Supplemental information on

Deciphering the Impact of AI on the EU's Net-Zero Ambition

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This file contains all supplementary materials referenced in the main manuscript, including the overview of the model, model inputs, assumptions, problem formulation, data sources, and extended results.

1 Problem description

AI factories, conceived as dynamic ecosystems built around AI-optimized supercomputing data centres, are designed to accelerate the development of AI models and drive digital innovation [1,2]. To better understand the energy consumption of AI-based data centres, it is essential to consider the wide variation in electricity usage across different AI workloads. For example, a simple text request in ChatGPT consumes approximately 0.0005 Wh, whereas generating a single image can require up to one thousand times more energy [3,4]. This disparity extends beyond daily usage, as training large-scale models entails considerable energy consumption. For instance, training ChatGPT-4 is estimated to have consumed around 50 GWh, roughly equivalent to the continuous electricity output of two days from a French nuclear reactor [5,6].

With the introduction of 5G, reducing latency constraints, AI computing facilities are increasingly located based on energy cost and availability, rather than user proximity. As a result, countries with abundant RES or strong digital infrastructure, such as the Nordics, Germany, Ireland, and France, are becoming key hubs [7]. Recent assessments by McKinsey indicate that countries with less grid congestion and more flexible energy infrastructure are more likely to support the rapid scaling of AI factories [8–10]. For instance, Nordic countries like Denmark, Sweden, Finland, and Norway are projected to experience up to triple increases in data centre demand, driven by abundant RES and naturally low ambient temperatures [11,12]. Meanwhile, established data centre hubs including the Netherlands, Germany, France, Ireland, and the UK, which currently host around 65% of the European data centre market, are expected to grow at a rate of 1.5 times. In contrast, emerging host countries such as Slovakia, Poland, Greece, Spain, and Italy may experience a three-to-fivefold increase over the next 10 years [13–15].

Taken together, the emergence of hyperscale digital infrastructure and the rapid growth of AI make it essential to incorporate AI load profiles as a new class of electricity demand at the country level and across different geographic regions in strategic long-term energy network planning. This occurs while widely used spatial optimization models such as PyPSA-Eur, Calliope, OSeMOSYS, and TIMES, primarily designed for long-term capacity expansion and cross-border transmission in Europe, have rarely incorporated emerging, geographically concentrated high-density demand, such as AI factories [16–18]. Figure 1 illustrates a comprehensive overview of these challenges and their implications.

Hence, it is time to decipher the impacts of AI on Europe's energy system through detailed numerical analysis—not just qualitative—based on precise optimization. This approach fills a critical gap in modelling tools by aligning with the ENTSO-E Ten-Year Network Development Plan (TYNDP) [19] framework while incorporating spatially heterogeneous AI-driven demand shocks.

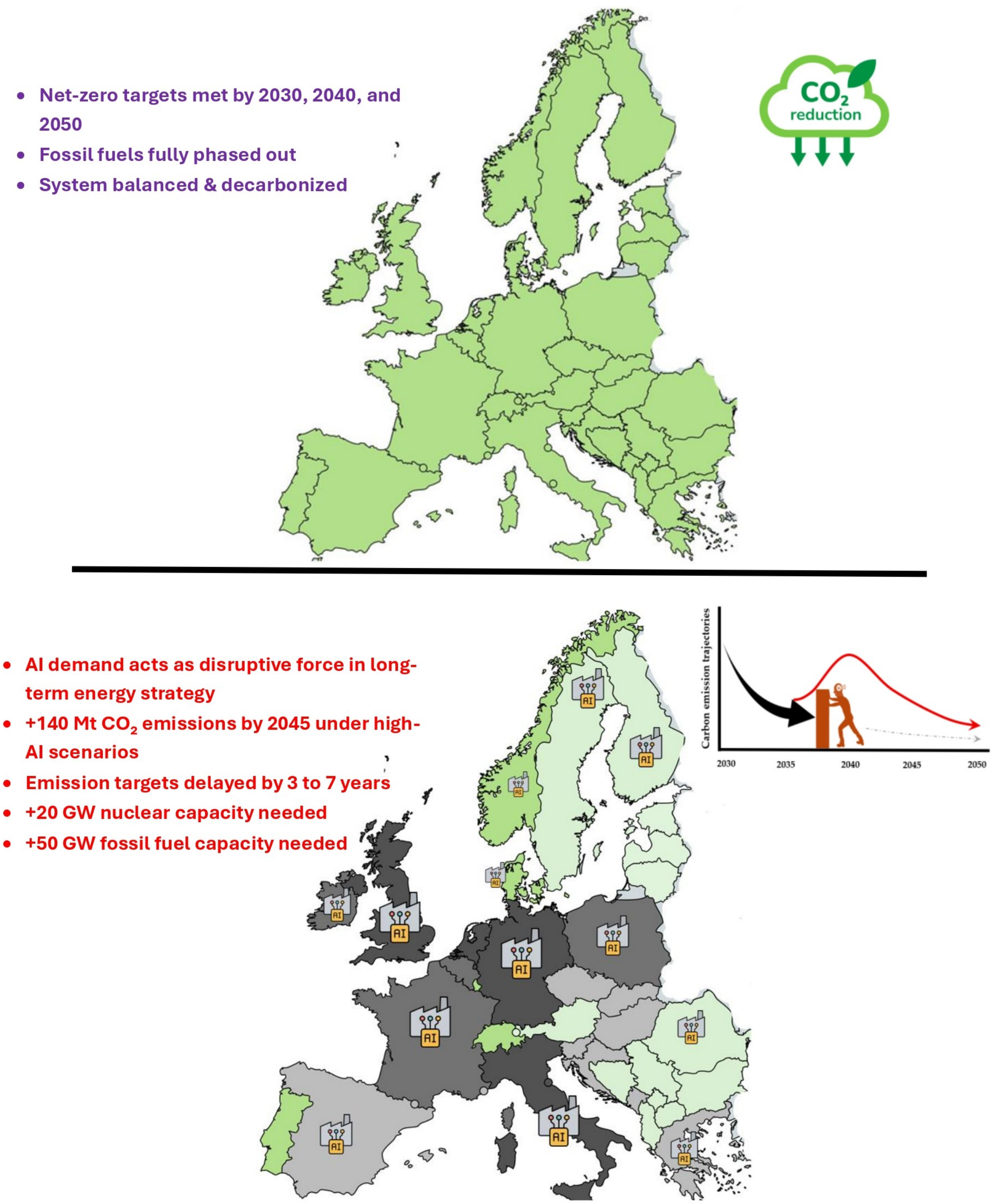

Figure 1: Problem description overview

1.1 AI-specific scenarios analysis

Although precise data on AI-based data centres' load profiles is limited, we have modelled four distinct scenarios with varying growth rates over different time periods. This approach allows us to comprehensively assess the impacts of diverse AI deployment trajectories on energy infrastructure and development plans. Existing estimates suggest that currently about 20% of total data centre electricity demand is related to AI workloads, but future growth trajectories remain uncertain. Figure 2 shows the current (2024) national data centre demand across Europe [18].

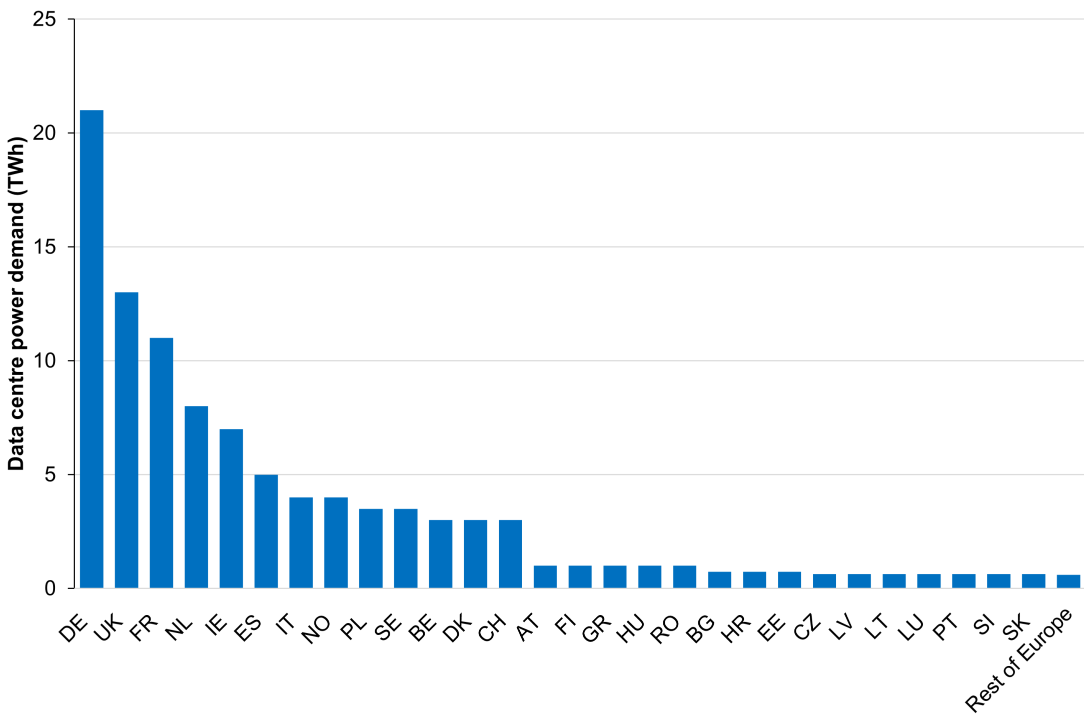

Figure 2: Current data centre electricity demand by country

Figure 3 spatially presents the AI demand profiles under these four scenarios for the years 2040 and 2050.

It is important to note that AI-related demand accounts for approximately 20% of total energy consumption in the IEA and ICIS scenarios, while this share rises to 35% and 50% in the McKinsey and Ambitious scenarios, respectively. On average, for the 10 countries with the highest AI energy consumption, the growth rates in the first five years are approximately 50% for the IEA scenario, 70% for ICIS, 130% for McKinsey, and 170% for Ambitious.

Overall, the IEA scenario follows a steady growth trajectory over time. In contrast, the ICIS scenario starts with moderate growth but experiences an explosive surge in the second five-year period, with growth rates nearly doubling compared to the first period. The McKinsey and Ambitious scenarios exhibit distinctly exponential growth patterns. Not only do they start with high growth rates in the initial five years, but this accelerated growth also intensifies during the 2040 to 2050, showing an even steeper increase. The four AI demand scenarios are developed, which vary in the number of AI factory sites, total electricity demand, growth rates, and commissioning timelines as given in Table 1.

Table 1: The characteristics of the AI demand scenarios

Attribute	IEA	ICIS	McKinsey	Ambitious
Total AI electricity demand (TWh, 2030)	242	354	1240	1500
Geographic concentration	Mostly Nordic, DE, ES, IT, and AT	Nordic, Central Europe, IE, UK	Europe-wide except Balkan	Europe-wide
Demand growth rate (2025–2030)	25%	60%	200%	250%

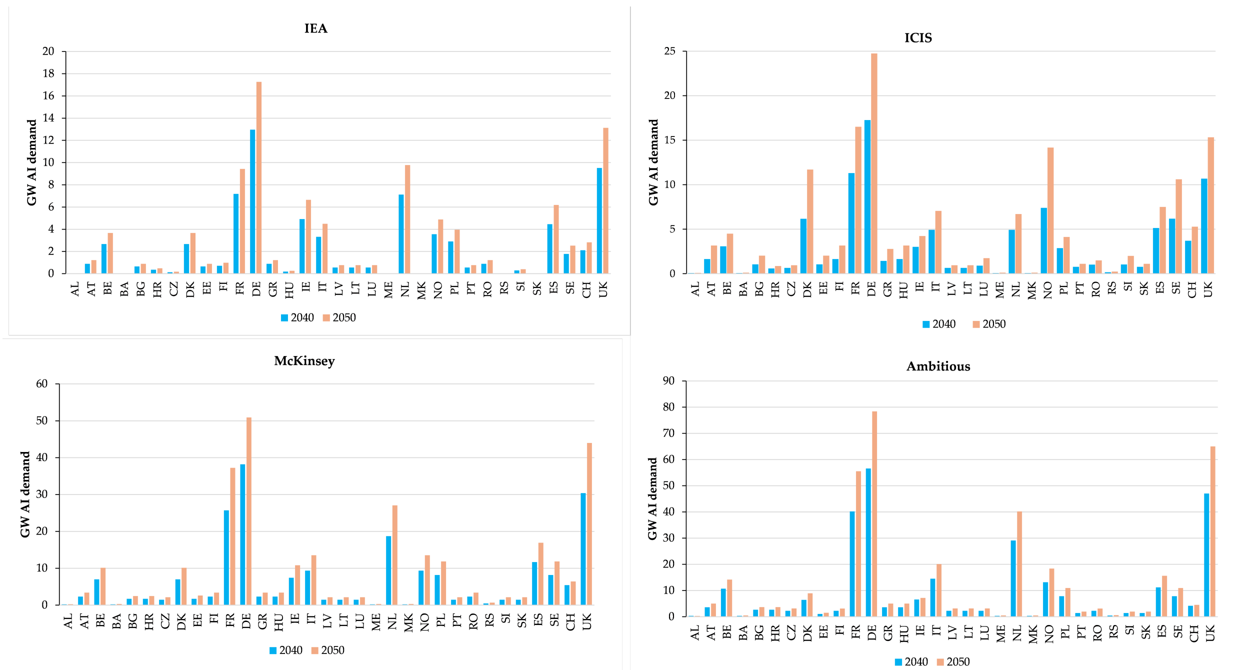

Figure 3: GW AI demand across all scenarios

2 Model overview and assumption

2.1 Input data

The classified input data—including techno-economic-environmental parameters of the technologies, demand profiles, carbon intensity factors, carbon reduction targets, and interconnections with neighbouring countries—can be accessed here: Input data.

The proposed optimization model is implemented in Pyomo 6.9.2 as an MILP formulation and solved using the Gurobi 12.0.1 solver. The complete model code is available here: Model code.

2.2 Optimization model and assumption

The proposed long-term expansion planning framework for Europe's future energy system is formulated as a spatially explicit MILP model. The objective is to minimize total system costs—including generation, storage, transmission, and emissions—while satisfying technical, spatial, and policy constraints. The model integrates the following key assumptions:

- The optimization operates at an annual resolution over a multi-decade horizon (2025–2050), with results computed for each year.

- Capacity expansion follows the Ambitious Scenario trajectory defined by ENTSO-E.
- Although ENTSO-E's Ten-Year Network Development Plan (TYNDP) provides targets only for milestone years (2035, 2040, 2050), linear interpolation is applied to estimate intermediate values for demand, carbon prices, fuel costs, and other time-dependent parameters.
- New generation capacity is added, subject to technology-specific build rate limits over five-year periods for each country.
- Given the absence of CCS technologies in current TYNDP scenarios, the model introduces CCGT-CCS and biomass-CCS units, with installation potential equivalent to their non-CCS counterparts, to explore enhanced decarbonization pathways.
- A uniform discount rate of 6% is applied throughout the planning horizon to account for the time value of investments.
- A system-wide reserve margin of 8% is enforced to ensure adequacy and system reliability across all countries and years.
- Battery storage (based on 33 ENTSO-E projects) and candidate transmission lines are activated based on their respective commissioning years.
- Battery storage technologies, including aggregated discharging potential from electric vehicles (EVs), are modelled as dispatchable generation units. It should be noted, EVs' charging demand is incorporated into the total load.
- The output allocation for variable renewable technologies—including solar, onshore wind, offshore wind, and battery discharge—is calculated using country-specific capacity factors. For all other generation technologies, a uniform capacity factor is applied across all countries.
- A clear distinction is made between existing and candidate transmission lines. Existing grid capacity is modelled as aggregated transfer capability without spatial distance (only central-to-central inter-country distances) or line-type differentiation due to a lack of data. However, Candidate transmission projects (aligned with 177 ENTSO-E-identified projects) are explicitly modelled based on line type (HVDC, HVAC, overhead, underground) and realistic distance.
- To explore the system's sensitivity to AI-driven demand growth, the model allows carbon emissions to temporarily exceed national targets by up to 20% in milestone years (2030, 2040, and 2050), enabling assessment of target deviation risks.
- The load factor of AI factories is assumed to be 1.0 across all scenarios, implying continuous operation throughout the year.

3 Problem formulation

In this section, the details of the proposed optimization framework, including the objective function and related constraints, are discussed

3.1 Objective function

The proposed Mixed-Integer Linear Programming (MILP) optimization framework aims to minimize the total system cost, as described in Eq. (1), includes generation investment cost (GIC), fuel cost (GFC), variable operation cost (GVC), fixed operation and maintenance cost ($GFOC$), transmission investment cost (TIC), carbon cost (CC), and the cost of load shedding ($VOLL$).

$$\min TC = GIC + GFC + GVC + GFOC + TIC + CC + VOLL \tag{1}$$

Each cost component in Eq. (1) is calculated as detailed in Eqs. (2)–(8). The generation investment cost, Eq. (2), includes the capital cost associated with new generation capacity, denoted as $PCap\_ne_{g,c,t}$, where $GICP_g$ refers to the capital expenditure required for capacity expansion. The fuel cost (Eq. 3) is computed based on the efficiency of each generation technology η_g, the fuel price $GFCP_{t,g}$ in each year t, and the electricity generation output $PG_{g,c,t}$ for each technology g, country c, and year t. The variable and fixed operation costs are calculated in Eqs. (4) and (5), respectively, where $GVCP_g$ and $GFOP_g$ represent variable and fixed operation costs, and $AY_{g,c,t}$ indicates the available or installed capacity of technology g in country c in year t. It should be mentioned that the fuel and variable operation costs are not applied to renewable technologies (solar, wind, and hydro). The carbon cost, Eq. (6), accounts for emissions within the system, where Cp_t represents the carbon price or tax applied to emitting technologies. The load shedding cost, or value of lost load ($VOLL$), is represented in Eq. (7), where $LShed_c$ indicates the curtailment price in country c, while $Dshed_{t,c}$ refers to the curtailed demand volume in year t and country c. Finally, the transmission investment cost is calculated in Eq. (8). The binary variable $Y_{l,c,c_1,id,t}$ identifies whether a candidate transmission line is active (1) or inactive (0), $Dist$ represents the geographical distance between interconnected countries, and $TICP_l$ is the cost coefficient of the corresponding line considering the transmission type. It is worth noting that this model distinguishes between different types of transmission infrastructure between neighbouring countries, based on 177 identified projects across Europe. Accordingly, multiple configurations may be considered between the same two neighbouring countries, including high-voltage AC, high-voltage DC, submarine cables, underground lines, and overhead lines, in line with realistic interconnection pathways.

$$GIC = \sum_{g\in G}\sum_{c\in C}\sum_{t\in T} dfc_t \cdot GICP_g \cdot PCap\_ne_{g,c,t} \tag{2}$$

$$GFC = \sum_{g\in G}\sum_{c\in C}\sum_{t\in T} dfo_t \cdot \left(\frac{PG_{g,c,t}}{\eta_g}\right) \cdot GFCP_{t,g} \tag{3}$$

$$GVC = \sum_{g\in G}\sum_{c\in C}\sum_{t\in T} dfo_t \cdot PG_{g,c,t} \cdot GVCP_g \tag{4}$$

$$GFOC = \sum_{g\in G}\sum_{c\in C}\sum_{t\in T} dfo_t \cdot AY_{g,c,t} \cdot GFOP_g \tag{5}$$

$$CC = \sum_{g\in G}\sum_{c\in C}\sum_{t\in T} dfo_t \cdot PG_{g,c,t} \cdot y_g^e \cdot Cp_t \tag{6}$$

$$VOLL = \sum_{c\in C}\sum_{t\in T} dfo_t \cdot LShed_c \cdot Dshed_{t,c} \tag{7}$$

$$TIC = \sum_{\substack{((l,c,c_1,id)\in NN \\ t\geq 1}} dfc_t \cdot PLmaxc_{l,c,c_1,id} \cdot TICP_l \cdot Dist_{l,c,c_1,id} \cdot (Y_{l,c,c_1,id,t} - Y_{l,c,c_1,id,t-1}) \tag{8}$$

3.2 Problem constraints

Generation output constraints for renewable and conventional units:

The annual electricity generation of each technology is constrained by its available generation potential, which is determined by the installed capacity and corresponding capacity factor (CF). In this formulation, a distinction is made between variable renewable energy sources—namely, onshore wind, offshore wind, and solar—as well as battery storage, whose generation availability is governed by $CFb_{c,g}$ values. These are typically region-specific and reflect temporal production patterns. The generation output for these technologies is calculated using Eq. (9) - the first part. For dispatchable technologies, generation output is further bounded by both minimum and maximum operating limits. These operational constraints are represented by PG^{min} and PG^{max}, and are enforced through Eq. (9) - the second part, and Eq. (10), ensuring that generation remains within feasible technical ranges for each unit in each country c and time period t.

$$PG_{g,c,t} = \begin{cases} AY_{g,c,t} \cdot CFb_{c,g} \cdot 8760, & \text{if } g \in \{\text{Battery, Solar, Wind Onshore, Wind Offshore}\} \\ \leq AY_{g,c,t} \cdot PG^{max} \cdot CF_g \cdot 8760, & \text{otherwise} \end{cases} \tag{9}$$

$$PG_{g,c,t} \geq AY_{g,c,t} \cdot PG^{min} \cdot CF_g \cdot 8760 \quad : \forall \ g \in G, \ \ c \in C, \quad and \ \ t \in T \tag{10}$$

Capacity expansion constraints:

The available installed capacity of each generation technology in a given year is determined by accounting for three components: the initial capacity at the base year,t_0, newly commissioned capacity investments, and decommissioned (retired) units in that same year. This dynamic capacity balance is formalized in Eq. (11), ensuring that the model accurately tracks the evolution of the technology fleet over time, in line with both investment decisions and lifetime assumptions.

$$AY_{g,c,t} = \begin{cases} Pcap\_T_{1,g,c}, & \text{if } t = t_0 \\ AY_{g,c,t-1} + PCap^{ne}_{g,c,t-Tp_g} - PCap\_re_{g,c,t}, & \text{if } t > t_0 \end{cases} \tag{11}$$

The total installed capacity of each technology in a given country and year must not exceed the predefined maximum allowable potential, which reflects technical, regulatory, and spatial limitations. This system-level constraint is enforced via Eq. (12), ensuring that modelled capacity expansion remains within realistic deployment limits for each region and planning horizon. In addition, renewable energy technologies—including onshore wind, offshore wind, and solar —are subject to land availability constraints. These limitations capture geospatial suitability and land-use competition, and are implemented through Eq. (13), which restricts the cumulative installed capacity of land-intensive renewables based on country-level land availability assessments.

$$AY_{g,c,t} \leq Pcap\_T_{t,g,c} \quad : \forall \ g \in G, \ \ c \in C, \quad and \ \ t \in T \tag{12}$$

$$AY_{g,c,t} \leq PLand_{g,c} \quad \text{for } g \in \{\text{Solar, Wind Onshore, Wind Offshore}\} \quad : \forall \ g \in G, \ \ c \in C, \quad and \ \ t \in T \tag{13}$$

The annual commissioning of new capacity for each technology g in country c and year t is constrained by technology-specific build rate limits, defined over rolling five-year planning intervals. This constraint, represented by Eq. (14). Furthermore, system-wide installed capacity must satisfy adequacy requirements by meeting the planning reserve margin. This is modelled through Eq. (15), which incorporates a technology-specific de-rating factor de_g and a predefined reserve margin Res, ensuring that the system maintains sufficient firm capacity to meet peak demand.

$$PCap^{ne}_{g,c,t} \leq BR_{g,c,t} \cdot \Delta t \quad : \forall \ g \in G, \ \ c \in C, \quad and \ \ t \in T \tag{14}$$

$$\sum_{g,c} AY_{g,c,t} \cdot de_g \geq (1 + Res) \cdot DPeak_t \quad : \forall \ g \in G, \ \ c \in C, \quad and \ \ t \in T \tag{15}$$

Carbon emission constraints:

Carbon emissions in each country c and target year t are calculated according to Eq. (16), where y^e_g represents the effective carbon intensity of generation technologies, adjusted for their efficiency and carbon capture capabilities. The total emissions in each year must remain within the national carbon targets, as enforced by Eq. (17). To assess the impact of AI-driven electricity demand under different scenarios, the model permits an emissions overshoot of up to 20 percent above the official targets for the milestone years

2030, 2040, and 2050. This design allows for sensitivity analysis on the extent to which emerging loads may compromise decarbonization pathways.

$$em_{t,c} = \sum_{g \in G} PG_{g,c,t} \cdot y_g^e \quad : \forall \ t \in T \ and \ c \in C, \tag{16}$$

$$em_{t,c} \leq CTarget_{t,c} \quad : \forall \ t \in T \ and \ c \in C, \tag{17}$$

Load shedding constraint:

The amount of curtailed load in each country and year is restricted by a predefined maximum curtailment threshold as given by Eq. (18), ensuring that the system does not rely excessively on involuntary load shedding to maintain feasibility.

$$Dshed_{t,c} \leq LShed_c \quad : \forall \ t \in T \ and \ c \in C \tag{18}$$

Power Balance Constraint

The energy balance for each country c and year t is governed by Eq. (19), which ensures that the total available electricity supply is equal to total demand and system outflows, accounting for all major system losses. On the supply side, this includes the aggregated generation from all technologies in country c, adjusted for distribution-level generation losses PLg_g, as well as electricity imports from neighbouring countries via existing and candidate cross-border transmission lines. Transmission losses are explicitly modelled for both existing lines TLe and candidate lines TL_l, reflecting the physical inefficiencies associated with long-distance power transfer. On the demand side, the constraint incorporates total electricity consumption—comprising conventional demand and AI-specific loads—as well as exported electricity and any unserved energy (curtailment). This formulation ensures that all energy flows are accounted for within a loss-adjusted system-wide balance.

$$\begin{aligned}
&\left(\sum_{g \in G} PG_{g,c,t} \cdot (1 - PLg_g) + \sum_{\substack{c_1 \in C \\ (c_1,c) \in NE}} PLe_{c_1,c,t} \cdot (1 - TL_e) \cdot Dist_{c,c1} + \sum_{\substack{c_1 \in C \\ (l,c_1,c,id) \in NN}} PL_{l,c_1,c,id,t} \cdot (1 - TL_l \cdot Dist_{l,c_1,c,id}) \right) \\
&= \left(\sum_{\substack{c_1 \in C \\ (c,c_1) \in NE}} PLe_{c,c_1,t} \cdot (1 - TL_e) \cdot Dist_{c,c1} + \sum_{\substack{c_1 \in C \\ (l,c,c_1,id) \in NN}} PL_{l,c,c_1,id,t} \cdot (1 - TL_l \cdot Dist_{l,c,c_1,id}) \right. \\
&\qquad \left. + Dem_{t,c} + DemAI_{t,c} - Dshed_{t,c} \right)
\end{aligned} \tag{19}$$

Transmission and power flow constraints:

To incorporate transmission investment costs into the model, a distinction is made between existing transmission infrastructure and candidate expansion lines, consistent with real-world interconnection projects. Transmission capacity is therefore categorized as either existing or candidate. A binary decision variable Y is used to represent the operational status of each candidate line: once a line is commissioned (as determined by its assigned commissioning year $TCom$), its status remains active ($Y_{l,c,c_1,id,t-1}$) for all subsequent years. This temporal investment constraint is modelled in Eq. (20).

The total net electricity flow over both existing and candidate transmission lines must remain within their respective technical transfer limits. Specifically, Eq. (21) and Eq. (22) constrain the power flow based on the thermal line rating L_r, ensuring that actual flows do not exceed the maximum energy exchange capacity of the transmission corridors. Finally, Eqs. (23) and (24) enforce non-negativity of power flows in both directions, maintaining feasibility and consistency in network operations.

$$PLe_{c,c_1,t} \leq PLmaxe_{c,c_1} \cdot 8760 \cdot L_r \quad : \forall \ (c, c_1) \in NE \tag{20}$$

$$PL_{l,c,c_1,id,t} \leq PLmaxc_{l,c,c_1,id} \cdot 8760 \cdot Y_{l,c,c_1,id,t} \cdot L_r \quad : \forall \ (l, c, c_1, id) \in NN \tag{21}$$

$$PL_{l,c,c_1,id,t} \geq 0 \quad : \forall \ (l, c, c_1, id) \in NN \tag{22}$$

$$PLe_{c,c_1,t} \geq 0 \ : \forall \ (c, c_1) \in NE \tag{23}$$

$$Y_{l,c,c_1,id,t-1} \leq Y_{l,c,c_1,id,t} \ : \forall \ (l, c, c_1, id) \in NN, \quad \text{If} \quad t > TCom_{l,c,c_1,id} \tag{24}$$

4 Extended results

This section presents additional results and extended analyses supporting the findings reported in the main text.

4.1 Analysing the existing energy system development plans

To provide a planning-consistent baseline, we model the evolution of the European electrical system using the ENTSO-E TYNDP Global Ambition scenario [20]. This scenario represents a high-deployment of renewables, a policy-driven pathway in line with EU decarbonization objectives, and it serves as a reference instance in which no AI-specific demand will arise. It offers a formal platform for identifying and assessing the extra implications of AI factories. Key assumptions on electricity demand, generation mix, and decarbonization targets for the European power system in 2040 and 2050, based on the TYNDP Ambition scenario, are summarized in Table 2.

Table 2: Key Assumptions on Demand, Energy Mix, and Decarbonization Milestones Based on TYNDP (2040–2050)

Indicator	**2040**	**2050**
Total demand (TWh)	6950	8700
Emission (million-ton CO_2)	426	0
Cross-border interconnection capacity (GW)	188	—
Total energy produced (TWh)	7150	9000
Installed Capacity (GW)		
Solar	1340	1772
Wind Onshore	671	857
Wind Offshore	390	528
Hydro	235	236
Nuclear	129	121
CCGT	148	118
H_2 CCGT	46	67
Biomass	14	14
Geothermal	1	1
Biofuel	2	2
Oil	0	0
Coal	0	0
Waste	0	0

Our result on the baseline scenario (without AI) showed that total installed capacity will reach around 4,177 GW by 2050, a difference of 3.5% from TYNDP forecasts. The simulated energy mix replicates major structural transitions found in the TYNDP scenario, such as the total elimination of coal and oil-fired generation. By 2050, the combined installed capacity of solar and wind technologies will reach 3,128 GW. This high level of congruence strengthens the model and provides a solid platform for comparison analysis in AI-driven scenarios.

To provide an overview of additional capacity requirements across AI scenarios, we present total installed capacity for three key milestones—2030, 2040, and 2050—compared to the baseline, as summarized in Table 3. Further details are discussed below.

Table 3: Total installed capacity across all studied scenarios in 2030, 2040 and 2050

	Without AI	IEA	ICIS	McKinsey	Ambitious
2030	1893	1027	2126	2476	2603
2040	3285	3326	3708	4199	4552
2050	4177	4227	4806	5282	5760

4.2 Spatial analysis of installed capacity for baseline scenario

Figure 4 depicts a spatial overview of Europe's installed generation capacity in 2050, highlighting the major technologies in each country. Both the size and composition of national energy portfolios are illustrated in this figure, revealing distinct geographical patterns—such as the dominance of wind power in Northern Europe, the prevalence of solar energy in Southern countries, and a more diversified mix in Central Europe, and the concentration of nuclear generation in France (50 GW), the UK (16 GW), Poland (14 GW), and Sweden and Finland (11 GW each). The CCGT capacity is prominent in Italy (38 GW), while the CCGTCCS in the UK (6 GW). Meanwhile, H2CCGT is positioned as a key flexible technology in the future energy mix of central European countries, with the largest installations projected in Germany (33 GW), the Netherlands (15 GW), and France (7 GW). Moderate additions are also anticipated in Austria and Belgium (3 GW each), as well as in Poland and Ireland (2 GW each).

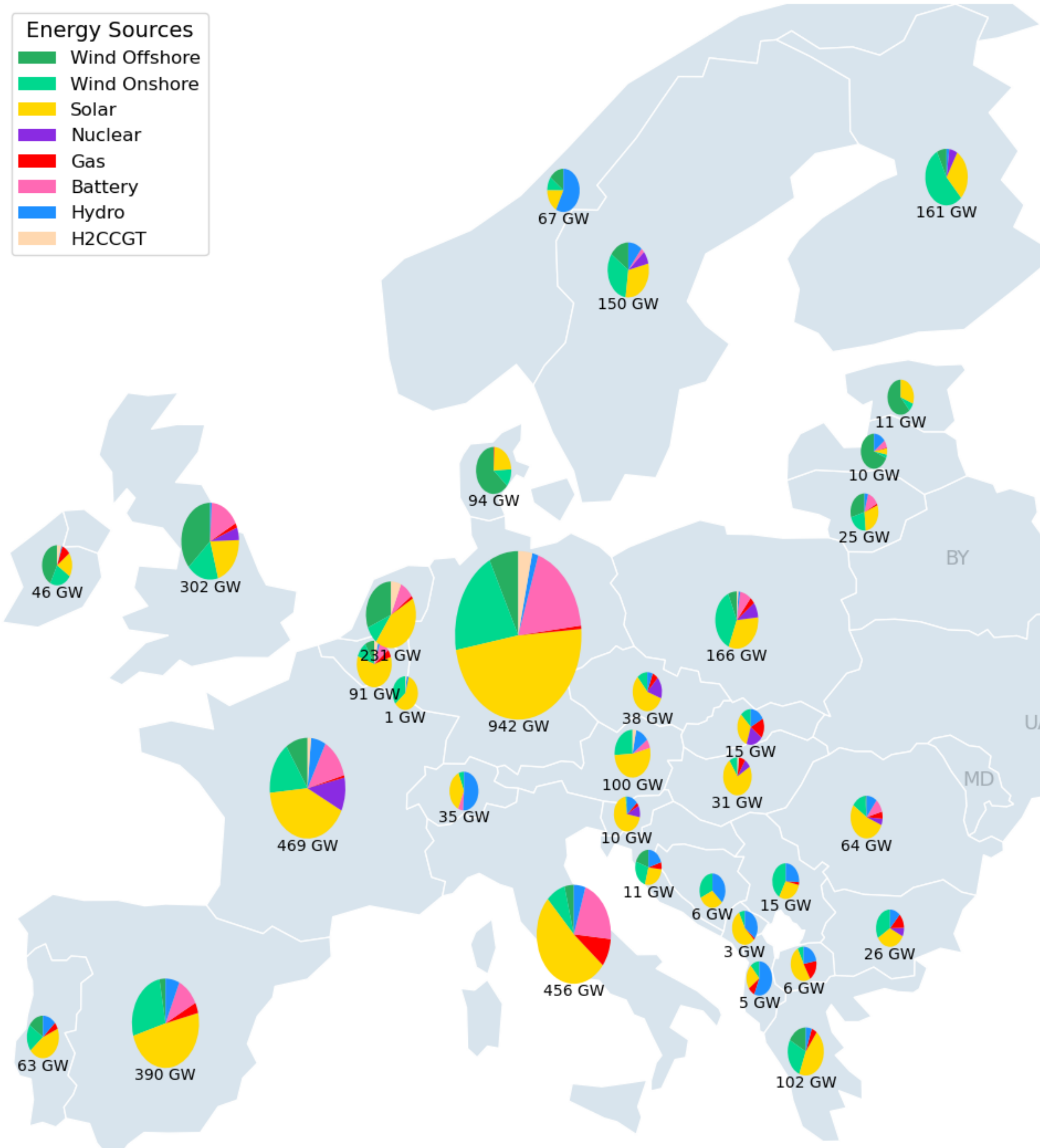

Figure 4: Spatial overview of installed capacity by dominant technology in the baseline scenario for 2050

4.3 Trajectories of installed power capacity by technology across AI scenarios

show the evolution of installed capacity and the spatial distribution of energy technologies in Europe under the four AI demand scenarios between 2025 to 2050.

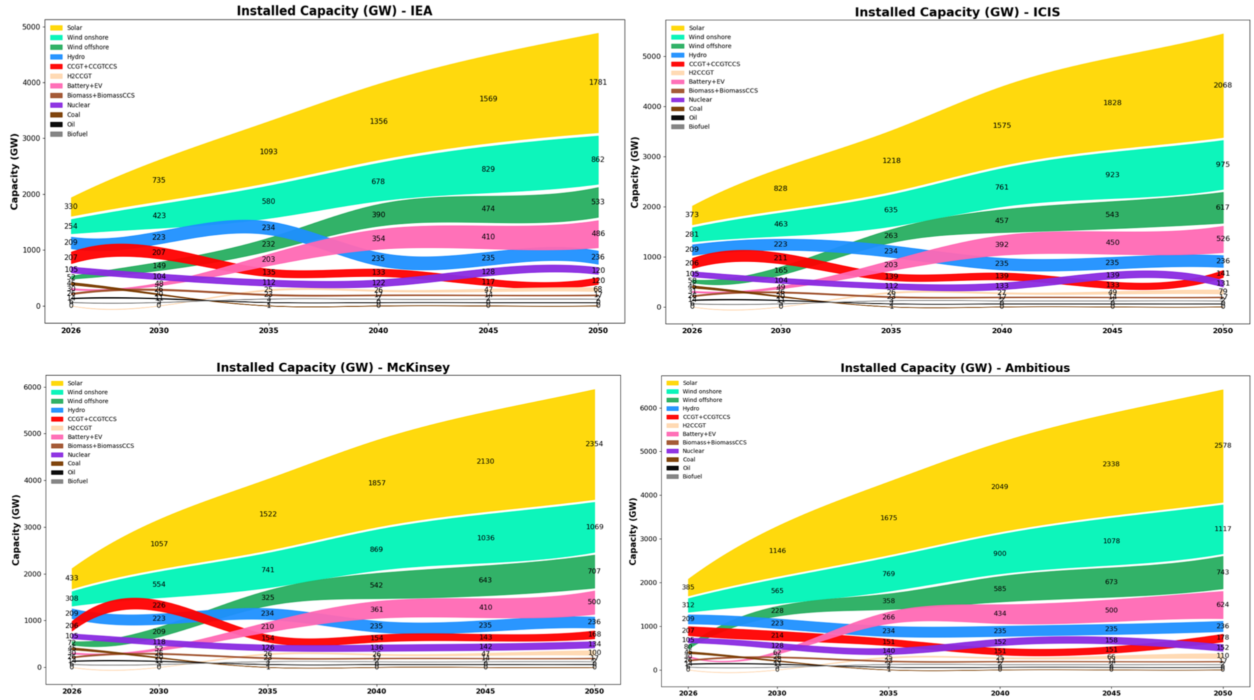

Figure 5: Projected installed power capacity by technology for AI scenarios, 2025–2050

4.4 Analysis of installation rate changes under AI-driven electricity demand

AI-driven demand significantly impacts generation expansion and delays the retirement of fossil-based technologies, as illustrated by changes in installed capacity over five-year intervals in Figure 6. Established forecasts (TYNDP, Ember, ACER) predict the fastest capacity growth between 2035 and 2040 [11, 18, 21], driven by H2CCGT deployment, consistent with the IEA and ICIS scenarios. However, the McKinsey and Ambitious scenarios show a much sharper increase, adding 300 GW and 400 GW respectively within five years—substantially exceeding earlier projections. Unlike the more moderate scenarios, minor but persistent oil and coal capacities remain beyond 2035 under high AI demand, indicating a delayed phase-out due to system stress. Additionally, gas capacity rises unexpectedly from 2035 to 2050, diverging from typical net-zero pathways.

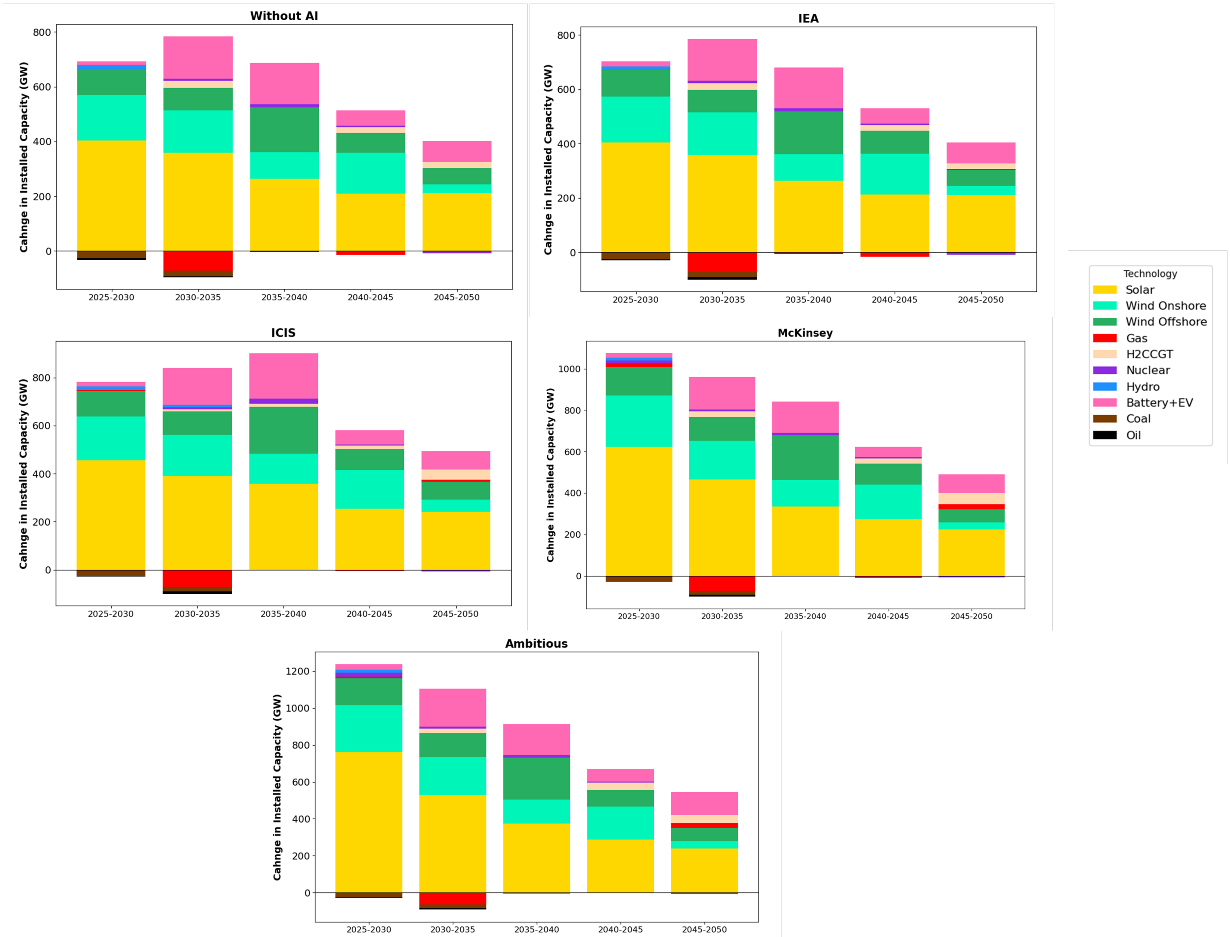

Figure 6: Comparison of installation rate trends across all scenarios, shown in 5-year intervals

4.5 Cross-Border electricity exchange

Figure 7 illustrates the annual power exchange volumes for each country across all AI scenarios. As observed, Germany and the UK consistently act as net importers. Notably, countries with a higher ratio of AI load to local demand—such as Sweden, the Netherlands, Belgium, Norway, and Denmark—exhibit significant fluctuations in import and export levels.

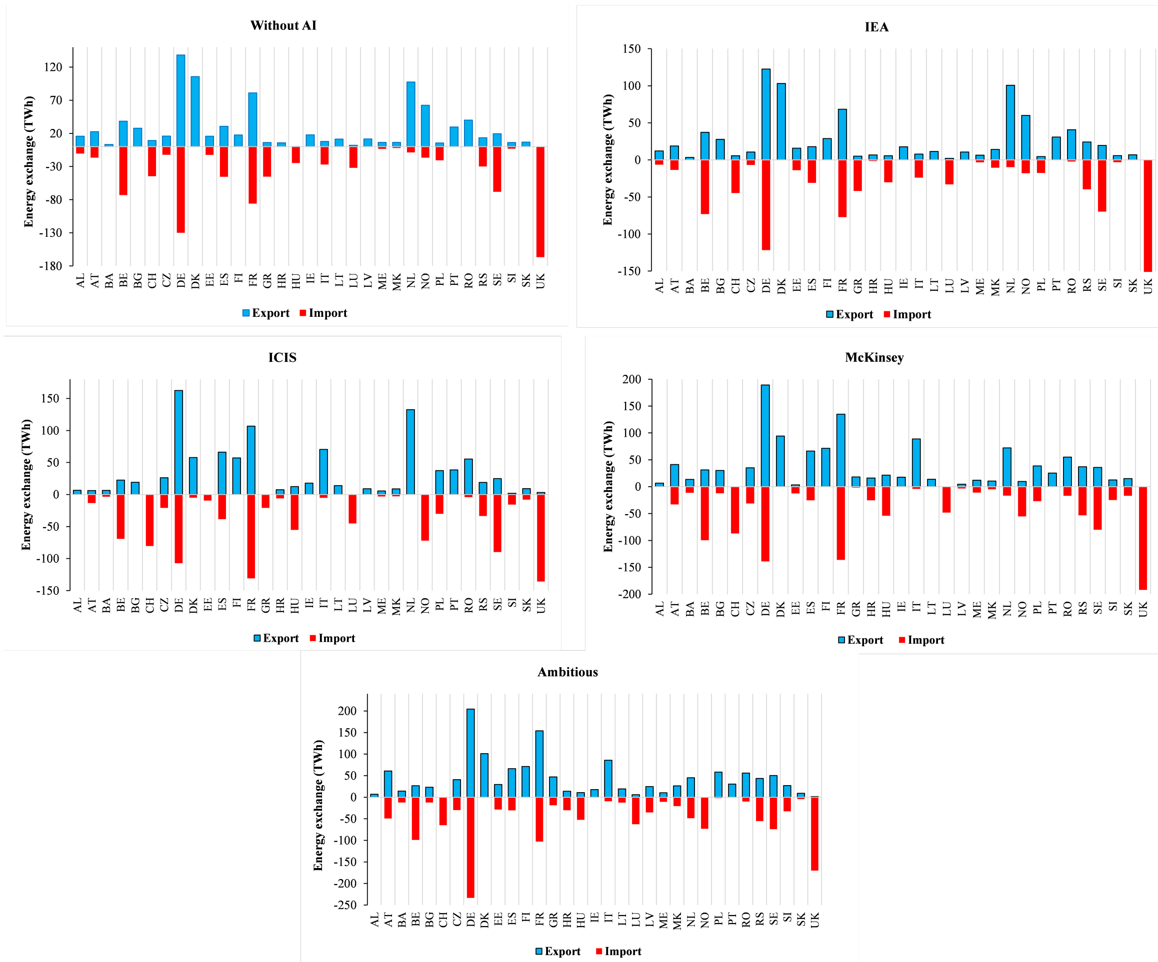

Figure 7: Energy exchange (import, export) per country across all studied scenarios

The electricity import-export heat-map for 2050 is given in Figure 8, which further illustrates Germany's dual role as a net importer and exporter, understanding its central importance role in Europe's transmission network. By 2050, the UK is projected to become a consistent net importer, with import volumes intensifying alongside rising AI demand. Denmark remains a net exporter, while under high AI growth scenarios, the Netherlands and Norway shift to net importers despite traditionally exporting power. Notably, Italy, which typically imports electricity from Greece, reverses this pattern under the McKinsey and Ambitious scenarios—exporting power to Greece, France, and Switzerland due to its relatively lower AI demand per domestic load.

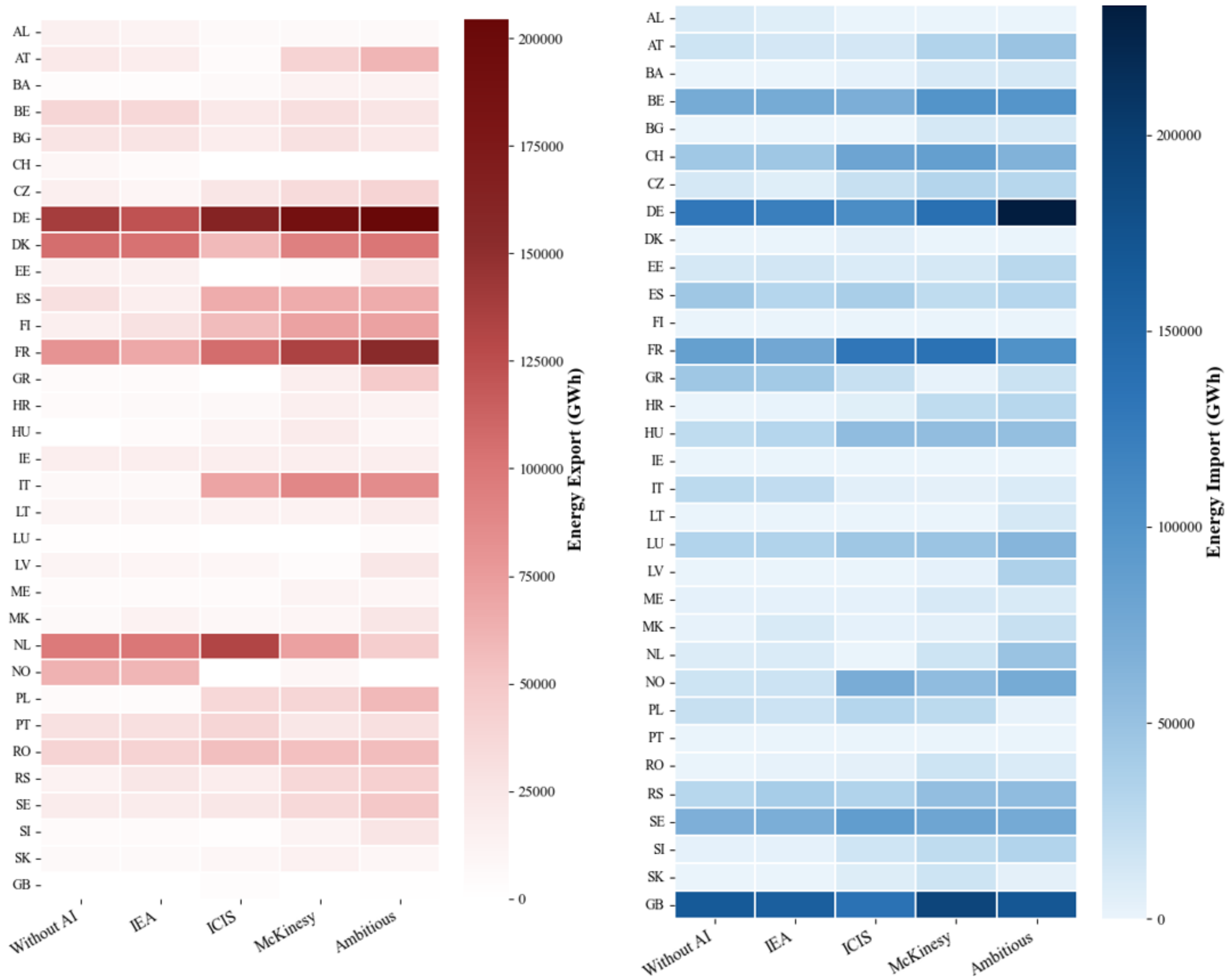

Figure 8: Change in energy imports and exports across all AI scenarios by 2050

4.6 Carbon intensity of electricity

This section provides a detailed analysis of the carbon intensity of electricity for selected countries, including Italy, Ireland, Germany, the UK, and Belgium, under all AI demand scenarios. Carbon intensity (CI) of electricity measures the amount of CO2 emissions produced per unit of electricity generated, typically expressed in grams of CO2 per kilowatt-hour (gCO2/kWh). Formally, it can be defined as:

$$CI_t = \frac{\sum_i E_{i,t}}{\sum_i G_{i,t}} \tag{25}$$

where $E_{i,t}$ is the CO2 emission from technology i and time t, and $G_{i,t}$ is the electricity generation by technology i at the time t.

Figure 9 provides country-specific CI trajectories for Italy, Germany, the UK, and Ireland, illustrating year-by-year variations and the divergence between scenarios, enabling a comprehensive assessment of AI-driven impacts on electricity decarbonization pathways. The results shown in this figure clearly demonstrate the impact of AI-driven demand on net-zero carbon targets, both at the country level and across Europe as a whole. Significant gaps emerge between projected pathways and actual outcomes under high AI demand, indicating that without dedicated sustainable strategies, Europe may struggle to achieve its net-zero targets in the presence of rapidly expanding AI factory loads.

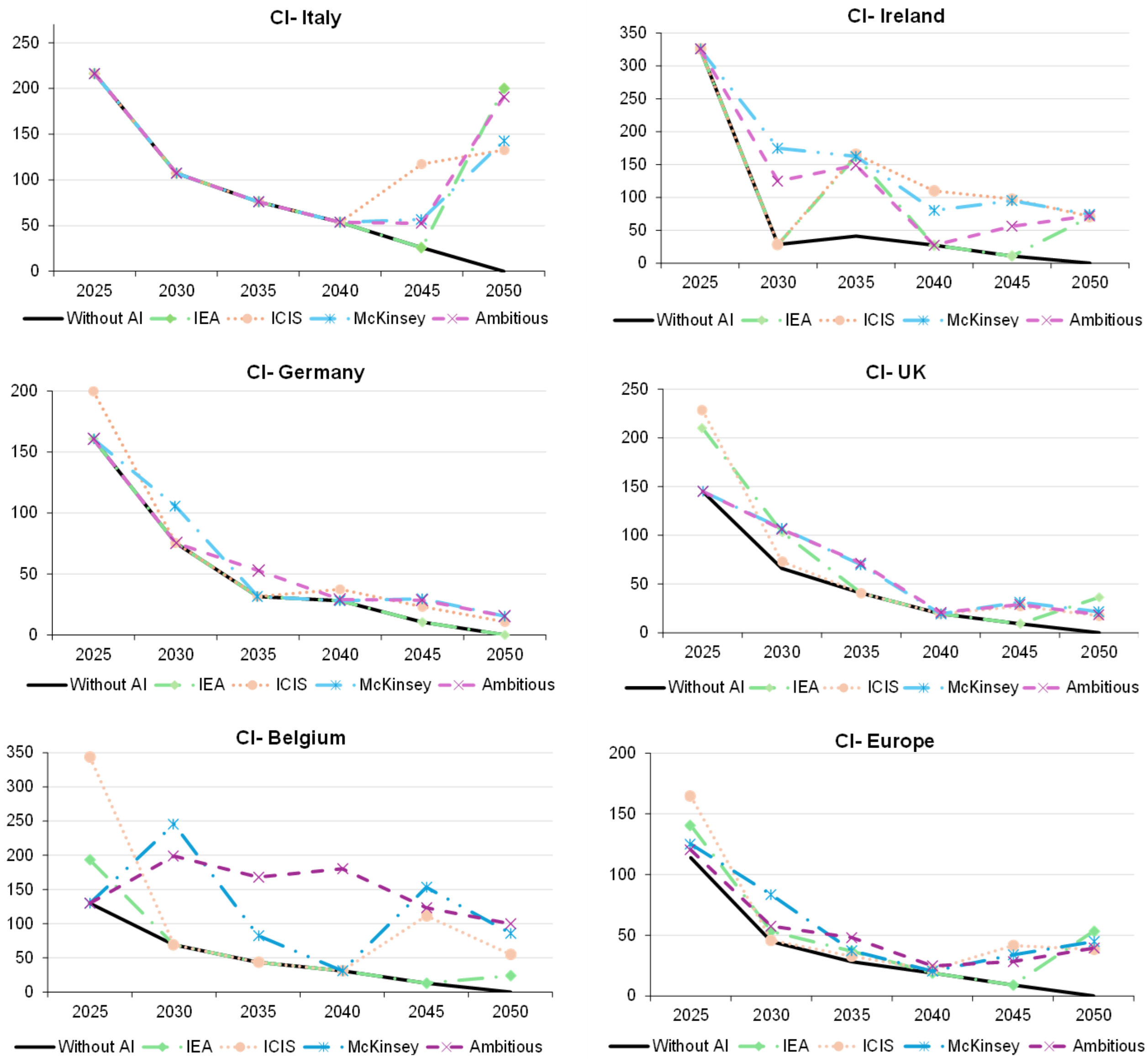

Figure 9: Carbon intensity of electricity generation (gr CO2/ kWh) for selected countries between 2024 to 2050

4.7 Economic analysis and cost breakdown

From an economic perspective, AI-driven demand has a significant impact on both capital investment and operational costs. As shown in Table 4, Europe's power system will require additional investments ranging from over €57 million to €1.6 billion (2–37% growth) to meet AI-driven demand, with the majority attributed to generation capital costs and fuel expenses.

Table 4: Cost Breakdown for All Studied Scenarios (billion Euro)

Cost Category	Without AI	IEA	ICIS	McKinsey	Ambitious
Generation CAPEX	2509	2661	2963	3490	3829
Fuel Cost	866	870	887	923	945
Fixed Operation Cost	727	735	782	859	899
Variable Operation Cost	60	60.5	61.3	64.3	68
Transmission Investment Cost	6.36	6	6	6.68	6.12
Load Shedding	0	0	0	0	27
Carbon Cost	308	310	323	348	354
Total	**4480**	**4537**	**5020**	**5686**	**6116**

The rise in AI-driven demand also affects the levelized cost of electricity (LCOE and the overall cost of power generation across the studied countries. To illustrate this, the LCOE in 2050 for five scenarios has been compared across twelve countries with high AI demand in Figure 10.

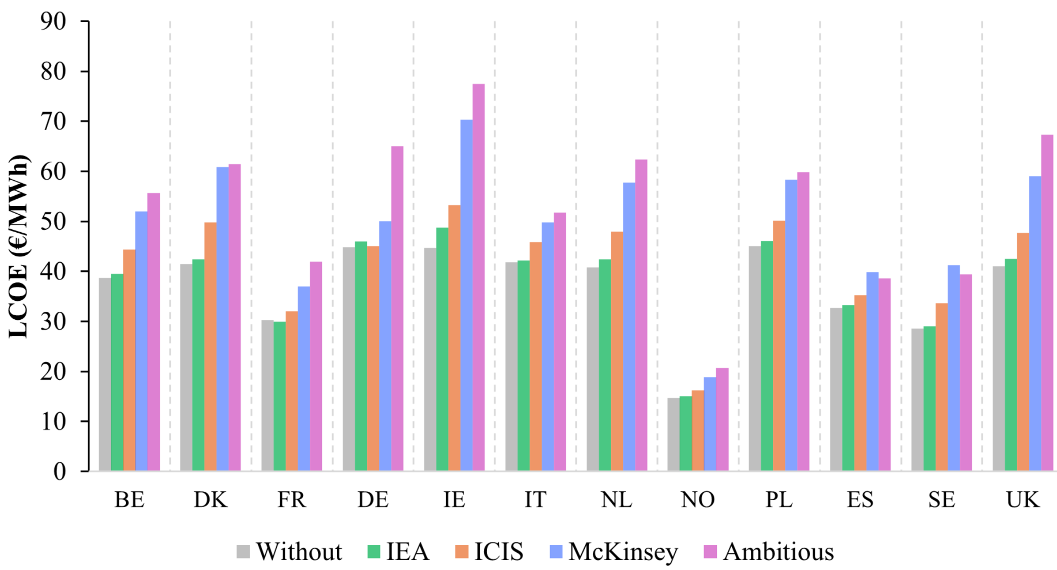

Figure 10: Evolution of LCOE under different scenarios for twelve countries with high AI demand

Table 5 summarizes the LCOE costs for the year 2050 across countries under the baseline (no AI) scenario and the four AI scenarios.

Table 5: LCOE in €/MWh per country and scenario by 2050

Country	Without	IEA	ICIS	McKinsey	Ambitious
AL	23.36	23.46	24.68	26.33	28.54
AT	26.97	27.15	28.6	31.42	33.16
BE	38.66	39.58	44.37	51.93	55.62
BA	22.85	22.88	25.38	28.49	28.47
BG	29.84	30.52	32.9	33.77	34.97
HR	32.58	32.99	35.18	40.76	43.77
CZ	35.78	35.69	37.5	41.32	46.01
DK	41.45	42.45	49.77	60.86	61.4
EE	45.03	45.05	51.5	60.6	131.25
FI	36.43	37.17	40.7	44.81	45
FR	26.29	26.7	28.86	37	43.79
DE	45.28	45.96	50.87	57.61	61.3
GR	40.77	41.7	45.83	52.44	56.27
HU	36.45	35.94	39.18	47	48.49
IE	44.68	48.71	53.21	70.35	67.52
IT	41.84	42.17	45.81	49.83	51.73
LV	38.63	38.78	41.28	44.35	43.63
LT	38.75	38.79	43.76	50.95	51.74
LU	46	46.36	48.21	52.11	54.38
ME	33.45	33.25	35.16	40.76	43.25
NL	40.84	42.4	47.89	57.75	62.36
MK	43.28	42.98	44.85	46.61	48.7
NO	14.75	15.03	16.26	18.91	20.67
PL	45.06	46.11	50.10	58.3	59.79
PT	35.14	35.46	36.64	37.21	37.39
RO	35.08	34.35	37.38	40.77	42.58
RS	40.23	39.77	42.96	44.69	46.86
SI	27.94	29.26	31.08	35.56	47.71
SK	36.49	36.56	37.49	39.35	40.52
ES	32.75	33.24	35.21	39.84	38.57
SE	28.52	28.98	33.69	41.27	39.42
CH	20.5	20.58	21.42	22.95	23.97
UK	41.05	42.48	47.7	59.02	67.31

4.8 Sensitivity analysis on the carbon target

We further develop a sensitivity analysis on the carbon target, focusing on its impact on installed capacity and total costs. Specifically, the analysis aims to assess how partial relaxations or stricter limitations of the carbon target in future years influence the trajectory of installed capacity and total costs under AI-driven demand, Figure 11. Our findings illustrate that increasing the emissions target by up to 20-30% results in a reduction of total costs and installed capacity by approximately 7% in the McKinsey and Ambitious scenarios. In contrast, under the IEA and ICIS scenarios, this reduction is below 4%. Conversely, if much stricter emissions targets are pursued (i.e., 10% lower than the forecasted target), the Ambitious and McKinsey scenarios experience increases in installed capacity and total costs by approximately 12% and 10%, respectively. This highlights the influence of carbon targets on the energy system development planning in Europe.

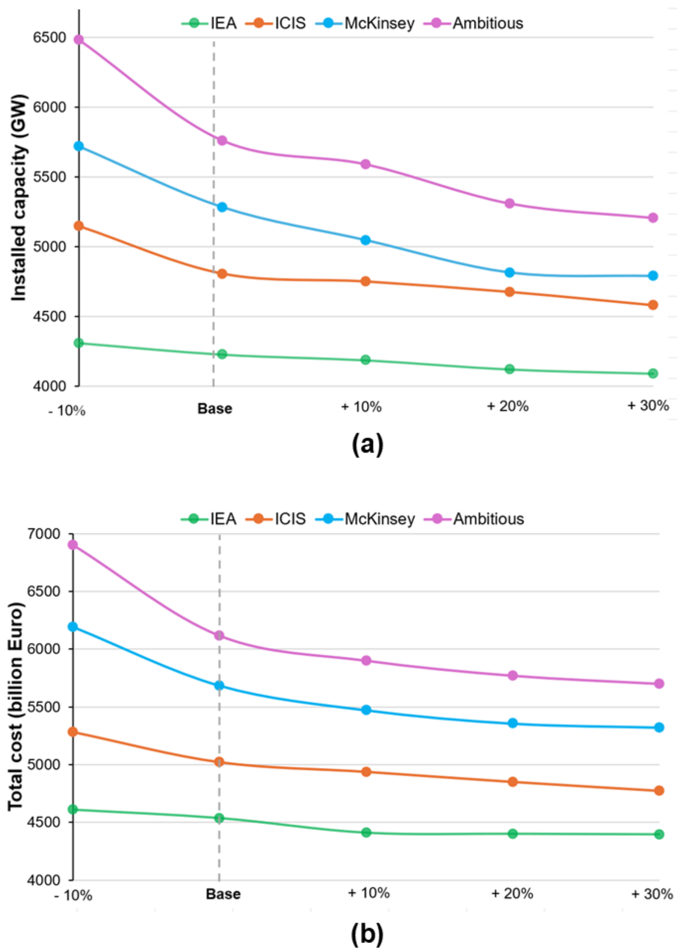

Figure 11: Sensitivity analysis of carbon target variations on (a) installed capacity and (b) total costs across different scenarios under AI-driven demand

5 Conclusion and future works

AI-driven digital expansion is rapidly adding unaccounted electricity demand to Europe's power system. While existing energy roadmaps pursue net-zero emissions through various decarbonization pathways, they largely fail to consider the spatial and temporal footprint of large-scale AI facilities. In this study, a spatially explicit optimization model is developed to assess how AI may reshape energy infrastructure investment, emissions trajectories, and electricity prices. In this study, a spatially explicit optimization model is developed to assess how AI-induced demand may reshape long-term generation and transmission pathways, emissions trajectories, and infrastructure investments across EU. The model is formulated as a mixed-integer linear programming (MILP) problem that minimizes total system costs under spatial and technological constraints. We explore four AI demand growth scenarios, including IEA, ICIS, McKinsey, and Ambitious. Findings highlight the urgency of integrating AI infrastructure trends into long-term energy planning, emissions policy, and spatial governance. With gas capacity projected to rise across all AI scenarios—especially in the final decade of the planning horizon to meet surging AI-driven electricity demand—Europe risks undermining its carbon-neutral goals unless policies adapt to its accelerating digital transformation.

While this study applies an annual resolution for system-level analysis, future research could enhance temporal granularity to capture intra-day dynamics. Incorporating hourly resolution would enable more accurate assessment of short-term balancing needs and the role of flexibility measures such as battery storage, demand-side response, and sector coupling. Moreover, integrating detailed operational modelling of AI data centres, including cooling requirements, temporal variability in computing load, and potential on-site generation, would significantly improve the representation of their impact on the energy system, which remains as future work.

Appendix 1: List of country codes

AL : Albania

AT : Austria

BE : Belgium

BA : Bosnia and Herzegovina

BG : Bulgaria

HR : Croatia

CZ : Czech Republic

DK : Denmark

EE : Estonia

FI : Finland

FR : France

DE : Germany

GR : Greece

HU : Hungary

IE : Ireland

IT : Italy

LV : Latvia

LT : Lithuania

LU : Luxembourg

ME : Montenegro

NL : Netherlands

MK : North Macedonia

NO : Norway

PL : Poland

PT : Portugal

RO : Romania

RS : Serbia

SI : Slovenia

SK : Slovakia

ES : Spain

SE : Sweden

CH : Switzerland

UK : United Kingdom

Appendix 2:Nomenclature

Indices

c, c_1 **:** Index for country

g **:** Index for generation technology

id **:** Index candidate transmission projects between country pairs where more than one project exists

l **:** Index for transmission type

t **:** Index for time period (year)

Sets

C **:** Set of regions or nodes

G **:** Set of generation technologies

L **:** Set of transmission types

NE **:** Set of existing transmission links between c and c_1, where $(c, c_1) \in NE$

NN **:** Set of candidate transmission projects for transmission type l, between countries c and c_1 with identifier id, where $(l, c, c_1, id) \in NN$

T **:** Set of time periods

Parameters

$BR_{g,c,t}$ **:** Building rate of technology g in country c at year t

CF_g **:** Capacity factor for generator except renewable and battery storage g

$CFb_{c,g}$ **:** Capacity factor for battery/renewable generator g in country c

Cp_t **:** Carbon price in year t

$CTarget_{t,c}$ **:** Carbon emission target for country c at year$t$

de_g **:** De-rating factor for generator g

$Dem_{t,c}$ **:** Domestic demand in country c at year t

$DemAI_{t,c}$ **:** AI demand in country c at year t

$DPeak_t$ **:** Peak demand in year t

dfc_t **:** Discount factor for capital costs in year t

dfo_t **:** Discount factor for operational costs in year t

$Dist_{l,c,c_1,id}$ **:** Distance of candidate transmission line (l, c, c_1, id)

η_g **:** Efficiency of generator g

$GICP_g$ **:** Investment cost per unit capacity for generator g

$GFCP_{t,g}$ **:** Fuel cost per unit energy for generator g in year t

$GFOP_g$ **:** Fixed O&M cost per unit capacity for generator g

$GVCP_g$ **:** Variable cost per unit energy for generator g

$LShed_c$ **:** Maximum allowable load shedding in country c

L_r **:** Thermal Line rating factor

$PcapT_{t,g,c}$ **:** Maximum planned capacity for generator g in country$c$ at year t

PLg_g **:** Distribution loss factor for generation technology g

PG_g^{max} **:** Maximum capacity of generator g

PG_g^{min} **:** Minimum capacity of generator g

$PLand_{g,c}$ **:** Land-based capacity limit for renewable generator g in country c

PLe_{c,c_1}^{max} **:** Maximum capacity of existing transmission line (c, c_1)

$PLc_{l,c,c_1,id}^{max}$ **:** Maximum capacity of candidate transmission line (l, c, c_1, id)

Res **:** Reserve margin requirement

$TICP_l$ **:** Investment cost per unit capacity and distance for transmission type l

TL_e **:** Distribution loss factor for existing transmission lines

TL_l **:** Distribution loss factor for candidate transmission lines of type l

$TCom_{l,c,c_1,id}$ **:** Commissioning year for candidate transmission lines l between countries c, c_1, with id

$TCom_g$ **:** Construction period for generation technology g

y_g^e **:** Emission factor for generator g

Decision Variables

$AY_{g,c,t}$ **:** Available capacity of generator g in country c at year t

$Dshed_{t,c}$ **:** Load shed in country c at year t

$em_{t,c}$ **:** Emissions in country c at year t

CC **:** Carbon cost c at year t

GIC **:** Generation investment cost c at year t

GFC **:** Generation fuel cost c at year t

$GFOC$ **:** Generation fixed O&M cost c at year t

GVC **:** Generation variable cost c at year t

$PCap_{g,c,t}^{ne}$ **:** New capacity installed for generator g in country c at year t

$PCap^{re}_{g,c,t}$ **:** Retired capacity of generator g in country c at year t

$PG_{g,c,t}$ **:** Power generated by generator g in country c at year t

$PLc_{l,c,c_1,id,t}$ **:** Power flow on candidate transmission line if $(l, c, c_1, id) \in NN$ at year t

$PLe_{c,c_1,t}$ **:** Power flow on existing transmission line if $(c, c_1) \in NE$ at year t

TIC **:** Transmission investment cost$c$ at year t

TC **:** Total cost$c$ at year t

$VOLL$ **:** Value of loss of load cost$c$ at year t

Δt **:** 5-year time step

Binary Variables

$Y_{l,c,c_1,id,t}$ **:** Binary variable indicating if candidate line (l, c, c_1, id) is active at year t

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