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Terawatts for Petabytes: Exploring the impact of AI data centres on Europe's net zero goals

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ABSTRACT

The unprecedented expansion of Artificial Intelligence is adding increasing electricity demand to Europe's power system. While incumbent plans pursue a net-zero future by 2050, they fail to consider the implications of large-scale AI-based data centres. In this study, a spatially explicit optimisation model is developed to assess how hyperscale data centres may reshape energy infrastructure investment, and emissions trajectories, across different AI demand growth scenarios. The results indicate that, after 2030, AI capacity deployment increasingly shifts toward regions with the ability to expand nuclear and gas-based generation, as firm and flexible power sources are essential for supporting the deployment of high-capacity AI data centres. By 2050, AI-driven electricity demand under high growth scenarios may reach up to 450 TWh, corresponding to 7% of total Europe's demand, with installed AI capacity reaching approximately 85 GW. This additional load leads to an increase of nearly 25 $MtCO_2$ in cumulative emissions between 2030 and 2050. Our analysis indicates that, depending on the AI growth scenario, meeting AI-related electricity demand by 2050 requires between 37 and 323 GW of additional capacity across Europe, ranging from the pessimistic to the lift-off scenario, including investments in nuclear (2-12 GW), gas (2-7 GW), wind (13-100 GW), solar (20-134 GW), and battery storage (0-70 GW).

Keywords: Data Centres, Artificial Intelligence, Net-Zero, Energy Systems, Capacity Expansion Planning, Sustainability

INTRODUCTION

Growing interest in generative artificial intelligence (GenAI) has triggered intense competition to advance the technology, driving the need for numerous high-intensity data centres, as well as greater electricity consumption [1]. 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 100-word ChatGPT-4 response consumes approximately 0.14 kWh of electricity [2]. Based on OpenAI's reported figure of roughly 285 million daily ChatGPT users, the platform's energy consumption can be estimated at about 0.39 TWh per day, or roughly 14.4 TWh per year [3]. In addition to inference-related demand, model training represents a non-negligible source of electricity consumption. For example, the training of ChatGPT's 4 model is estimated to have required 50 GWh of electricity, equivalent to the output of a French nuclear reactor operating at full capacity for about two days, with further retraining cycles implying recurring energy requirements [4].

By end of 2024, data centres account for approximately 1.5% of global annual electricity consumption [5]. Looking at the Europe, the International Energy Agency (IEA) estimates that the current energy use of data centres, at around 70 TWh in 2024, will increase to approximately 115 TWh by 2030 [6]. McKinsey indicates that data centre electricity demand in Europe is expected to reach 150 TWh by 2030 [7], while the Independent Commodity Intelligence Services (ICIS) forecasts it will rise to 168 TWh by 2030 and further increase to 236 TWh by 2035 [8]. Although more precise forecasts for data centre demand are rare and prediction rates vary widely across the literature, nevertheless even under conservative scenario, the resulting demand could absorb as much as 20% of newly added renewable energy resource (RES) capacity in Europe and lead to emissions of approximately 39 million tons of CO_2 annually, equivalent to nearly one-third of Italy's emissions in 2024 [9]. Consequently, the increasing demand of these infrastructures raises significant concerns regarding power system reliability and the Europe's Net Zero 2050 objectives.

Although only a limited number of studies have forecasted future data centre energy consumption and capacity in Europe up to 2030 [10, 11], no comprehensive approach has yet examined the impact of data centres on the future European energy system and national or continental development plans. Spatially explicit planning models such as PyPSA [12], and the ENTSO-E Ten-Year Network Development Plan (TYNDP) [13] do not incorporate emerging forms of geographically concentrated, high-density demand, such as AI data centres. To date, no planning-oriented framework has quantitatively evaluated how AI-driven electricity demand may influence Europe's grid expansion, infrastructure needs, or energy transition. Given high uncertainty in future AI trends, beyond even IEA forecasts, assessing Europe's current position, identifying regions suitable for hyperscale data centres, and understanding their potential impact on net-zero 2050 goals is essential [14, 15].

Motivated by the gaps identified above, this study develops a long-term expansion planning model to systematically evaluate how growing demand from AI may reshape Europe's power system development. A spatially explicit optimisation model is proposed, covering 33 countries and formulated as a Mixed-Integer Linear Program (MILP). The model incorporates current infrastructure plans, including 177 cross-border transmission projects, operational constraints, land-use restrictions for renewables, and climate targets, with an hourly temporal resolution. To reflect incumbent "myopic" planning under high uncertainty from data centres, a rolling-horizon solution approach is employed.

The main contributions of this work are as follows:

- Developing a European-scale modelling framework to evaluate whether existing power-sector development plans can accommodate AI-driven electricity demand growth.
- Investigating the effects of AI-driven demand on the spatial evolution of generation, transmission, and cross-border electricity flows across Europe.
- Identifying the optimal capacity of hyperscale data centres and the country's most suitable for their deployment under AI growth scenarios.
- Identifying the main trends in data centre-driven electricity demand and energy system development under various scenarios.

The remainder of this paper is organized as follows. First, we present the research methodology and problem description and discusses the main assumptions. Then we report and analyse the main results for the benchmark case and the alternative AI-driven demand scenarios on various elements of the future European energy system. Finally, concluding remarks are drawn.

METHODOLOGY

Problem Description

Europe's long-term energy strategy focuses on establishing a net-zero system through a deep transformation of the energy sector, driven by large-scale deployment of renewable, low-carbon, and storage technologies. Analyzing such a complex integrated system to obtain optimal decisions across the planning horizon requires a comprehensive spatial and temporal optimisation framework [16-18]. We employ a MILP model to formulate the capacity and transmission expansion planning problem for integrated European power system from 2025 to 2050. Subject to operational, technical, and climate policy restrictions [19], the model minimises the total system cost, our model includes investment in generation and transmission infrastructure, fixed and variable operating costs [20], emissions costs [21], value of loss of load (VOLL) costs, as ell as renewable curtailment costs. The overall form of the objective function is provided in Eq. (1).

$$TSC = \sum_t FCC_t + FOC_t + FFC_t + CC_t + VOLL_t + Curt_t + TIC \tag{1}$$

Where TSC is the total system cost over the planning horizon, FCC_t denotes facility investment cost, FOC_t denotes variable operating cost, FFC_t is fixed operating cost, CC_t is emissions cost, $VOLL_t$ is load shedding cost, $Curt_t$ is cost related to renewable curtailment, and finally TIC is the transmission investment cost.

An hourly resolution is adopted to accurately capture operational constraints, system flexibility requirements, and the temporal interaction between variable renewable generation and electricity demand, while maintaining computational tractability for the 33-country European power system. To this end, the planning horizon from 2025 to 2050 is discretized into five-year investment periods. Within each representative year, a time-reduction technique based on k-medoids clustering is applied to select 12 representative days, with three typical days assigned to each season, ensuring adequate coverage of seasonal variability [22, 23]. Operational variables, including generation dispatch, storage operation, and cross-border exchanges, are then resolved on an hourly basis for these representative days, with appropriate weighting factors used to approximate full-year system behavior. To provide a planning-consistent baseline, we model the evolution of the European electrical system using the ENTSO-E TYNDP Global Ambition scenario [13]. To ensure a more realistic system representation, the model includes reliability (LOLE, loss of load expectation) constraints, must-run for thermal units, renewable curtailment costs, and land availability limits for renewable expansion [24]. It is worth noting that, in addition to conventional generation technologies, carbon capture and storage (CCS) options, including Combined-cycle gas turbine with CCS (CCGT-CCS) and bioenergy with CCS (BECSS), are considered as candidate technologies to facilitate compliance with decarbonization targets [25].

Regional Data Centre Capacity

Although obtaining precise current and future capacity data at the country level is highly challenging and no standardized forecasting methodology exists for installed data centre capacity, the EUDCA provides current capacity estimates and annual projections for hyperscale and colocation data centres across Europe according to Colocation and hyperscale data centre database, Pb7 Research [26]. The database is compiled and maintained by Pb7 Research using a combination of publicly available sources, targeted online searches, and validation checks. Where direct data are unavailable, values are estimated based on complementary sources (e.g., the number of racks or building layout). The estimates were obtained through data gathering and interviews with owners and operators of data centres throughout Europe. Overall, the reported capacities show reasonable consistency with the figures presented in the IEA report.

It should be noted that all reported values refer to IT capacity. These values are converted into total allocated capacity using the projected PUE values provided by the IEA (1.45 in 2024 and 1.29 in 2030) [27]. The 2024 capacity for each country is therefore used as the initial condition and baseline input for optimisation model.

Data Centre Load Profile

In addition to installed data centre capacity, both the associated energy consumption and the contribution of data centres to each country's total electricity demand must be considered. To this end, we incorporate realistic data centre load profiles into the model. Based on the dataset reported in, half-hourly percentage utilisation data for 87 data centres in the UK are available for the period 2023– July 2025 [28]. By clustering these load profiles, all data centres are classified into three voltage levels: low, medium, and high voltage. The reported utilisation percentage represents the ratio of the actual kVA import of each data centre to its contracted (maximum) kVA capacity from the perspective of the regional electricity network operator. Since hyperscale data centres with capacities exceeding 10 MW (at minimum) require high-voltage connections (110, 230, or 400 kV) and are typically connected to the transmission or sub-transmission network [29, 30], we derive a representative load profile from 57 data centres connected at high-voltage levels using K-medoids clustering. Fig. 1 illustrates the representative load profile of a high-voltage-connected data centre employed in the model.

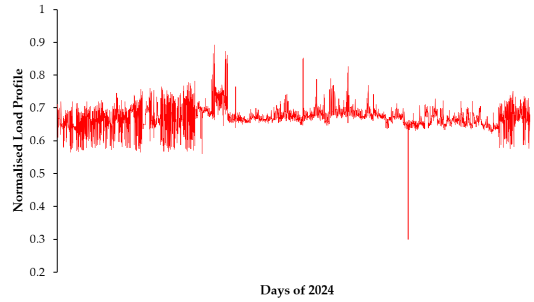

Figure 1. Historical hourly load profile of hyperscale data centre [28].

Hence, the energy consumption by AI is calculated as follows:

$$DemandAI_{t,c,h} = DCProfile_h \times CapAI_{t,c} \quad (2)$$

where $DemandAI_{t,c,h}$ is a variable representing AI electricity demand in year t, country c, and hour h, $CapAI_{t,c}$ denotes the optimal AI capacity in year t and country c, and $DCProfile_h$ is the normalized hourly demand profile used as model input.

RESULTS & DISCUSSION

In this section, we present the results of the proposed optimisation framework across all scenarios. First, a benchmark analysis for the base case validates the model by comparing its outputs with TYNDP projections. Next, AI-based data centres are incorporated to assess the impacts of AI-driven demand on capacity investment, generation mix, and emissions trajectories.

Base Case Analysis (Without AI)

The results of this scenario closely match the TYNDP Global Ambition trajectory [13]. Fig. 2-(a) illustrates the evolution of total installed capacity from 2025 to 2050, closely following the stated decarbonisation pathway. The model projects total installed capacity to reach approximately 4, 700 GW by 2050, which is about 3.3% higher than the TYNDP projection of 4, 548 GW. The resulting energy mix reproduces the main structural transitions of the TYNDP scenario, including the complete phase-out of coal and oil-fired generation by 2035 and the subsequent dominance of renewable energy sources. By 2050, the combined installed capacity of solar and wind reaches around 3, 300 GW, representing a 3.0% increase relative to the TYNDP estimate of 3, 205 GW. Regarding nuclear capacity, the model projects 141 GW by 2050, approximately 15% higher than the TYNDP forecast. This deviation is primarily driven by adequacy and spinning reserve constraints, which increase the value of firm, low-carbon generation in maintaining system reliability. In term of spatial distribution of installed capacity, Fig. 2-(b), Germany will have the largest total capacity in Europe, at around 11, 000 GW, more than 50% of which is solar. Following Germany, Italy (490 GW), France (377 GW), the UK (333 GW), and Spain (286 GW) are next.

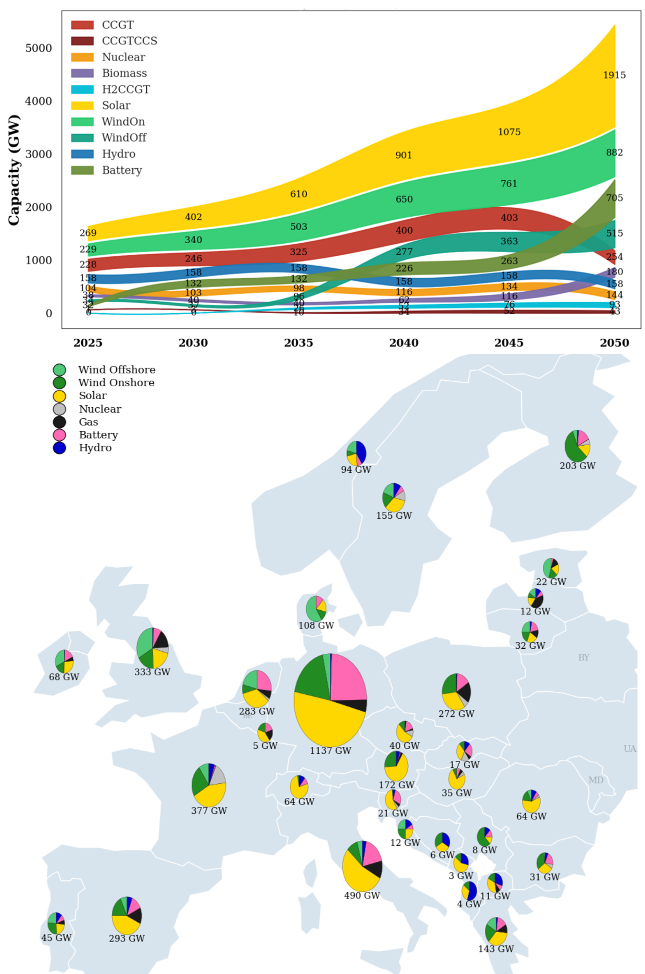

Figure 2. Base case analysis: **(a)** Installed capacity trajectories, **(b)** Country-level installed capacity.

The need for flexibility and firm capacity is clearly visible in countries such as the UK (50 GW CCGT, 10 GW CCGT-CCS), Italy (42 GW CCGT, 9 GW CCGT-CCs), Poland (40 GW CCGT), Spain (25 GW CCGT, 16 GW CCGT-CCS) where the model requires significant gas-based generation to meet reliability and reserve requirements. However, the gas installed in Germany and the Netherlands is mainly based on H2-CCGT technology (close to 60 GW in both countries) by 2050. Overall, Europe will have about 140 GW of nuclear capacity, with France leading at 62 GW, followed by the UK (18 GW), Sweden (17 GW), and Finland and Poland (10 GW each). In terms of wind capacity, the UK leads with 170 GW, Finland (130GW), followed by Denmark and the Netherlands (each 78 GW). High solar capacity in Southern Europe is also evident due to higher solar resource potential.

Impact of different Data Centres growth on the evolution of the power system

In this section, the impact of AI-driven electricity demand on Europe energy system are analysed under one lift-off scenario and two collapse scenarios (pessimistic–med and pessimistic–deflation). The lift-off scenario represents an optimistic pathway, characterized by sustained and rapid growth in AI deployment through 2050. In contrast, the deflation collapse scenario assumes that a contraction of data centre activity begins in 2035 and persists until 2045, while in the medium collapse scenario, the contraction starts in 2035, but AI demand partially recovers after 2040, albeit at a lower growth rate than in the lift-off scenario (cf. Fig. 4 red, dashed line).

Fig. 3 illustrates changes in the installed capacity under the three AI scenarios relative to the base case for the milestone years 2030, 2040, and 2050. Under the lift-off scenario, the system experiences a significant demand shock as early as 2030, requiring approximately 60 GW of additional onshore wind capacity, primarily in Germany, Spain, and Portugal. At the same time, around 10 GW of offshore wind and 35 GW of additional solar capacity are required compared to the base case. To accommodate the increased variability associated with higher renewable penetration, the system also requires approximately +37 GW battery by 2030.

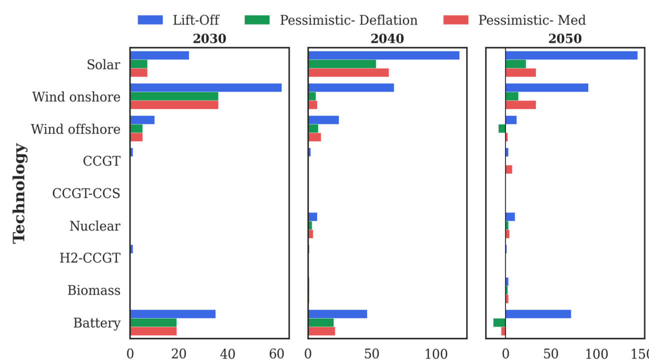

Figure 3. Change in Installed capacity under AI scenarios.

By 2040, the lift-off scenario requires approximately +130 GW of solar, +60 GW of onshore wind, and +10 GW of offshore wind compared to the base case. High AI-driven load also necessitates +3 GW of nuclear, primarily in France, to maintain system adequacy. By 2050, additional nuclear requirements range from 1 GW in the deflation scenario to 10 GW in the lift-off scenario, while lift-off and medium scenarios need 5 GW and 3 GW of CCGT, respectively. The growing reliance on gas generation under tighter emissions constraints may challenge long-term decarbonisation goals.

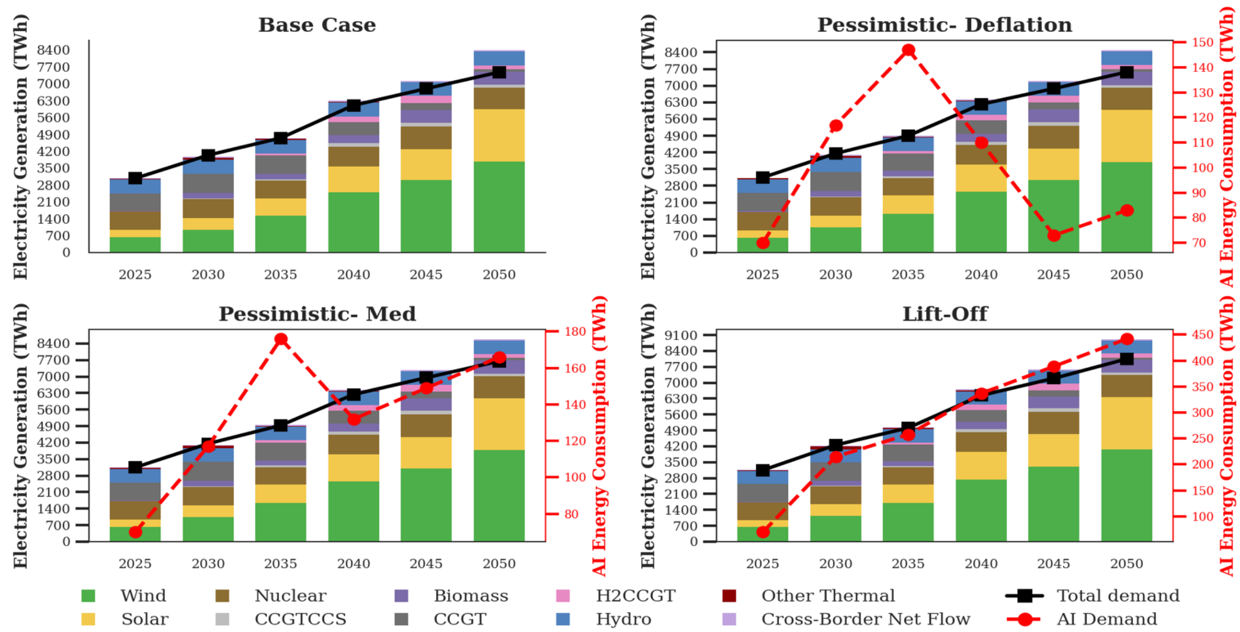

Figure 4: Energy mix trajectory under different scenarios, as well as AI energy consumption (red, dashed line)

Under the collapse scenarios, the system exhibits similar behavior until 2035. By 2040, in the deflation scenario, declining AI demand is primarily accommodated through additional renewable and storage capacity (+50 GW solar, +9 GW wind, and +15 GW battery). In contrast, the pessimistic-medium scenario requires not only renewables but also firm capacity additions (+2 GW nuclear and +3 GW CCGT). By 2050, the deflation scenario leads to partial retirement of offshore wind and battery capacity, with offshore wind reduced by about 7 GW in Finland and Denmark due to sustained AI contraction, although nuclear capacity remains 2 GW above the base case and gas capacity is unchanged. Under the pessimistic-medium scenario, renewed AI growth in the final decade drives additional investments of approximately +25 GW solar, +25 GW wind, +3 GW nuclear, and +4 GW CCGT relative to the base case.

Impact on power generation and interconnection

Fig. 4 compares the evolution of the European energy mix under different AI demand scenarios relative to the base case. The AI-driven electricity demand profile is highlighted in red for all three scenarios. Comparing this profile with total system load shows that, by 2050, AI demand accounts for approximately 450 TWh of total electricity consumption in the lift-off scenario, around nine times higher than in the deflation scenario and three times higher than in the medium scenario. As AI penetration increases, the capacity factors of nuclear and gas technologies rise by up to 15%, and 10 % respectively. As shown, unlike the base case, where coal and nuclear generation are almost entirely phased out after 2040, approximately 8 TWh of electricity between 2040 and 2045 is supplied by these technologies under the lift-off scenario. Cumulatively over the period 2030–2050, the system requires around +150 TWh of nuclear and +97 TWh of additional gas generation compared to the base case in lift-off scenario. In the final decade, tighter emissions constraints increase reliance on H_2-CCGT for flexibility, adding 26 TWh more while Wind captures the largest share of energy mix growth and emerges as the most dominant option for supplying AI-related demand, contributing more than +650 TWh over the same period. Overall, these results indicate that the highly concentrated electricity demand associated with hyperscale data centres can significantly alter the energy mix at critical planning milestones.

Optimal allocation of data centres

From a spatial optimisation perspective, AI-related electricity demand is primarily deployed in countries with sufficient potential to expand nuclear and thermal generation capacity. This pattern is consistent across all scenarios. In the lift-off scenario, Poland (14 GW), France (13 GW), and the UK (11 GW), experience high growth data centre deployment during the 2040–2050 period, driven by their ability to expand firm nuclear and gas capacity (Fig. 5-a). Under lift-off scenario, Portugal emerges as a favorable location for data centre development (3.4 GW), alongside Spain (6 GW), where a combination of low-cost solar electricity and available gas capacity exists.

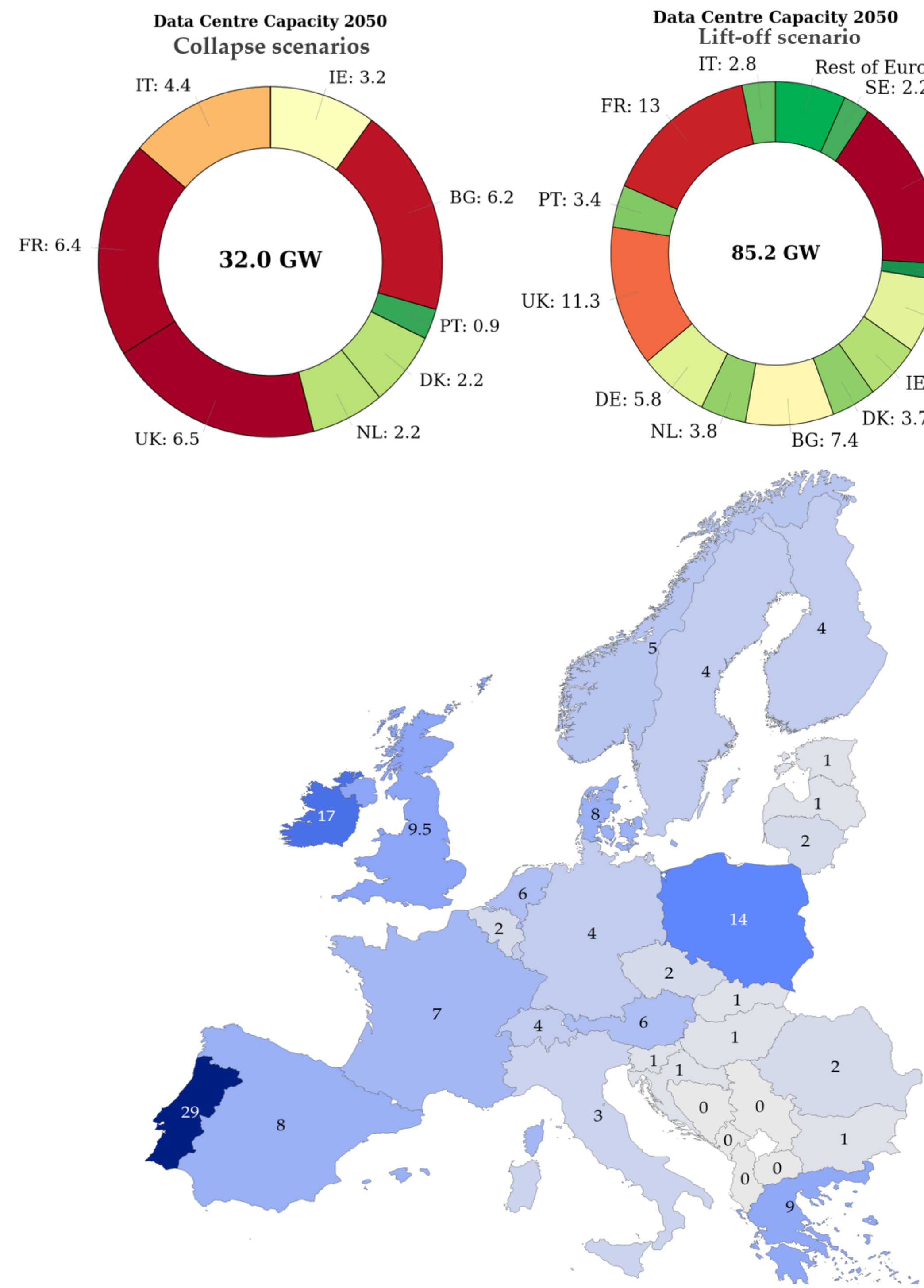

Figure 5: (a) Optimal data centre capacity, (b) Share of AI as a percentage of total demand per country (lift-off).

Between 2030 and 2040, Bulgaria and Greece also exhibit notable growth potential, reaching 7.5, and 1.5 GW in lift off scenarios. In contrast, Ireland, Germany, and the Netherlands face binding constraints from 2030 onward, or experience capacity reductions under collapse scenarios, due to stringent carbon limits, rapid growth in base electricity demand, and the absence of nuclear power options.

Under the pessimistic-medium collapse scenario, total AI-based data centre capacity reaches approximately 32 GW by 2050. Owing to the decline in AI demand prior to 2045, baseload nuclear generation is largely sufficient to accommodate the additional load. As a result, France, the UK, and Bulgaria, benefiting from adequate nuclear expansion potential, together host nearly 20 GW of AI capacity. Italy, enabled by the deployment of CCGT-CCS in the final five years, accommodates around 4.4 GW. Furthermore, driven by the development of H_2-CCGT alongside wind capacity between 2035 and 2045, Ireland and the Netherlands recover from the post-2030 collapse and expand their AI capacity to approximately 3.2 GW and 2.2 GW, respectively. These results indicate that even under a market collapse scenario, Europe's power system continues to rely on nuclear and gas-based technologies, particularly CCGT-CCS alongside renewables to ensure system adequacy.

Spatial AI Demand Shares and Associated Emissions Trajectories

By 2050, AI-based data centres may account for approximately 3–7% of Europe's total electricity consumption, ranging from the pessimistic to the lift-off scenario. The share of AI-driven electricity demand in total national consumption varies widely: 23% in Portugal, 14% in Poland, 9.5% in the UK and Greece, and 7% in France (Fig. 5-b, lift-off scenario). Even at these levels, AI-driven demand has a significant impact on emissions. Across Europe, it contributes approximately 25 $MtCO_2$ cumulatively between 2030 and 2050, driven by an additional 10 TWh of oil- and coal-fired generation and 97 TWh of gas-fired generation. Country-specific impacts vary: Portugal sees only 0.02 $MtCO_2$, the UK ~4 $MtCO_2$, Germany and the Netherlands ~8 $MtCO_2$ combined due to higher gas and coal use, France ~0.2 $MtCO_2$, and Poland nearly 5 $MtCO_2$. These differences reflect each country's mix of AI load, existing capacity, and reliance on flexible fossil generation.

CONCLUSION

This paper investigates the effects of AI-driven demand growth on Europe's power system development toward 2050 using a comprehensive optimisation framework. Rapid AI expansion substantially increases generation capacity needs, placing high pressure on long-term complemented by flexible gas generation. Across all scenarios, only countries able to simultaneously expand renewable energy while retaining nuclear and gas options infrastructure planning can accommodate sustained AI growth. Between 2030 and 2050, AI demand contributes an additional 323 GW additional capacity from different generation technologies, as well as ~25 $MtCO_2$, posing a challenge to Europe's climate targets under the lift-off scenarios. While Poland, UK and France see significant capacity growth, Southern European countries (Spain, Portugal, Greece) also emerge as key locations for AI deployment under both lift-off and collapse scenarios.

These findings underscore that successfully integrating AI at scale will require the coordinated expansion of flexible, low-carbon generation and infrastructure across Europe. Ongoing work in our group focuses on systematic representations of growth uncertainty [31, 32] via means of multi-stage stochastic programming to elucidate further aspects of optionality.

Figure 5: (a) Optimal data centre capacity, (b) Share of AI as a percentage of total demand per country (lift-off).

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