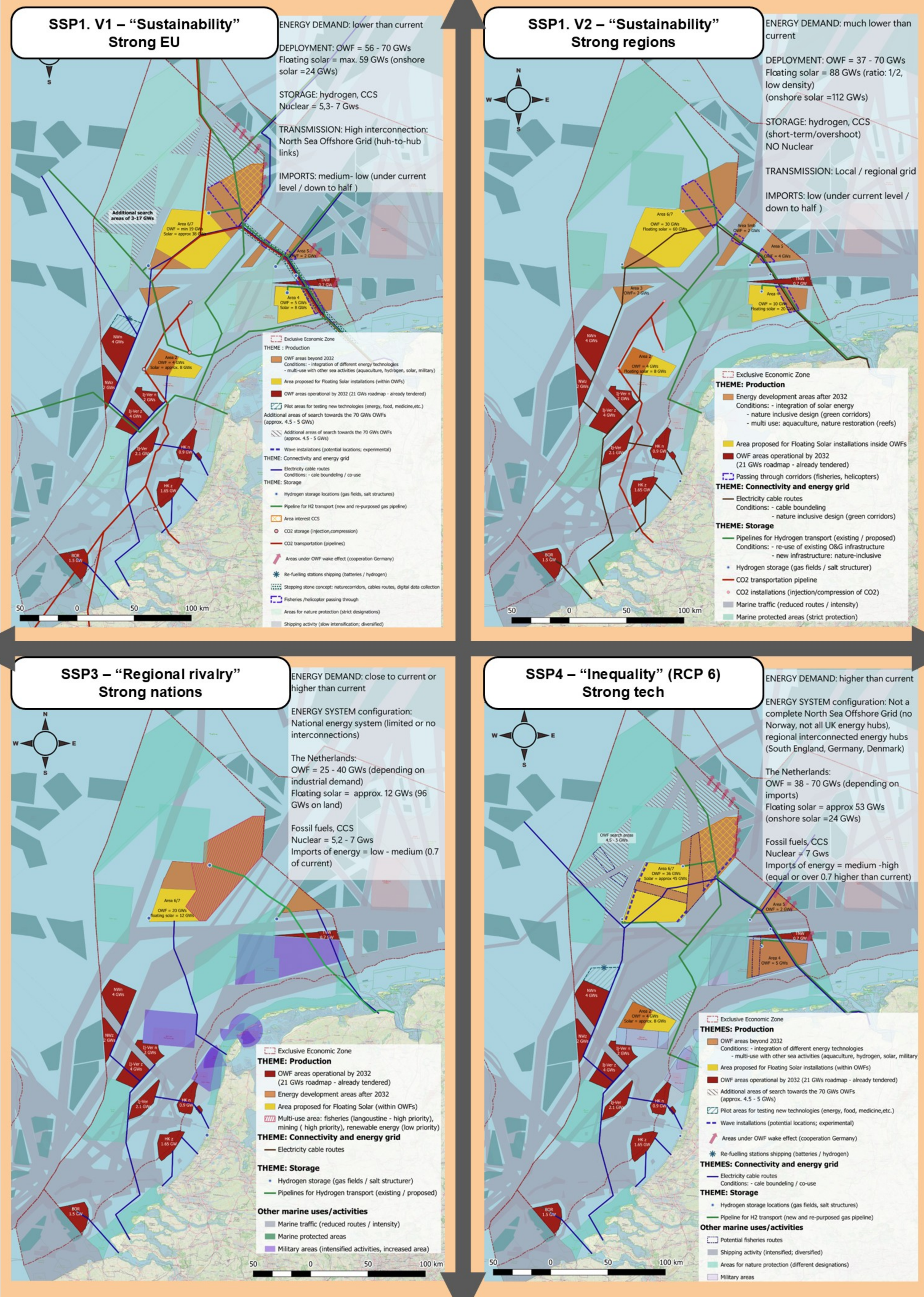
What are the **key energy system interconnections** to be deployed to secure a stable and efficient future energy system?

What are the **legal and institutional conditions** can best **balance negative impacts** from a large-scale deployment on other offshore uses?

To 4 European SCENARIO NARRATIVES

<p>SSP1.V1 – “Sustainability” Strong EU</p> <ul style="list-style-type: none"> Consolidated EU Balance economic growth and nature protection High cooperation <p>Highly interconnected and centralised EU energy system (renewable)</p>	<p>SSP1.V2 – “Sustainability” Strong regions</p> <ul style="list-style-type: none"> Empowerment of regions and communities High nature protection Lower material and energy consumption <p>Highly de-centralised regional energy system (renewable energy communities)</p>
<p>SSP4 – “Inequality” Strong tech</p> <ul style="list-style-type: none"> strong business elite High economic growth High competition <p>Mixed energy system (fossil fuels + renewables, high degree of innovation)</p>	<p>SSP3 – “Regional rivalry” Strong nations</p> <ul style="list-style-type: none"> High geopolitical tensions (protectionism, self-sufficiency) National economic growth and local resources <p>National energy system (fossil fuels + renewables)</p>

And spatial claims in the North Sea...



Spatio-Temporal Graph Neural Networks for Implicit Weather-aware Behind-the-Meter Load Disaggregation

Llan Almendariz¹, Tarek Alskaf¹, Wilfried van Sark²,

¹ Information Technology Group, Wageningen University · ² Copernicus Institute of Sustainable Development, Utrecht University

Motivation & Contribution

Disaggregation models decompose net-load signal into its behind-the-meter (BtM) load and PV components to enhance grid visibility. However, existing models overly rely on weather data and PV system metadata that are often unavailable, limiting real-world deployment. We propose a **weather-agnostic ST-GNN** that implicitly captures latent spatio-temporal patterns across neighbouring households to do uncertainty-aware disaggregation.

Architecture

Uncertainty-aware ST-GNN combining 1D-CNNs for temporal extraction with GATv2 for spatial attention.

Evaluation

Critical comparison of weather-informed vs weather-agnostic disaggregation.

Case Study

Proprietary Dutch Smart Meter & solar PV dataset provided by smart monitoring company EARN-E.

Methods

We assume the following disaggregation identity for prosumer household i at time t :

$$NL_t^i = L_t^i - PV_t^i$$

where NL_t^i is the observed net load, L_t^i the latent BtM load, and PV_t^i the latent PV generation. Spatial dependencies across $N = 127$ households are encoded as a k -NN graph:

$$G = (V, E), \quad V = \{1, \dots, N\}, \quad E \subseteq V \times V$$

where edges $(j, i) \in E$ connect household i to its k geospatially nearest neighbours.

The architecture is evaluated under three configurations: *weather-informed*, *weather-agnostic*, and a spatial-ablated baseline in which the GATv2 block is omitted.

Proposed Architecture

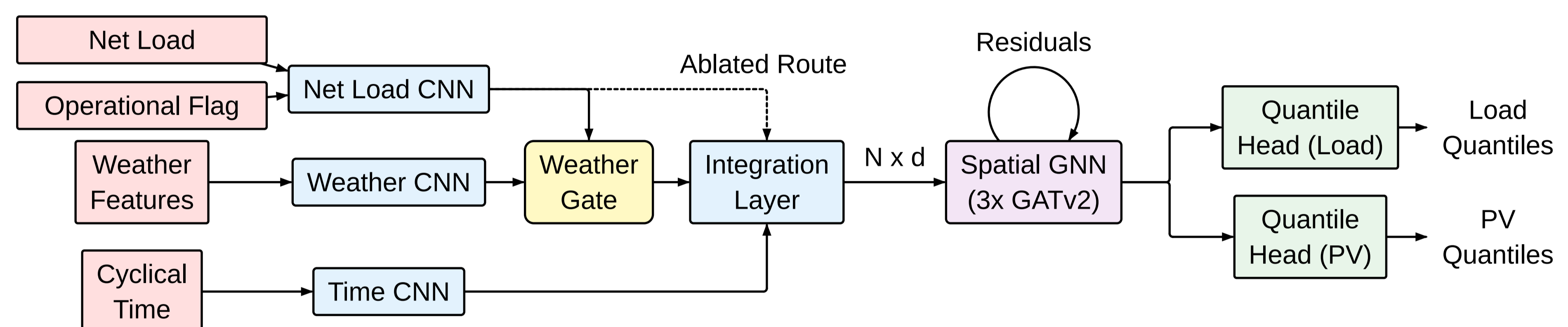


Figure 1: Proposed architecture to evaluate weather implicit (dashed line), and weather explicit BtM disaggregation. The proposed architecture uses 1d-CNNs for temporal feature extraction, and a GATv2 block for spatial aggregation that is used for uncertainty-aware BtM PV and load estimation.

Performance Metrics: Weather-Agnostic vs Weather-Informed

..... Load true PV true — Load Q50 — PV Q50 — Load 80% CI — PV 80% CI

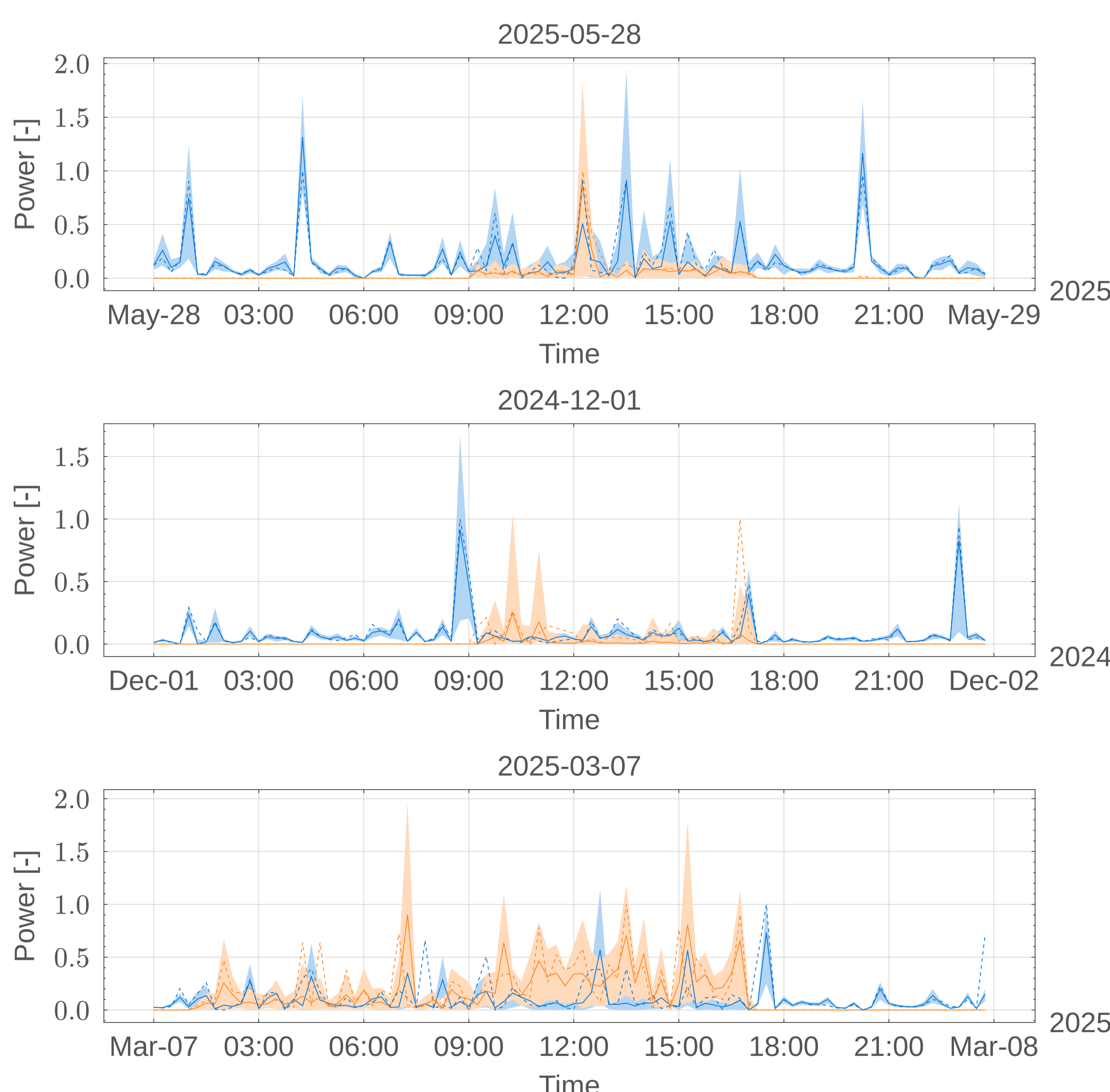


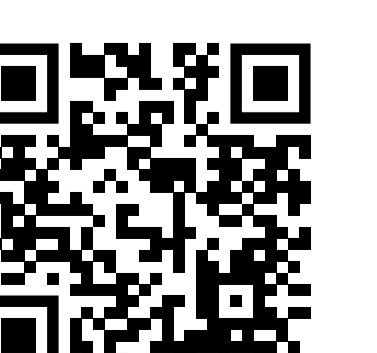
Figure 2: Sample profiles of the weather-agnostic model (W-MP3). Values were normalised based peak values and timestamps were standardised to UTC time

Table 1: Disaggregation performance across experiments. RTE (%) measures relative total energy bias. Coverage is the empirical probability of the true value falling within the 80% prediction interval (Q10–Q90). Sharpness is the mean interval width in Watts. Bold denotes best result per metric per target.

Experiment	Load				PV			
	W+ MP0	W+ MP3	W- MP0	W- MP3	W+ MP0	W+ MP3	W- MP0	W- MP3
RMSE	1030.77	1018.27	943.34	929.13	783.99	1161.05	783.99	860.68
MAE	423.92	386.92	370.40	366.44	256.92	308.59	251.24	249.85
R ²	0.59	0.60	0.66	0.66	0.74	0.65	0.79	0.75
RTE (%)	21.88	19.43	21.17	17.88	3.67	18.90	17.24	23.19
Coverage	0.86	0.79	0.88	0.75	0.73	0.79	0.69	0.84
Sharpness	1590.33	1242.86	1469.37	1023.85	1030.62	1381.46	876.62	806.23

Key Take-aways:

- 1 Spatial graph structure information improves net load disaggregation in absence of explicit weather information.
- 2 *Weather-agnostic (W- MP3)* achieves superior performance compared to *Weather Informed (W+ MP3)*.
- 3 Weather-agnostic model tracks the peaky nature of Load and PV (Figure 2)
- 4 PV can be disaggregated with MAE of 249.85 Watt, and 80% CI of 800 Watts
- 5 Load can be disaggregated with MAE of 929.13 Watt, and 80% CI of 1023 Watts



1 Motivation

- Regional energy systems present unique challenges. Supporting planning and policy in these contexts requires models that are transparent, participatory, and able to integrate high-resolution, context-specific data.
- Energy system models (ESMs) at regional and urban scales remain far less mature and accessible than their national counterparts.
- A critical barrier is the limited availability of suitable modeling platforms and the inconsistent quality of energy-related data at finer spatial scales [1,2].
- Our research aims to close this gap by developing transparent urban-scale ESMs and strengthen data infrastructures. Our focus is on the urban context, but our approach is transferable to regional scales.

2 Method Overview

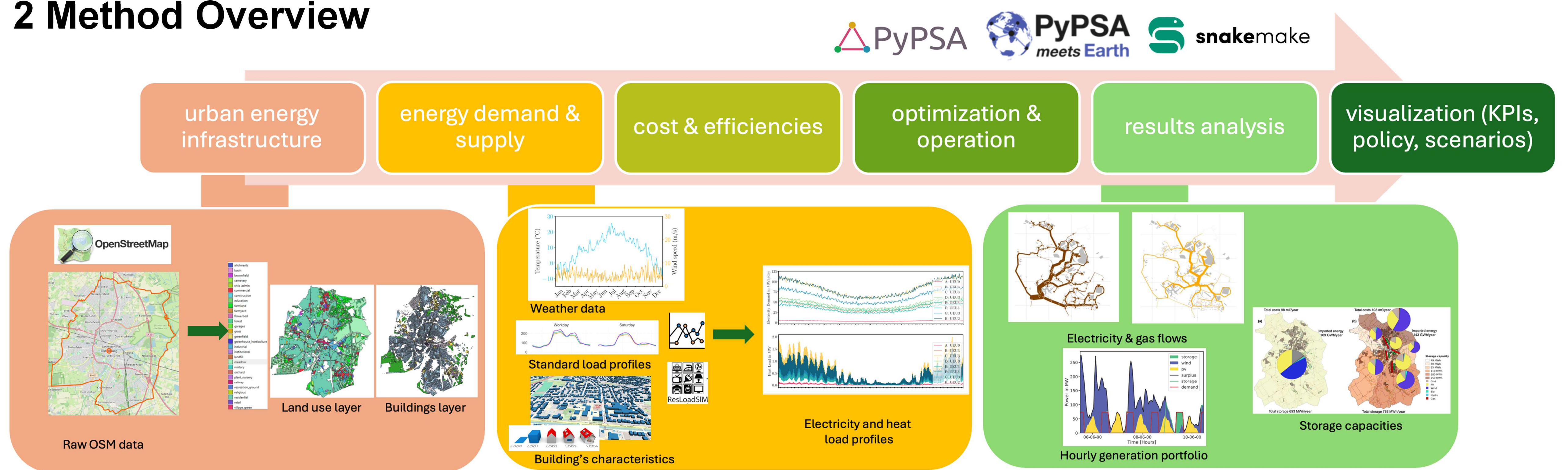


Fig. 1: Example workflow of the urban energy system model (based on PyPSA)

Our approach addresses modelling and data gaps in urban-scale ESMs, complemented by use cases on flexibility, climate impacts, mitigation, and adaptation for urban resilience [3].

Concretely, our approach consists in:

1. Develop and integrate datasets that captures infrastructure and electricity and heat demand of residential and non-residential buildings
2. Further developing PyPSA-distribution [4] into an open-source toolbox for simulating and optimizing urban-scale energy systems
3. Addressing data gaps critical through improved acquisition, processing, and integration workflows
4. Evaluating decarbonization pathways and climate change impacts on grid capacity and operational stability across all energy sectors

3 Toolbox development

PyPSA-Distribution framework will be extended by enhancing its capabilities to model the heat and electricity sectors [5]. This includes integrating high-resolution data of energy demand, generation, and distribution by leveraging data sources such as OpenStreetMap [6], cadastral and census records.

To expand the data foundation, advanced methodologies such as Machine Learning and Remote Sensing [7] will be used to improve existing datasets and create synthetic counterparts.

These enhancements will enable detailed urban-scale ESMs. While the current analysis focuses on Europe, with the Netherlands as a case study, the framework is transferable to other regions worldwide.

4 Contact & References

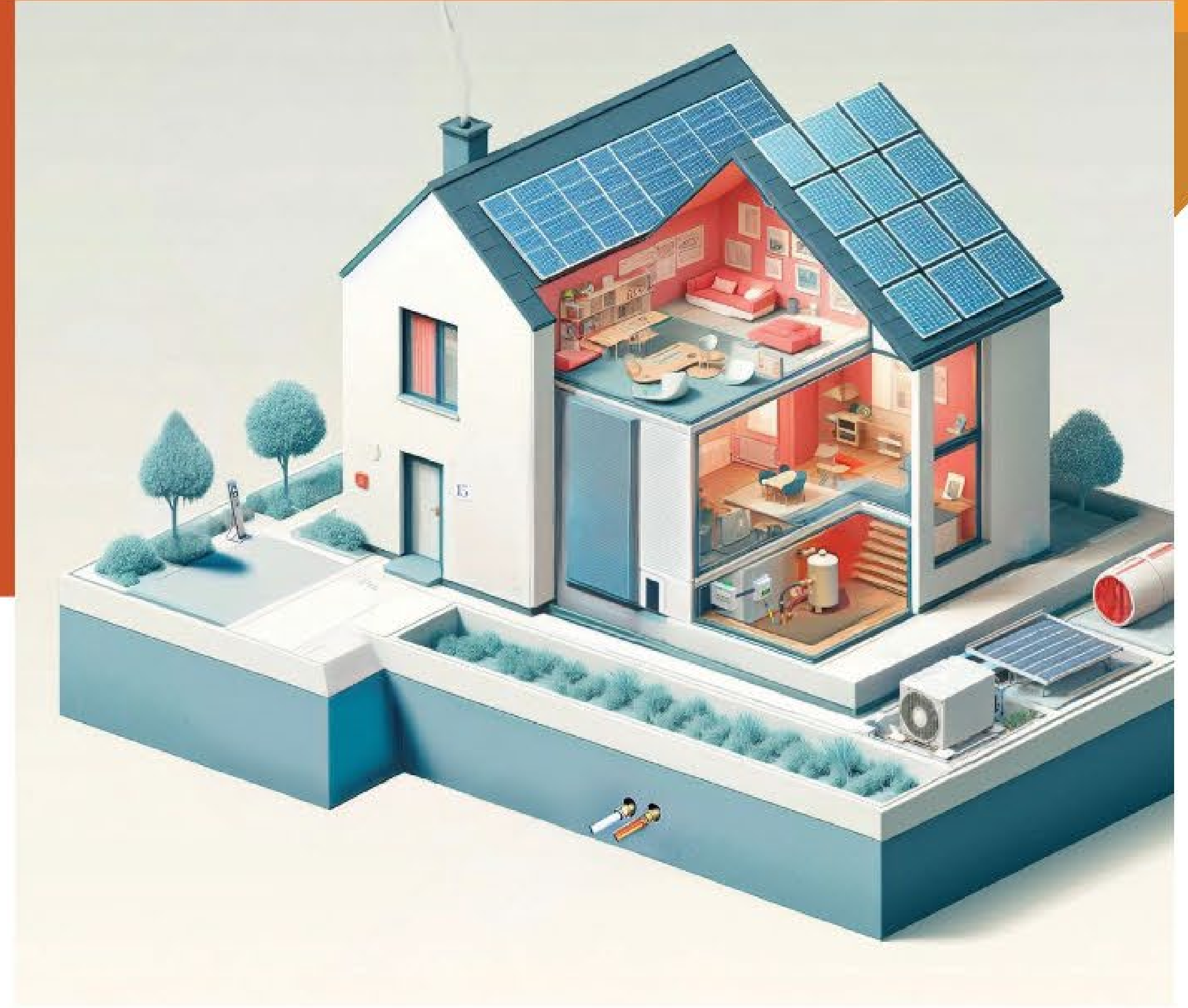
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INBUILT: Integrated Energy Modeling of Buildings and their Clustering

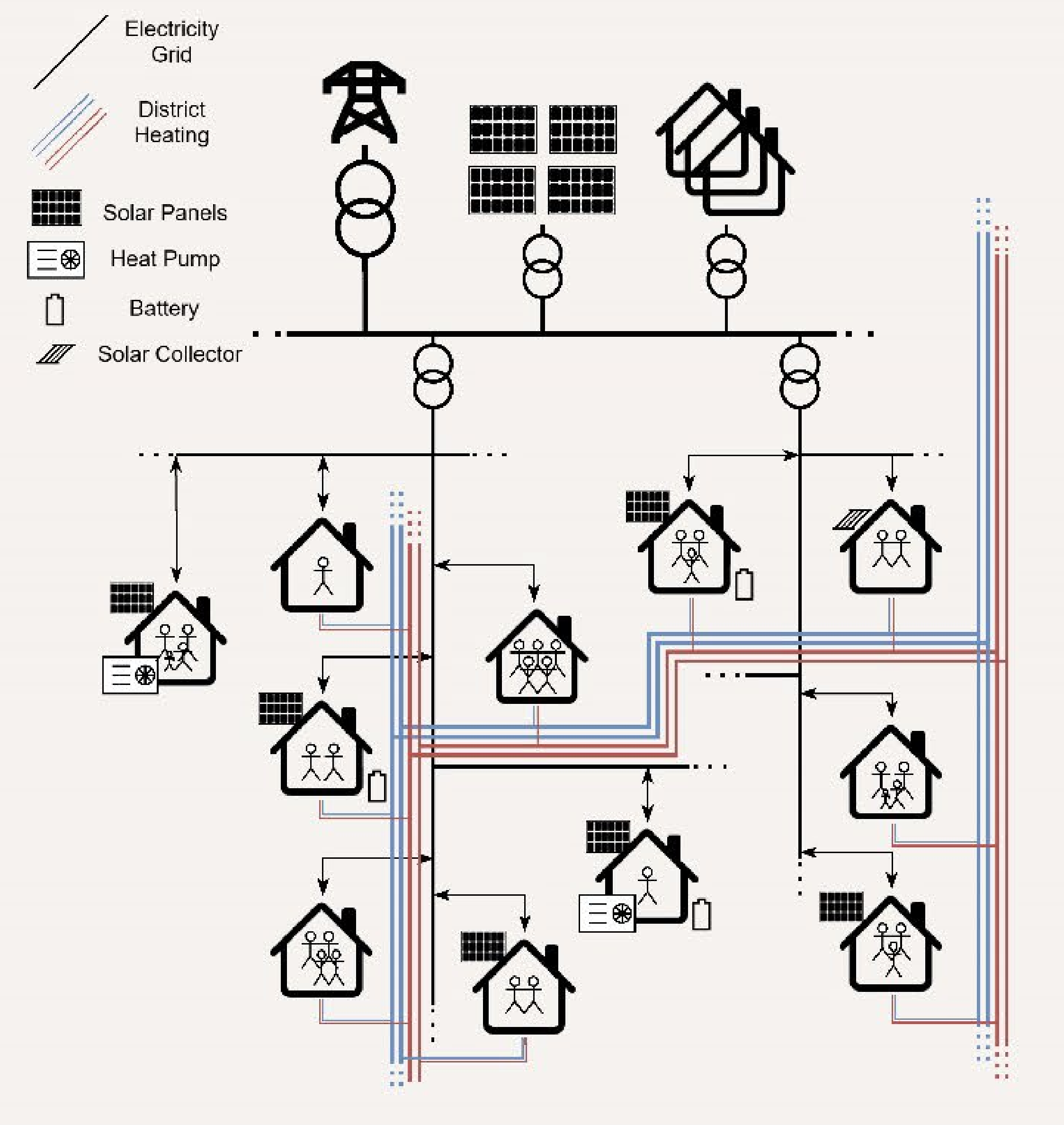
SOCIETAL RELEVANCE

The project contributes by developing dynamic models to determine flexibility in buildings which can be used by users to:

- Address upcoming network congestion
- Reduce Carbon Emissions
- Reduce Energy Costs



NEIGHBORHOOD OF GRID INTERACTIVE BUILDINGS



PROJECT GOAL

Developing models to unlock multi-energy flexibility in the built environment.

- 1 Dynamic Grid-Interactive Building Model.
- 2 Clustering of Grid-Interactive Buildings.
- 3 Mechanisms to unlock integrated Flexibility.



NEXT STEPS

- Study Design and Operation of Grid Interactive Buildings
- Develop Smart Home Potential Tool
- Determine Multi-Energy Flexibility in Residential Building

ELECTRICAL ENGINEERING, ELECTRICAL ENERGY SYSTEMS
BUILT ENVIRONMENT, BUILDING PERFORMANCE



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