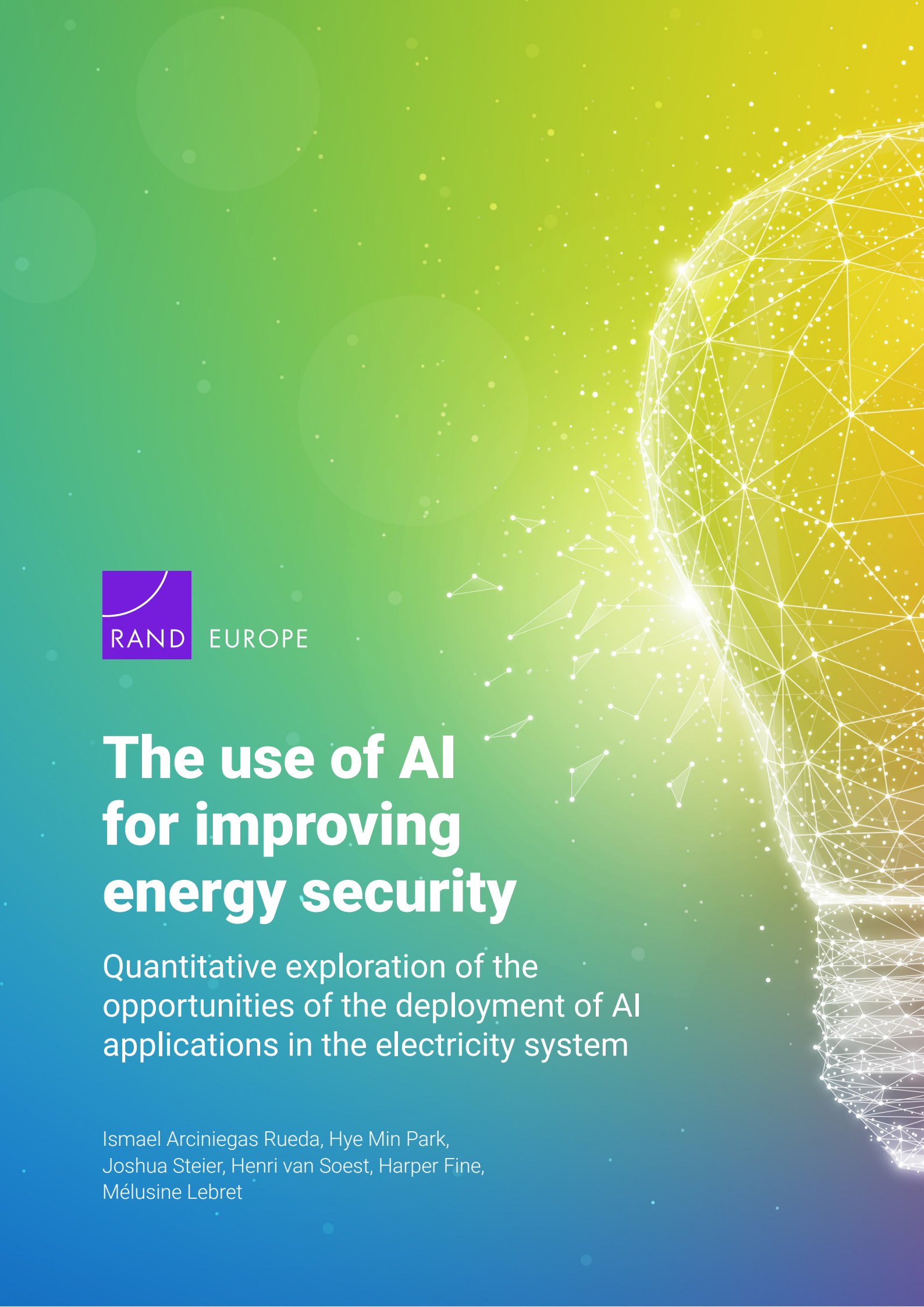


RAND EUROPE

The use of AI for improving energy security

Quantitative exploration of the opportunities of the deployment of AI applications in the electricity system

Ismael Arciniegas Rueda, Hye Min Park, Joshua Steier, Henri van Soest, Harper Fine, Mélusine Lebret

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Preface

Modern civilisation is critically dependent on access to electricity. Electricity systems underpin practically all the essential life functions we take for granted. Most economic activity would be impossible without access to electricity. However, existing grid systems were not designed to handle present – let alone future – electricity demand. At the same time, climate change urgently demands drastic changes to our energy systems. Developing and modernising grid infrastructure requires substantial investment, and securing necessary funding for these projects is complicated by finite resources and competing budget priorities.

Artificial intelligence (AI) applications have potential to solve many of the challenges facing the grid. They can fulfil a range of functions throughout the electricity system, making electricity cheaper and more reliable. In many cases, the deployment of AI simply extends existing methods and approaches. For example, AI applications that help increase electricity market clearing can build on many existing data applications. AI tools can also open up new ways of interacting within the electricity grid, such as dynamic charging and discharging of electric vehicle batteries to provide flexible storage. These opportunities could help improve the overall energy security of the electricity system. However, the deployment of AI applications could also give rise to cybersecurity risks, the risk of unexplained or unexpected actions, or supplier dependency and vendor lock-in. The speed at which AI is developing means many of these risks are not yet well understood.

This technical report accompanies the main policy report titled 'The Use of AI for Improving Energy Security' (RR-A2907-1). It describes the methods, tools and results of our quantitative exploration of the impact of AI-based applications on the energy security of the European power grid.

This study was made possible by internal RAND funding through the RAND Initiated Research (RIR) programme. We would like to thank participants in the backcasting workshop held in Brussels on 9 September 2023 for making time for this project and sharing their insights. We would also like to thank our quality assurance reviewers Lucia Retter and Andy Skelton for their useful feedback. Finally, we would like to thank Nancy Staudt, Lisa Jaycox and the members of the RIR administrative team for their support over the course of this project.

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EXECUTIVE SUMMARY

Background and context

Electricity systems around the world are under pressure due to aging infrastructure, rising demand for electricity and the need to decarbonise our energy supplies at pace. AI applications help address these pressures and increase overall energy security. For example, AI applications can reduce peak demand through demand response, improve the efficiency of wind farms and facilitate the integration of large numbers of electric vehicles into the power grid. However, the widespread deployment of AI applications could also come with heightened cybersecurity risks, the risk of unexplained or unexpected actions, or supplier dependency and vendor lock-in. The speed at which AI is developing means many of these opportunities and risks are not yet well understood.

This technical report accompanies the main policy report titled 'The Use of AI for Improving Energy Security' (RR-A2907-1). It describes the methods, tools and results of our quantitative exploration of the impact of AI-based applications on the energy security of the European power grid.

Study objectives and research approach

The objective of this study was to assess the current state of AI applications for the power grid and their impact on various energy security metrics. To do this, we used PyPSA-Eur, a Python-based power system model, to explore the extent to which different AI applications can improve energy security under different AI deployment scenarios. Our research focused on the European energy system and the short term (less than five years), assuming a static power grid topology and considering AI applications at deployment readiness level (TRL 8 and 9).

We developed quantitative methods to evaluate the performance of AI on energy security on alternative scenarios of AI deployment in the European power grid. To measure energy security attributes for each scenario, we examined four key dimensions of energy security: availability (ensuring sufficient supply reserve to meet demand), affordability (average and marginal cost of electricity), accessibility (determining whether electricity generation is relying on imported fossil fuel) and acceptability (evaluating the carbon emissions of the electricity).

This technical report provides quantitative evidence for the impact of AI on energy security and translates the evidence into policy insights on the role of AI in the power grid. Our research also provides observations and lessons learned on the advantages and challenges of using open-source modelling for research on power grids.

Primary findings

We evaluated the impact of three AI applications across four scenarios: AI-driven load reduction, AI-driven load shifting, AI-driven wind wake steering, and all three applications combined. Comparing these scenarios to a baseline without AI applications, we found that AI-driven load reduction provided benefits across all energy security metrics, ranging

from 3% to 22%. However, the distributional impact varied between countries, ranging from significant improvements to negligible changes.

AI-driven load shifting improved two energy security metrics (availability and affordability), but left the others unchanged compared to the benchmark scenario. The distributional impact was mixed, with some countries showing improvement and others remaining unchanged or even deteriorating compared to the benchmark.

Wind wake steering had minimal impact due to the low penetration of wind energy in the current system but could become more significant as Europe deploys more wind energy to achieve its clean energy goals. In the all-application combined scenario, the reserve margin metric performed best, while average and maximum locational marginal prices (LMPs) were worse than in Scenario 1: AI-driven load reduction. Other metrics were on par with that scenario. These findings highlight that the impact of AI on energy security will depend on how it is rolled out, and that in the case of the European power grid trade-offs between member states are possible.

Policy recommendations

Our analysis found that each AI scenario improved at least one energy security metric, but the magnitude varied and trade-offs between countries and different metrics were observed. AI-supporting policies should align with the security metric of greater saliency. The impact of AI applications may depend on energy market rules and market incentives. Policymakers should consider AI's role in current policy discussions on market restructuring or design. Implementing different AI applications together could have effects on energy security. Policymakers should recognise that AI's impact on energy security is not necessarily additive and carefully consider interactions between applications to avoid adverse impacts.

Load-reducing behind-the-meter (BTM) AI applications have significant positive impacts on all four energy security metrics. Policymakers should incentivise the use of AI heating, ventilation and air conditioning (HVAC) control technology for buildings, smart metering, virtual power plants, and distributed energy resources to improve energy security.

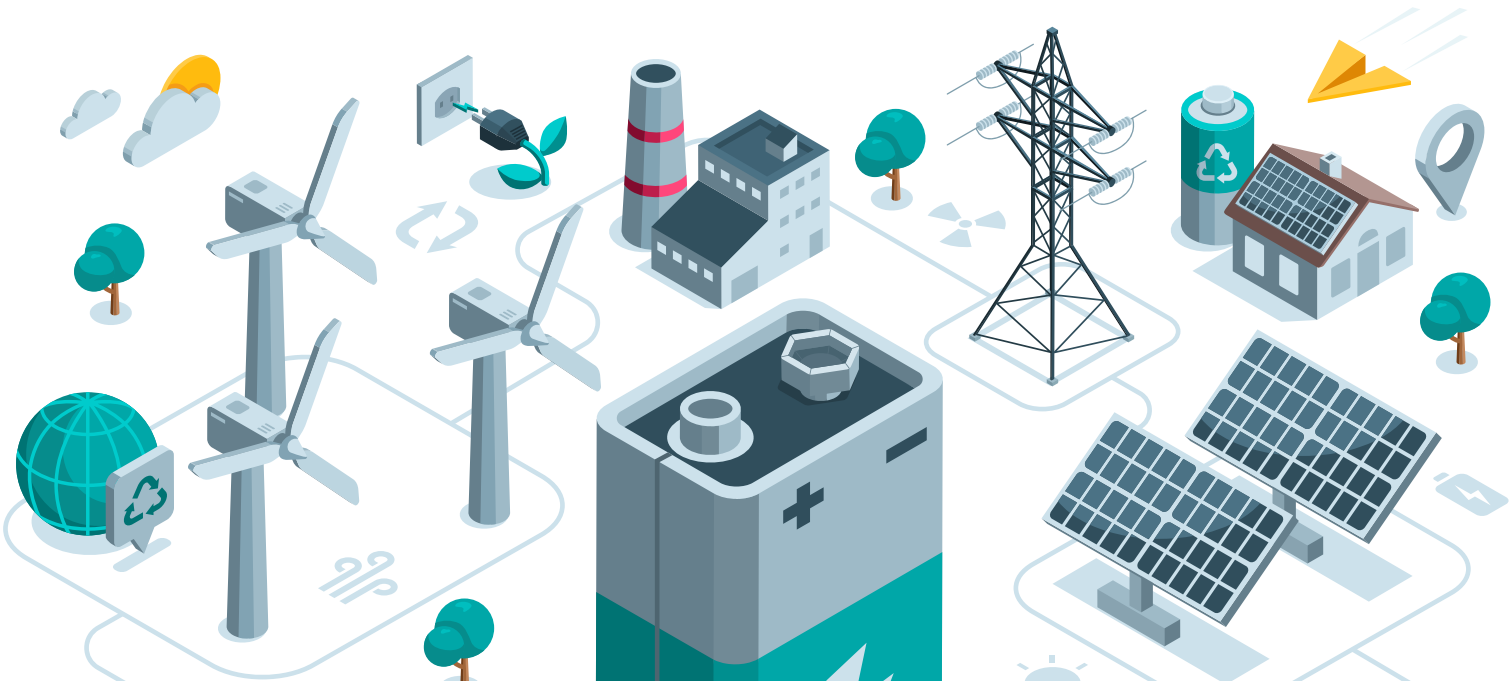


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Abbreviations and acronyms

AC	Alternating current
AI	Artificial intelligence
BTM	Behind-the-meter
CCGT	Combined cycle gas turbine
DC	Direct current
ELCC	Effective load carrying capacity
ENTSO-E	The European Network of Transmission System Operators
EU	European Union
EV	Electric vehicle
FD	Fossil fuel dependency
GHG	Greenhouse gas
HVAC	Heating, ventilation and air conditioning
IFOM	In-front-of-the-meter
LMP	Locational marginal price
LNG	Liquified natural gas
ML	Machine learning
OCGT	Open cycle gas turbine
OFFWIND	Offshore wind
ONWIND	Onshore wind
PHS	Pumped hydro storage
ROR	Run-of-river
TRL	Technology readiness level
VRE	Variable renewable energy



Chapter 1.
INTRODUCTION

This research project investigates the opportunities and risks that may flow from the deployment of AI applications in the electricity system. In this introductory chapter, we set out the background for the research. Electricity systems around the world are changing rapidly due to rising demand, the need to replace aging infrastructure and the need to decarbonise the electricity system. These changes are increasing the electricity system's vulnerability to disruption. In this fast-changing environment, AI applications may help improve the resilience of the electricity systems, but they may also exacerbate vulnerabilities and increase new risks.

This technical report accompanies the main policy report titled 'The use of AI for improving energy security' (RR-A2907-1). It describes of the methods, tools and results of our quantitative exploration of the impact of AI-based applications on the energy security of the European power grid.

Context

In 2021, gas prices began to rise in Europe as the economy reopened following the COVID-19 pandemic, leading to a rise in electricity prices, with negative impacts on affordability. This was further exacerbated by the Russian war in Ukraine, which had a profound impact on Europe's energy relationship with Russia. At the time of writing this report (summer 2023), the energy crisis in Europe seems to have eased somewhat, in part due to diversification of energy suppliers and a mild winter. However, energy concerns remain, driven by increasing energy demand from China, which will increase competition with Europe for liquefied natural gas (LNG) imports[1] and the possibility of colder winters to come.[2]

1 Kemp (2023).

2 Eddy et al. (2023).

Against this backdrop, we wanted to understand quantitatively whether and how AI applications could help the constrained European electric system by asking the following questions:

1. To what extent could AI applications at technology readiness level (TRL)[3] 8 or 9 help improve energy security, if such applications were widely adopted in the short term (< 5 years)?[4]
2. Which AI applications perform better than others, and are there trade-offs between different energy security attributes (i.e. accessibility vs. affordability) related to different AI applications?
3. Are there any policy implications arising from this analysis?

Methods

Our quantitative exploration relies on a python-based European electricity model called PyPSA-Eur.[5] Our approach follows the steps below:

- First, we construct a benchmark case for the European electricity system during the winter when the electric system is most constrained. We use PyPSA-Eur to replicate the electricity system for a week in January 2013 where the EU system reached its maximum load for the year. This particular year was also selected as the data needed to run PyPSA-Eur was already curated by the developers. Data curation of additional years was not possible within our budget constraints, and we recommend it as an area of further research.
- Second, we parametrise in PyPSA-Eur three AI/ML applications both behind the meter and in front of the meter.[6] The selected applications were limited to those at technology readiness level 8 or 9, so they could be deployed on the grid in the short term. The parametrisation focused on capturing how each AI/ML application impact could be reflected on the grid (such as energy savings potential, generation efficiency improvement, energy density improvement).
- Third, we run the PyPSA-Eur 'benchmark' scenario as a baseline, and with AI/ML applications added subsequently. This generates two different model outcomes which can be compared.
- Fourth, we take the definitions of energy security developed in the companion policy document and operationalise them using the model output. We develop five metrics associated with energy security.[7] We compare the model outcomes on their performance in relation to the energy security metrics. This process allows us to demonstrate whether and by how much AI/ML applications could affect the selected energy security metrics of the European electricity system compared to a benchmark scenario.

---

3 Moorhouse (2012).

4 We assume power grid topology to be static and the applications considered to be at deployment readiness level (TRL 8 or 9).

5 Hörsch et al. (2018); GitHub (2023). More detail on PyPSA-Eur is provided in section 4.2.

6 Behind-the-meter refers to anything that happens on the customer side that is behind the customer meter; in-front-of-the-meter refers to anything that happens on the grid side.

7 The companion policy document 'The Use of AI for Improving Energy Security' defines energy security in terms of availability, affordability, accessibility and acceptability.

Chapter 2.
ENERGY SECURITY

Energy is an essential requirement of all economic activity. Secure access to energy has therefore always been a core government concern. Because of its critical nature, energy security has been well researched in academia, government and the private sector.[8] However, there is no consensus on the definition of energy security.

Definition of energy security

In this technical report, we follow the 'four As' definition of energy security developed by the Asia Pacific Energy Research Centre.[9] The four As are availability, accessibility, affordability and acceptability. We do not create a single compounded index to measure 'energy security' as identifying potential weights for each attribute is out of scope. Instead, we intend to measure the impact of AI on each attribute and identify possible trade-offs. Each attribute is defined below:

- **Availability** means that the energy required to fulfil the needs of the economy and society is available at all times.
- **Affordability** relates to the price of the energy provided.
- **Accessibility** deals with sourcing and transporting energy supplies, and the geopolitical challenges this may entail.
- **Acceptability** deals with environmental issues and debates around sustainability.[10]

We further develop specific metrics aligned with energy security as defined above. The metrics identified and defined below are just one example for each energy security category and not intended as an exhaustive list. Our selection of metrics is dependent on the available outputs generated by our quantitative exercise as applied to the European energy system.[11]

Notations

$n \in N\ \{1, ..., 27\} n \in N = \{1, ..., 27\}$: 37 Nodes

$t \in T\ \{1, ..., 168\} t \in T = \{1, ..., 168\}$: 168 hourly snapshots (1/16/2013 0:00 ~ 1/23/2013 0:00)

- $s \in S = \{solar, hydro, coal, \ldots .\}$: Different generator/storage types at each node
  - $VRE = \{solar, wind\}$: Variable renewable energy includes solar and wind generation
  - $Fossil = \{coal, CCGT, OCGT, lignite, oil\}$: Fossil fuel-based generation.
- $d_{n,t}$: Exogenous load at each node n at time t
- $\bar{\bar{d}} = \sum_n d_{n,t} - \sum_{n,s\text{-}VRE} g_{n,s,t}$: Net load at time t is calculated by load at t minus variable renewable energy (VRE) at t
- $g_{n,s,t}$: Dispatch of generator s at node n at time t
- $\eta_{n,s}$: Efficiency of generator s at node n
- $\bar{g}_{n,s}$: Available capacity of generator s at node n (non-VRE only)
- $lmp_{n,t}$: LMP for node n at time t for one MWh.

8 Ang et al. (2015).

9 Intharak et al. (2007).

10 We explain our methodology to quantify the energy security metrics using PyPsa-Eur in Chapter 2.3.2; Cherp et al. (2014).

11 ENTSO-E includes 39 companies from 35 different countries. For the full list of countries and companies please see, as of 24 April 2024: https://www.entsoe.eu/about/inside-entsoe/members/

Metrics calculation

1. **Availability/reliability**: To calculate availability, we use the metric of reserve margin. This refers to the amount of excess capacity available in a power system to meet unexpected increases in demand or unexpected outages of power plants or other energy resources. We calculate this by (maximum capacity minus net load)/ net load, where 'maximum capacity' is the available non-VRE capacity reflecting the efficiency and 'Net load' is demand minus VRE. The reserve margin is expressed as a percentage and higher values represent greater energy security or better preparedness for unexpected events. However, keeping the reserve margin too high could also mean inefficient operation and result in a higher electricity price.

$$RM\,(\%) = \frac{\sum_{n,s} g_{n,s} \times \eta_{n,s} - \max(\bar{\bar{d}}_t)}{\max(\bar{\bar{d}}_t)} \times 100$$

   We use net load to calculate Reserve Margin to account for the contribution of intermittent resources and its availability at time t.[12]

2. **Accessibility**: Defined in terms of fossil fuel dependency (FD) or the degree to which a society or economy relies on fossil fuels such as coal, oil or natural gas to meet its energy needs. We calculate this by subtracting power generated (MWh) from the fossil fuel divided by all source generation for the study period.

$$FD\,(\%) = \frac{\sum_{n,s,t} g_{n,s} \times fossil,t}{G} \times 100$$

- **Acceptability:** Defined in terms of total CO_2 equivalent emissions (CO_2e, CO_2-equivalent-tonne). This refers to greenhouse gas (GHG) emissions from power generation during the study period and is calculated by multiplying the emissions factor[13] for each generator type (e_s, CO_2-equivalent-tonne-per-MWh) by total generation (MWh).

$$E_{CO2} = \sum(e_s \times g_s)$$

4. **Affordability**: Defined in terms of the locational marginal price (LMP). This reflects the cost of generating and transmitting electricity to a specific location. We estimate two metrics: System average marginal price and maximum LMP. System average marginal price (lmp_{avg}, euro per MWh) is calculated by averaging the LMP at each node n at time t weighted by hourly total generation at node n at time t. Maximum LMP (lmp_{max}, euro per MWh) is calculated by taking the maximum of all LMP across the node N and time T.

$$lmp_{avg} = \frac{\sum(\mathrm{lmp}_{n,t} \times g_{n,t})}{G}$$

$$lmp_{max} = \max(lmp_{n,t})$$

12 In California, the regulatory process uses a capacity value of intermittent resources such as effective load carrying capability (ELCC) factor to account for probabilistic contribution of VRE – but these factors vary depending on the power mix and load shape. We were unable to find 'capacity value' for ENTSO-E or other European countries, and so we simply subtracted VRE generation from the load each hour to get the net load profile to estimate the reserve margin.

13 EIA (2023).

Chapter 3.

AI IN ENERGY

AI is an umbrella term for a wide variety of statistical and algorithmic techniques. It can be used to draw out trends from large volumes of data, control processes, make decisions or predictions, and interact with its environment based on this data. One of the most widely used forms of AI is machine learning (ML). ML involves the use of algorithms and statistical models to enable a system to improve its performance on a specific task over time. ML algorithms are designed to learn from data, identify patterns and relationships and make predictions or decisions without being explicitly programmed to do so. This allows ML systems to adapt and improve their performance on a given task as they receive more data and experiences.

Potential of AI for energy systems

In this study, we quantify the AI impact on energy security using a power system optimisation tool. There are great opportunities for AI in the electric grid, where information exchange is essential to achieving near instantaneous production, delivery and consumption.[14] However, the potential of AI applications for power-system-wide energy security benefits are largely unknown. Most literature quantifies the impact at the facility or AI application level, such as bill and energy savings. There is limited understanding in the literature of the extent to which AI can benefit our energy system when broadly deployed. This is partly due to the complexity of the power system and uncertainties surrounding both the development of AI and the power systems themselves. Our study does not aim to solve these uncertainties by projecting or predicting the future system impact of AI applications. Rather, we attempt to showcase a modelling approach to quantitatively explore AI applications' impact and present the magnitude and potential trade-offs of different impacts. With the lessons learned from this exploratory exercise, we identify caveated, yet important, policy implications of AI implementation in the energy system.

AI applications for energy

The electricity system consists of a plethora of control elements. These are increasingly connected to the internet, creating a network of connected nodes, each of which generates data that can be shared, collected and analysed. There are major benefits to this digitalisation, as measurements made by individual components can be shared and interpreted (e.g. by AI), leading to significant insights into the operation of the electricity system. Those insights may help improve the efficiency of the system and reduce costs. Real-time measurements can also be used to pinpoint anomalies in the grid.

As AI technology has progressed, researchers began investigating how AI techniques could be applied to energy systems. Research on the topic began to pick up in the early 2000s, but there has been an explosion of research in the past 10 years, with progress achieved along

14 Entezari et al. (2023).

several different energy systems and goals (see Table 4.1.).

In this report, we do not explore all the applications above; instead we focus on applications that control the time (e.g. load shifting) and use (e.g. load reduction) of energy by consumers (e.g. buildings, air conditioning) and applications that improve performance of wind power (e.g. wake steering). These applications were selected because they are relatively easy to model in our selected tool.

Table 4.1. Recent AI applications in energy by system and goals

System	Goals
Solar power, wind power	Decision-making
Stochastic systems	Forecasting
Air conditioning, buildings	Sustainable development
Smart power grid	Energy management
Electric vehicles	Environmental impact
Power transmission networks	Performance assessment
Energy storage	Social, economic assessment

Source: Entezari et al. (2023).

Chapter 4.

QUANTITATIVE MODELLING

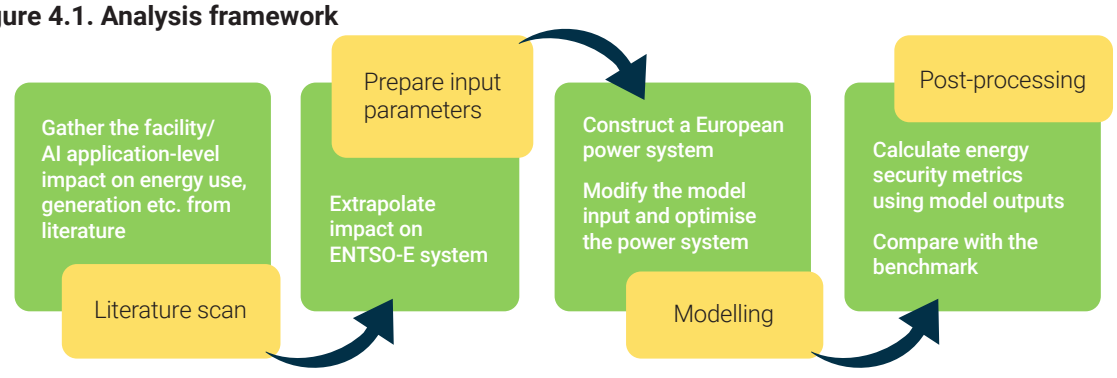
To quantify the impact of AI on energy security, we used a power system optimisation tool. Our study focuses on grid managed by the European Network of Transmission System Operators for Electricity (ENTSO-E). As we noted in the introduction, at the time we developed our research proposal, Europe was going through an energy crisis due to the Russian invasion of Ukraine[15] and there was significant concern over energy shortages and unaffordability during the upcoming winter. Given these concerns, we proposed to explore in more detail how AI applications could help with a constrained European electric system.

Modelling approach

Within the research approach, we followed a series of steps, as depicted in Figure 4.1. First, we reviewed a range of literature sources to gather evidence of AI application-level impacts on the electric grid. Then we examined the full potential for such AI applications for the European system by assuming wide deployment and accounting for feasibility and sectoral differences in energy demand, where applicable. We used an open-source European electricity system analytic tool, PyPSA-Eur, to optimise the power system before and after applying the AI options. Finally, we quantified and evaluated the impact on energy security from the model output.

The optimal dispatch in a power system is the result of complex interactions between the system of demand, available supply and costs, and grid topology at given locations and time steps. The objective of this study is to quantitatively explore differences in the impact of various AI applications on energy security metrics. We include explanations of what causes certain results wherever possible given complexity of the model. Similarly, we discuss potential policy implications from the results where appropriate.

Figure 4.1. Analysis framework



Source: RAND analysis.

15 Zettelmeyer et al. (2022).

Modelling limitations

There are some limitations to our approach largely due to the following constraints on computational resources and publicly available data:

1. We used a deterministic modelling approach, rather than a stochastic approach, due to the computational capability of the solver[16] available to us. This means our analysis was done under a perfect foresight approach with no uncertainty. AI implementations that can reduce uncertainty – such as improvements in forecasting accuracy – were therefore not considered.
2. We used the open source PyPSA-Eur[17] model to construct a European electricity system that includes generation, storage, demand and transmission infrastructures from open data. Modelling the European system requires the curation of large amounts of data from different countries. We limited our analysis to demand and weather for the coldest week of the year 2013, for which data had already been curated by the developers. We did not have the resources to curate any additional years' demand/weather for our simulations.
3. We used the network topology provided by the latest update from the developers (year 2020). We did not have resources available to update the model topology ourselves. Therefore, our simulation exposed the European grid topology as from 2020 to the coldest weather in 2013 assuming different AI deployments. We believe this exercise is still useful for two reasons. First, 2013 was an extremely cold winter. Second, changes in power grid topology (e.g. new transmission lines) take several years to be implemented, and so we consider 2020 topology to be a good approximation to the current set-up.
4. We focused on a short-term horizon, with the configuration of the grid as given. While there could be more opportunities with AI to enhance the energy system and lead to changes in configuration/ topology, a long-term timeframe introduces more uncertainty and new infrastructure buildouts. We limited new transmission and capacity expansion in our modelling and optimised dispatch of existing resources only. Therefore, we considered only AI applications at TRL 8 or 9 (rather than earlier readiness levels).
5. Our model approach also assumed a high level of central coordination when optimising the European electric system to minimise costs given the constraints of meeting demand with supply. In reality, the European electric market is more 'decentralised' – meaning there is no central place to bid and clear energy dispatch.[18] European markets are covered by several power exchanges that operate with different market rules, products (i.e. day-ahead, intra-day) and mechanisms (i.e. capacity), hindering central coordination.[19]

Due to these complexities and limitations in model representation, our study focused on investigating changes – and the direction of changes – from the benchmark, rather than the model results themselves.

16 CBC solver was used for our analysis. We explored Gurobi, Highs, and CPLEX.

17 PyPSA-Eur 0.7.0 (Feb 2023 release) was used for our analysis.

18 Ahlqvist et al. (2022).

19 IRENA and KEEI (2021).

Power system model and PyPSA-Eur

Modelling the impact of AI on the European grid required a tool capable of measuring impact on outcomes. We limited the scope to open-source options due to project resource constraints. We explored several open-source modelling applications (Switch Power System Planning Model[20] and Gridpath[21]) and opted for PyPSA-Eur as the most suitable model to help address our research questions and effectively cover our geographic location of interest.

Why PyPSA-Eur?

PyPSA is a toolbox for simulating and optimising power systems. It is free, publicly accessible and open source. It was originally developed in 2018 at the Frankfurt Institute for Advanced Studies. It is currently maintained and developed by a group of nine academics associated with leading European research universities. PyPSA is designed to provide users with great flexibility and adaptability, and to be easily scalable to large networks and long time series. It can be used to model conventional generators, variable renewables and storage units, as well as early-stage technologies such as green hydrogen and electric vehicle storage. The PyPSA-Eur model[22] was developed for power system analysis of the European electricity system. The PyPSA model has become widely adopted, and an active community of researchers is working on extending the model to other regions of the world. We could foresee a follow-up project expanding the same methodology to the United States, Australia and other regions of the world.

PyPSA-Eur, the European electricity model, was selected as the most suitable model for our research due to the following features:

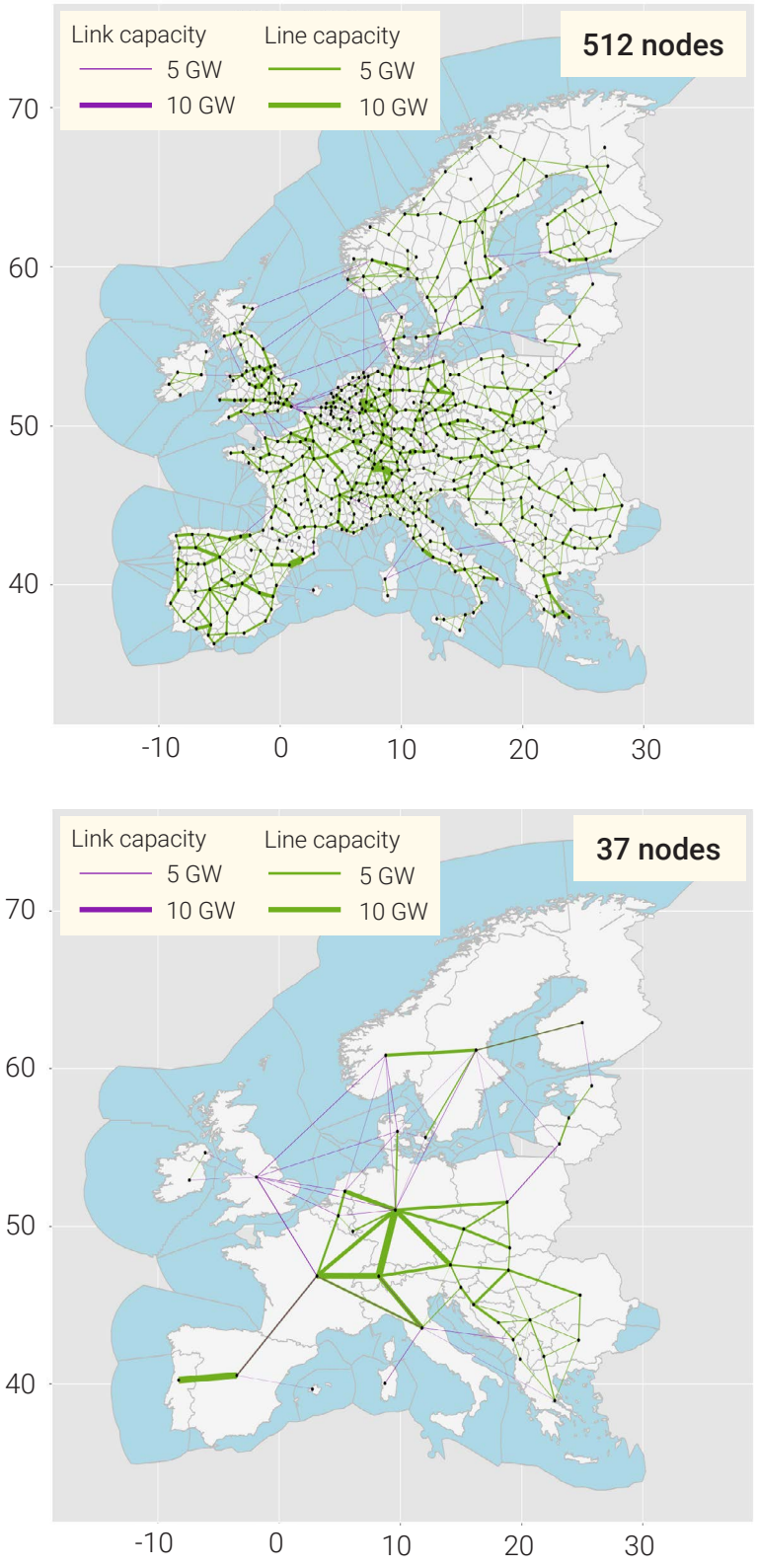
- Data availability: power system modelling requires a wide range of input data including the grid network topology, electricity demand, power plant type and capacity, and renewable energy generation profiles contingent on the weather pattern in a given location. These datasets should represent the right geographical and temporal resolution to simulate the real-time balance of power supply and demand, as well as consider limitations of physical infrastructure and operational constraints. PyPSA-Eur incorporates a workflow to build a model of the European power system and necessary input data from open sources. In addition to links to the different data sources, PyPSA-Eur developers have also made available a fully curated dataset for 2013.
- System requirements and flexibility: power system modelling can be computationally challenging and demand significant computational resources to solve large-scale problems. Our interest was to identify a flexible modelling application so that the system could be customised as needed and made feasible for use with computational resources available at RAND. PyPSA-Eur provides a clustering feature that enables us to balance necessary network resolution and our computing system capabilities. Figure 4.2. below shows how with PyPSA-Eur a system of 512 nodes can be clustered into 37 nodes.

20 Github (2023). As of 24 April 2024: https://github.com/switch-model

21 GridPath (2023).

22 Github (2023). As of 24 April 2024: https://github.com/PyPSA/pypsa-eur

Figure 4.2. Clustering of European power grid



Source: Neumann et al. (2020).

- Configurable and easily modifiable input parameters: PyPSA-Eur is highly configurable as it allows users to select analysis scope, customise assumptions and define policy goals. It is easy to modify and select target counties, reference year, time periods, temporal resolution, demand, GHG reduction goals, cost assumptions, weather dataset, etc.
- Power system optimisation:[23] the mathematical optimisation model is widely used in the power sector ranging from electricity market operation to long-term energy planning and modelling climate mitigation strategies.[24] PyPSA-Eur can optimise the dispatch of generation and storage and the capacity of generation, storage and transmission infrastructure to yield the cost-optimal energy system operation subject to various constraints, such as reliability, transmission capacity limit, fulfilling CO_2 emission reduction targets and others. This approach allows the user to explore the impact of changes in fuel prices or electricity demand on the power system. The model input and output satisfy the context and granularity of energy security parameters.
- Scenario analysis: the objective of our analysis is to quantify the difference between energy security outcomes with and without AI applications on the power system. This requires modifications to input data to reflect the impact of different AI applications to test different scenarios. PyPSA-Eur is modular, making inputs and system parameters relatively easy to modify.

Scenarios

A core component of our analysis relied on exploring four scenarios and comparing their outcome against the benchmark. Each scenario tested a different set of AI applications, selected to ensure we could effectively apply the PyPSA-Eur optimisation feature. Table 4.2. summarises the scenarios and corresponding alterations to the model.

For each of the scenarios described above, PyPSA optimises the system for lowest cost, while meeting hourly demand and physical constraints. In our simulations, we changed input parameters such as load or generation asset performance to incorporate an AI impact into the model, as supported by the literature. In this way, we were able to assess differences in the output – such as hourly generation dispatch profiles – by location, hourly clearing prices, etc. The PyPSA optimisation model generates extensive datasets as a model output. Not all of the data was relevant or interesting for our study purposes. We focused on presenting several outputs of most interest – for example, those showing which electricity generation resources are used and to what extent (e.g. how much is dispatched), resulting GHG emissions, and impact on marginal prices in the system and on individual countries.

Below, we present the assumptions, input parameters, model results (and comparison to the benchmark) and limitations for each scenario. Finally, we present the summary findings on energy security for all scenarios and compare them.

23 While PyPSA provides other features such as power flow or contingency analysis, to explore behaviour of the power grid, we limited ourselves to power simulation and the use of other features were out of scope.

24 Roald et al (2023).

Table 4.2. Summary of scenarios

Scenario name	Description	Parameters altered in the model	Source
Benchmark	The coldest week in winter of 2013 for ENTSO-E power system, no AI explicit[25, 26]	16-22 January 2013 across 33 European countries	PyPSA-Eur uses various opensource data to construct the system
S1 Load reduction (BTM)	Energy consumption reductions across the commercial and industrial sectors by AI controlling HVAC more efficiently	AI-driven 14% reduction in energy consumption modelled by changing the load scaling factor in the configuration	Merabet et al., 2021[27]
S2 Load shifting (BTM)	AI automatically adjusting electricity consumption time to reduce the peak demand	AI-driven 9% of peak load reduction across the EU power system is modelled by adjusting load shapes for each country manually in the load.csv file	Söder et al., 2018[28]
S3 Wind wake steering (In-front-of-the-meter (IFOM))	Wake steering[29] coupled with AI technology increasing net wind plant power production and reducing fatigue loads from wake turbulence	AI-driven 3% increase in annual energy production is modelled by altering the correction factor[30] in the configuration	Harrison-Atlas et al., 2021[31]
S4 All together (BTM + IFOM)	S1+S2+S3	S1+S2+S3	All of the above

Source: RAND analysis.

25 Although it is possible that some operators are using AI algorithms, to our understanding this is mostly in pilots and not at the level of ubiquity that we are considering in our scenarios.

26 Saroj (2022).

27 Halhoul Merabet et al. (2021).

28 Söder et al. (2018).

29 A wind farm control strategy in which upstream wind turbines are misaligned with the wind to redirect their wakes away from downstream turbines.

30 This factor represents wake losses for wind energy production.

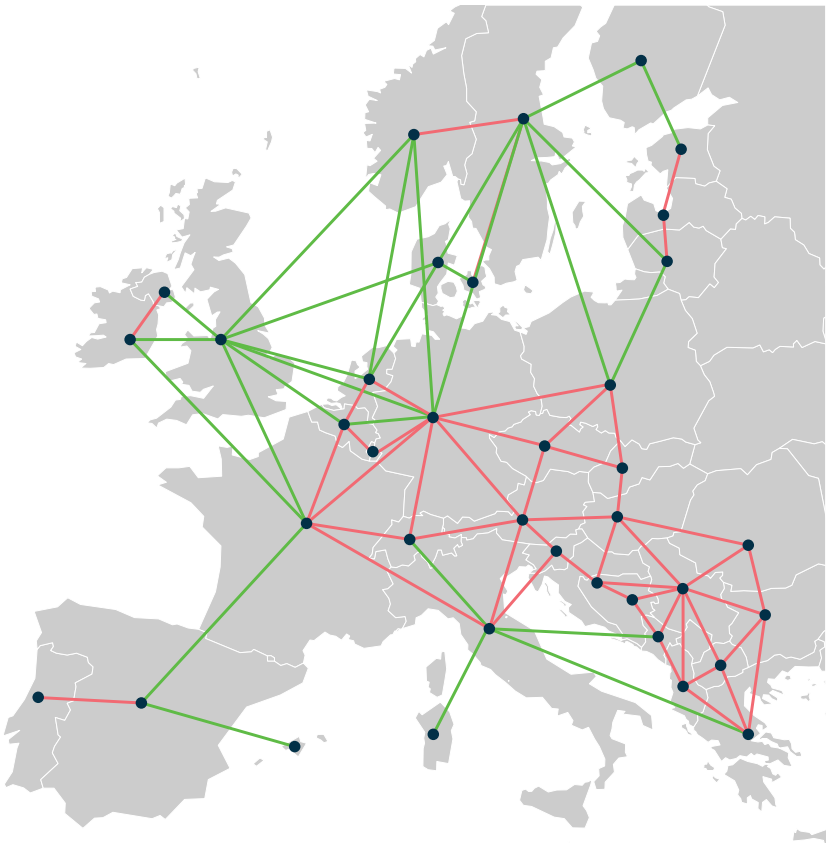
31 Harrison-Atlas et al. (2021).

Benchmark

Model setup

In our study, we utilised the PyPSA-Eur tool to construct a network of the electric grid across 33 European countries.[32] These countries included Albania, Austria, Bosnia and Herzegovina, Belgium, Bulgaria, Switzerland, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, UK, Greece, Croatia, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Montenegro, North Macedonia, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Sweden, Slovenia and Slovakia. Due to limitations in computing resources and solver capability, we clustered the network into 37 nodes using k-means.[33] Figure 4.3. shows the network of European grid that we constructed for our analysis. Lines between nodes represents transmission lines that can transmit power from one node to another. There is a limit to how much power each line can transmit, based on the ENTSO-E data for existing infrastructure.

Figure 4.3. Our construction of the European grid network (37 nodes)



Source: RAND analysis.

32 42 TSOs from 35 countries are members of ENTSO-E which extends beyond EU borders. We include only 33 countries within the EU.

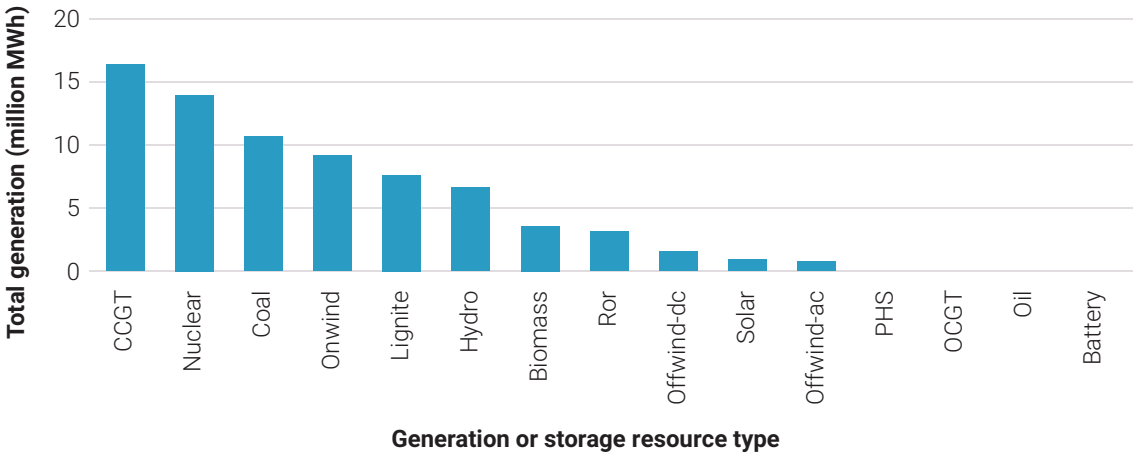
33 K-means is an algorithm often used in data mining to identify the centre of clusters in a way that minimises intraclass variance.

We solved the network by minimising the system costs[34] for the coldest week of 2013, specifically 16-22 January 2013. By analysing this week, we were able to gain insights into the performance of the electric grid during a period of historical peak demand, as extreme cold weather typically results in increased energy consumption for heating purposes. For our study we only optimised power plant and storage dispatch for existing resources, without adding new capacity to the system. By restricting new capacity, we can understand how AI can support energy security without major infrastructure investments in grid configuration in a relatively short time frame.

Model results

Here we present results from our run, which were then used to generate energy security metrics. Figure 4.4. represents generation by resource type for the benchmark scenario. The largest generation was from combined cycle gas turbines (CCGT), generating more than 16 million MWh and accounting for 22% of total generation.

Figure 4.4. PyPSA output: Electricity generation/discharge by source for benchmark

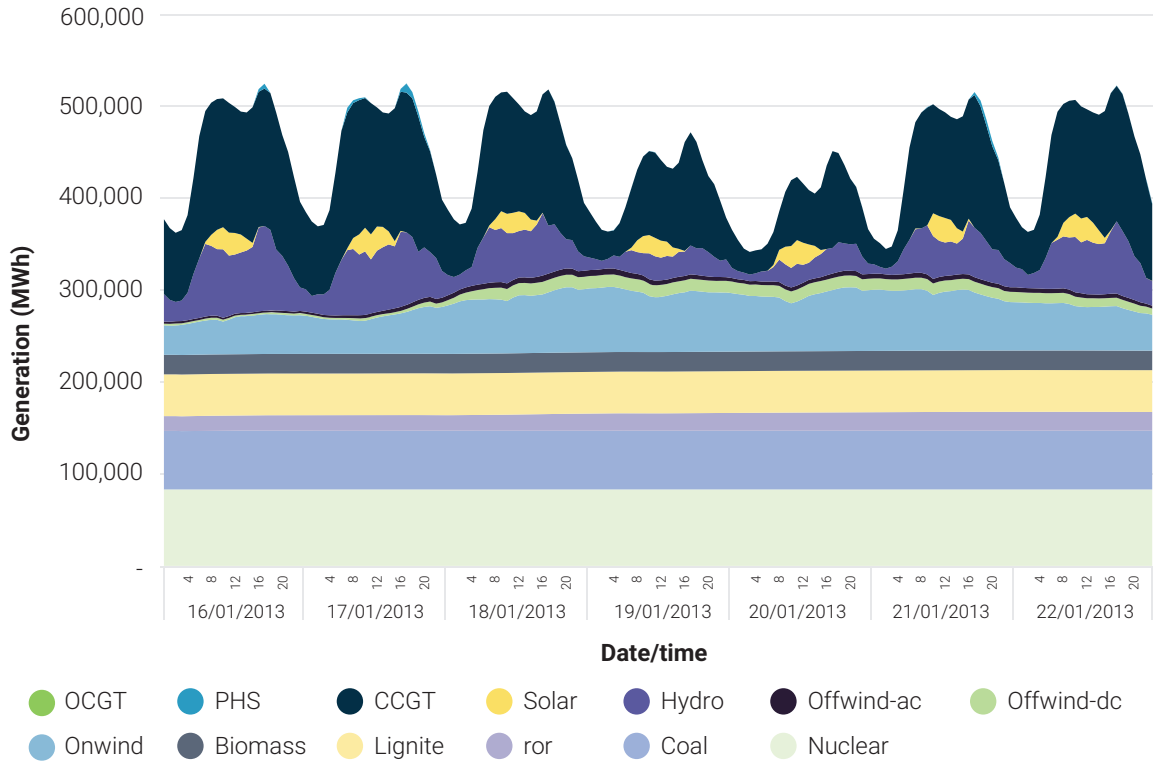


Source: RAND analysis.

34 Typically, optimisation problems such as this examine how to achieve an objective given different constraints on how the power grid operates - in this case meeting electricity demand instantaneously at the lowest cost possible.

Figure 4.5. below represents the hourly dispatch of different resources. This graph shows differences for baseload generation, variable renewable energy and dispatchable generation. The system peak load appeared at 17:00 on 17/1/2013 Universal Coordinated Time (UTC) and CCGT accounts for the highest share of generation during the peak.

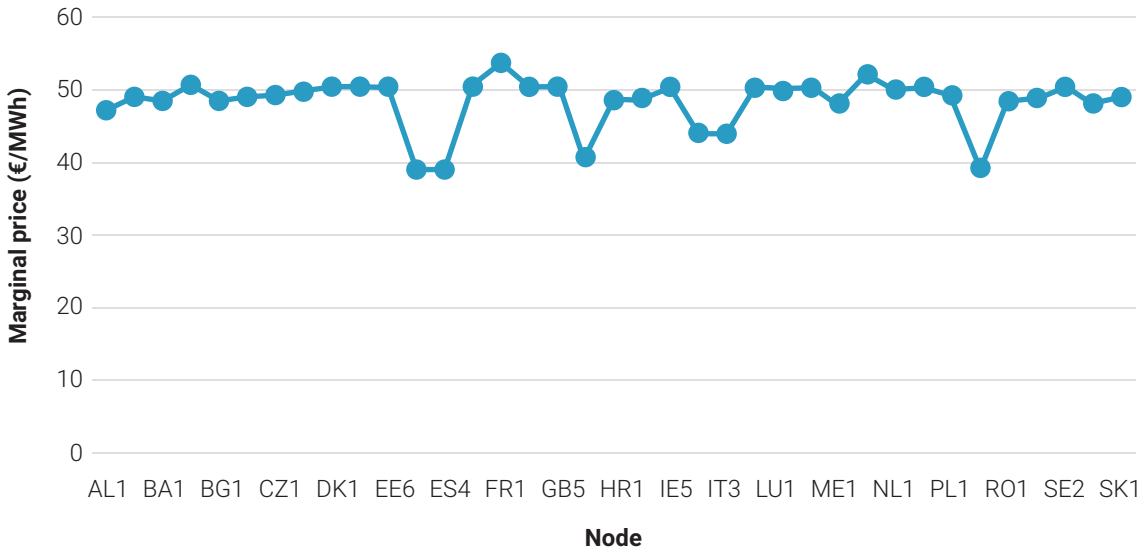
Figure 4.5. PyPSA output: Hourly power generation by source for benchmark



Source: RAND analysis.

Figure 4.6. shows LMPs for 37 nodes after clustering. LMP is the cost of optimally supplying an additional load (kWh) at a particular node while satisfying operational constraints (i.e. transmission capacity limit). In PyPSA, these are the shadow prices of the constraint that the power balances at each node for each hour. We obtained 6,216 LMPs (168 hours times 37 nodes) from the model run. LMPs fluctuate each hour depending on network constraints, load and generation availability at the node. Node FR1 (France) showed the highest marginal price for our study period. This is mainly because demand at FR1 is 2.9 TWh higher than its generation (nuclear power is the largest energy source in its portfolio).

Figure 4.6. PyPSA output: Maximum LMP of electricity by node for benchmark



Source: RAND analysis.

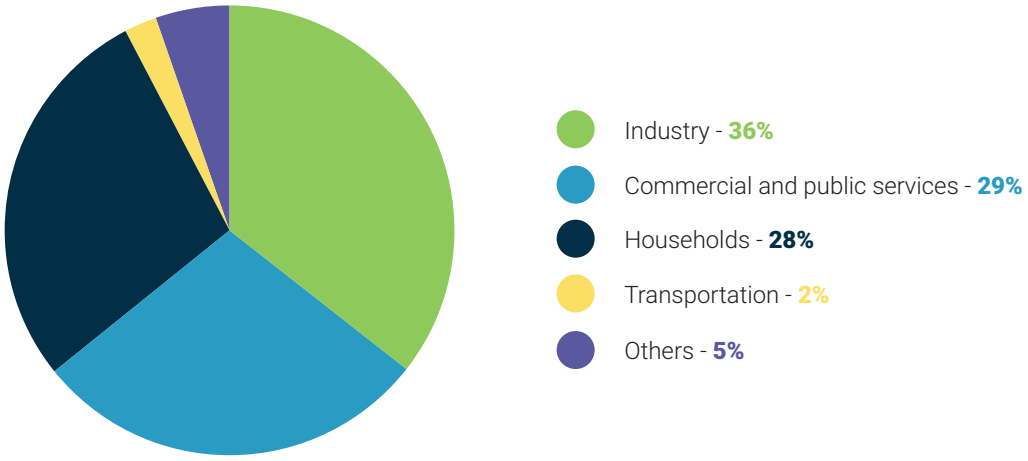
Scenario 1 (S1): AI-driven load reduction

Assumptions and input parameters

We researched the literature discussing energy savings opportunities from efficient utilisation of HVAC using AI technology. We gathered data on the potential impact of energy consumption reduction through the application of AI technology from various sources, including pilot studies, commercial applications, academic and non-academic literature. We assessed this literature to identify the TRL of the AI described, as well as its potential impact.

Our study found a wide range of actual and potential energy savings ranging from 4% to 45%. We selected a lower bound value of 22%, which was identified through a systematic review of literature conducted by Merabet et al. in 2021. This value was then applied to the commercial and industrial sector load (approximately 65% of total load) based on the annual consumption data from 2013 in the EU (as shown in Figure 4.7.) We therefore estimate that the implementation of energy reduction AI technologies could result in a 14% (i.e. 22% times 0.65) reduction in overall energy consumption within the EU.[35]

Figure 4.7. Annual electricity consumption by sector in 2013 for EU countries



Source: RAND analysis.

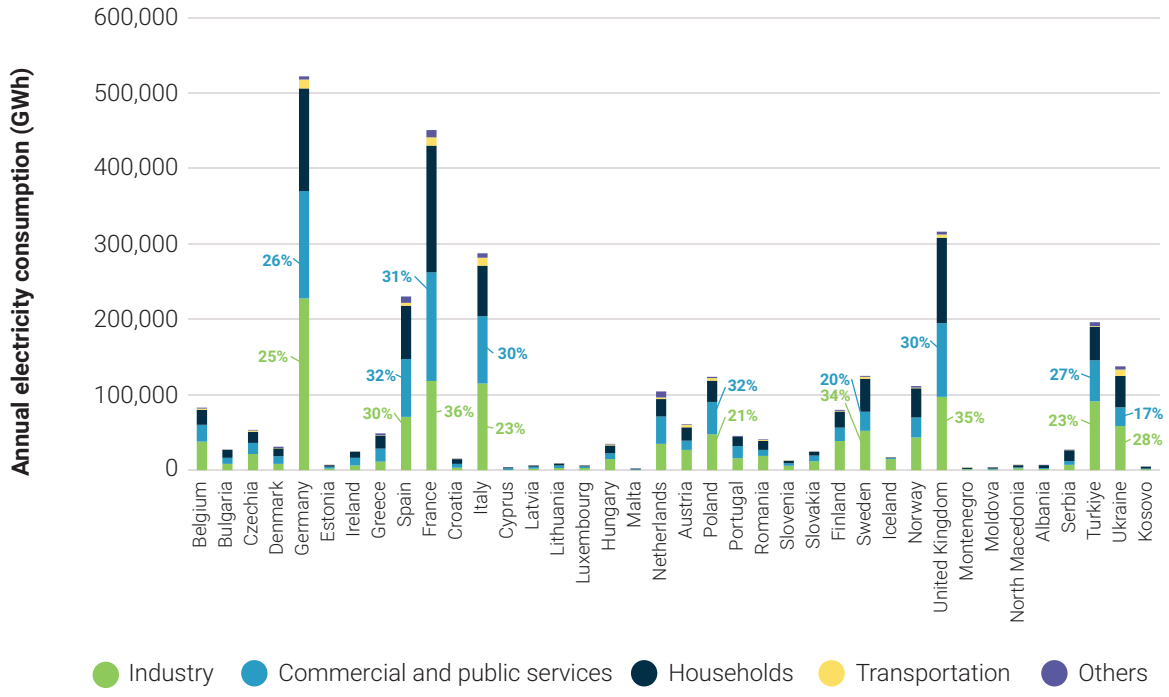
35 Our analysis focused on the commercial and industrial (C&I) sector as we did not find results of AI-driven pilot applications at the residential level. In general, deployment of demand response applications happens first at C&I level, where the most significant savings occur.

Limitations

While our study may provide a useful estimate of the impacts that could be achieved through the application of AI in the operation of buildings, there are several limitations that should be considered when interpreting the results:

- **Using a deterministic approach to assessing energy reduction potential:** Our study estimates a single energy reduction potential for the application of AI in the commercial and industrial sector, despite the wide range of energy savings reported in the literature. This variation in potential savings is due to differences in building design, age and use. While our study provides a useful estimate for exploratory purposes, it is important to recognise that actual savings may vary depending on the specific context in which the technology is implemented.
- **Applying the same energy savings potential across all countries:** Our study assumes that all countries have the same potential for energy savings through the application of AI. However, each country has a unique composition of consumption by sector, which may affect the potential for energy savings. Therefore, the use case for AI in different countries may vary, and our results may not accurately reflect the potential for energy savings in specific countries. Figure 4.8. shows how electricity consumption varies by sector for EU countries. Among major energy consumers, however, the magnitude of variation for commercial and industrial proportion is not huge, ranging from 45% to 67%.

Figure 4.8. Annual electricity consumption by sector in 2013 for EU countries



Source: RAND analysis.

- **Assuming constant energy savings across all hours:** There is limited data available on the hourly impact of AI on energy savings, and it is possible that the magnitude of energy savings could vary throughout the day. In our model, we assumed that the energy savings are constant across all hours of the day and the same for each day. This assumption may not accurately reflect the actual energy savings that could be achieved with AI.

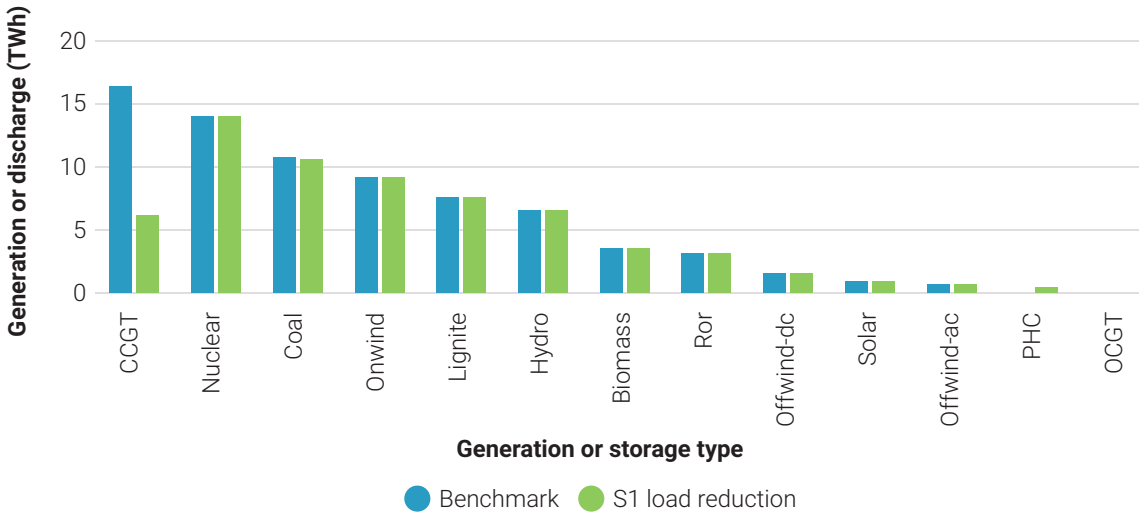
Model results and comparison against benchmark

Figure 4.9. below represents power dispatch from generation and storage resources, comparing the benchmark against S1.

Compared to the benchmark, we can see a significant reduction in CCGT generation for S1. This indicates that CCGT is the marginal resource that is dispatched to meet additional load in the benchmark.

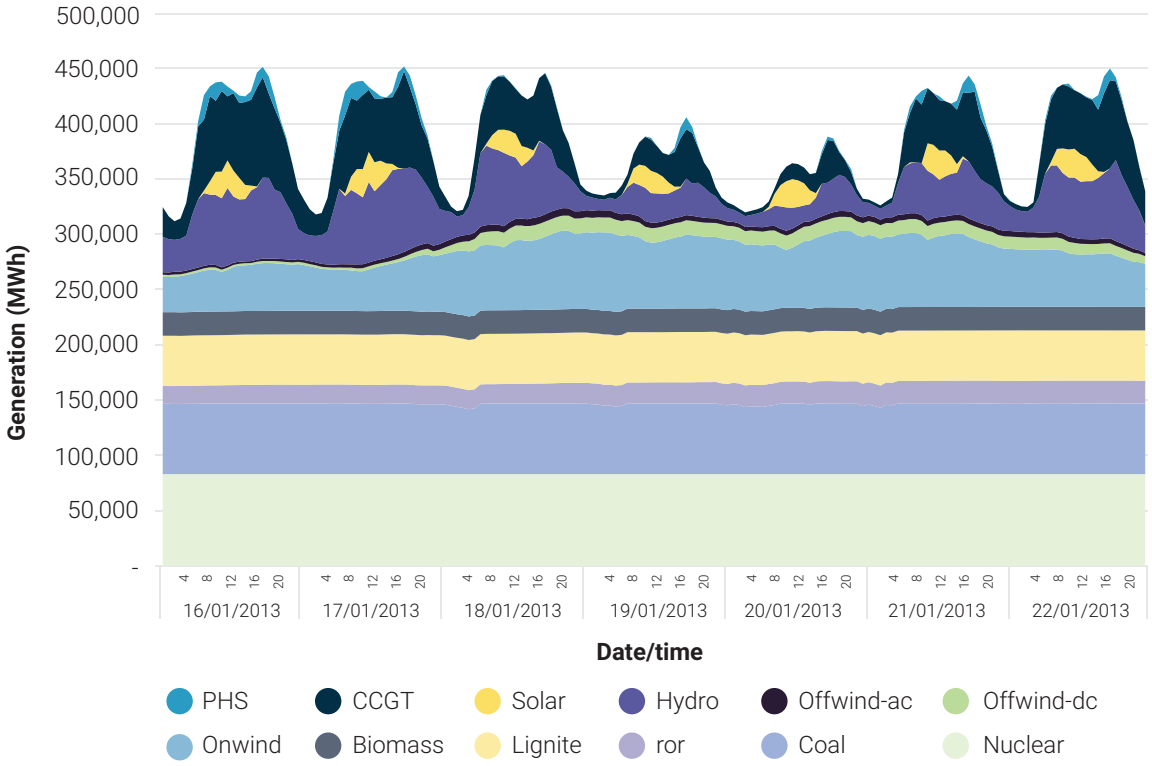
Figure 4.10. below shows the hourly power generation dispatches for S1. Compared to the benchmark scenario, we can see fewer CCGT and more PHS dispatches. Reduced load changes the dynamics of generation dispatch at a given time and location. We can infer that CCGT has been the marginal resource for most of the hours and PHS charging and discharging was economically favourable for some hours. This is due to the economics of unit commitment and the grid network.

Figure 4.9. PyPSA output: Electricity generation/discharge by source for benchmark versus S1



Source: RAND analysis.

Figure 4.10. PyPSA output: Hourly power generation by source for S1

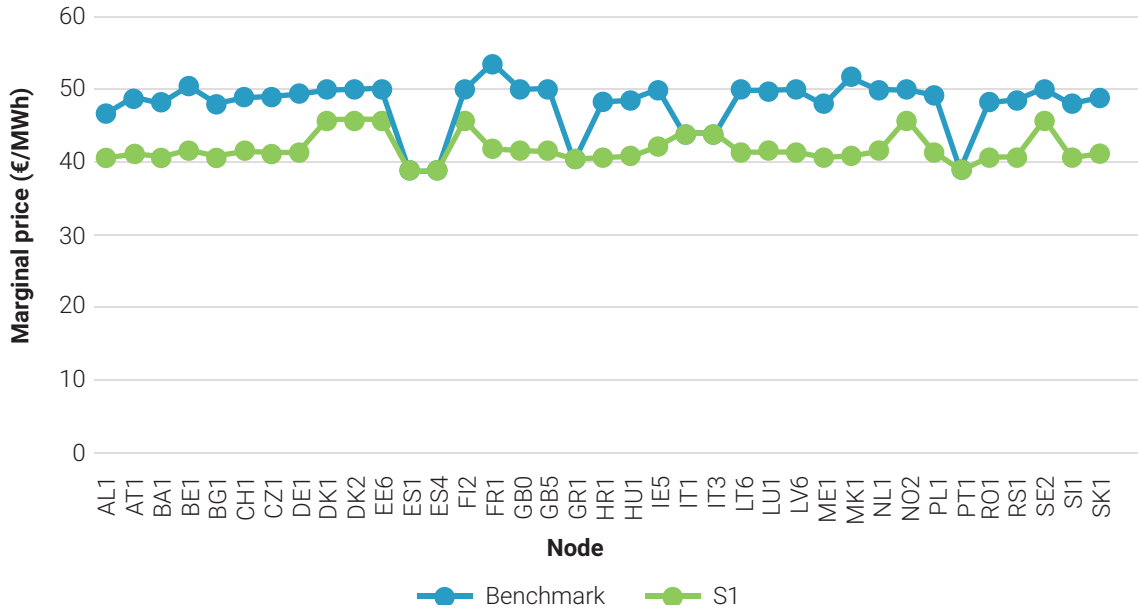


Source: RAND analysis.

Figure 4.11. below represents the maximum LMP per node comparing benchmark with S1. We mostly observe price decreases – except for ES1 and ES5 (Spain), GR1 (Greece), IT1 and IT3 (Italy) and PT1 (Portugal). These nodes are associated with lower LMPs for the benchmark and additional load reduction did not have much impact on LMPs. This indicates that energy providers for the higher LMP areas have most incentive to roll out demand-side AI applications.

In summary, an AI-driven load reduction seems to be associated with a change in the marginal units being dispatched. Note that the change is only reflected at the level of dispatchable generation such as CCGT, and not at the level of base generation such as nuclear. Our analysis indicates that the reduction in load is not enough to affect coal units, which have some level of dispatchability but less than CCGT.

Figure 4.11. PyPSA output: Maximum LMP of electricity by node for benchmark and S1



Source: RAND analysis.

Scenario 2 (S2): AI-driven load shifting

Assumptions and input parameters

AI applications can help shift electricity consumption between different hours within a day based on the cost or carbon-intensity of electricity. A flexible load is a controllable load, where more or less energy can be used for a given time. Load shifting is valuable in today's energy markets because it helps energy market operators to better manage peaks and incorporate more energy from intermittent renewable sources into the grid.[36]

A review of the literature[37] suggests a potential of 15% to 30% of flexible peak load in Northern Europe. Taking the lower bound of 15% flexible peak load and applying it for a 58%[38] smart meter rollout,[39] we modelled that the opportunity for load shifting by AI in EU countries can achieve 9% (i.e. 15% times 0.58) of system peak load reduction.[40] We have adjusted the load shape of the system load as shown in the Figure 4.12. using a 'flattening the shape' approach. This approach used the average system load as a reference value; any load exceeding the reference will be reduced by 50%, any load below the average will be increased by 50%,

36 Scott (2019).

37 Söder et al. (2018).

38 58% is the average smart meter rollout rate weighted by each country's peak load.

39 ACER and CEER (2022).

40 A 58% smart meter rollout can be seen as conservative. For instance, the Energy Information Administration (EIA) reported on their website a 69% penetration in the US commercial sector and 68% in the industrial sector, as of 25 October 2023.

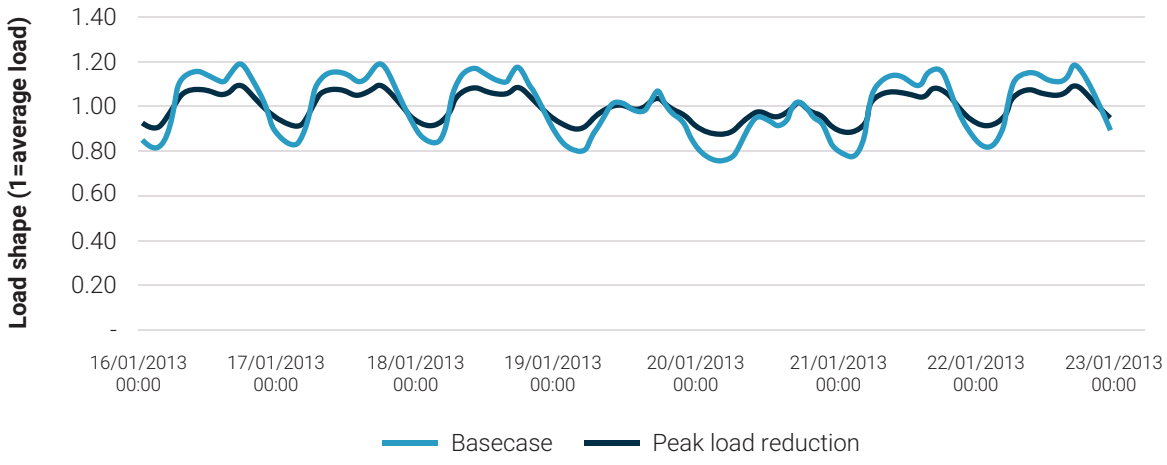
while the total consumption remains the same. We then disaggregated the adjustment based on the load share for each country's hourly load.

For modelling, we predetermined the load shape as exogenous input as opposed to taking flexible load as endogenous input that can be optimised by the model. Currently, there is a limited market in Europe for flexible load to directly participate in resource planning or the electricity spot market that grid operators can access to optimise for the system.[41] It is possible that AI algorithms may take price signals, retail rates or customer needs as a priority to shape the load given incentive structures. Given this condition, we take the load shape changes as an input to system optimisation.

It is important to note that after disaggregation, not every country had the result of a reduced peak load, and some countries even showed an increased load. The system peak load appeared on 17:00 of 17/1/2013 UTC while Albania's peak load appeared on 17:00 of 20/1/2013 UTC.

Countries could also have their own policies to incentivise load shifting. Figures 4.13. and 4.14. show the differences between these two ways of shifting the load for Albania. Centralised load shifting at the European system level resulted in increased peak load for Albania almost every day while Albania's decentralised load shifting shows lower peak load every day. The current discussion of advantages and disadvantages between centralised versus decentralised markets is out of scope – however, the results above suggest that AI deployment could be an additional angle to add to that debate.

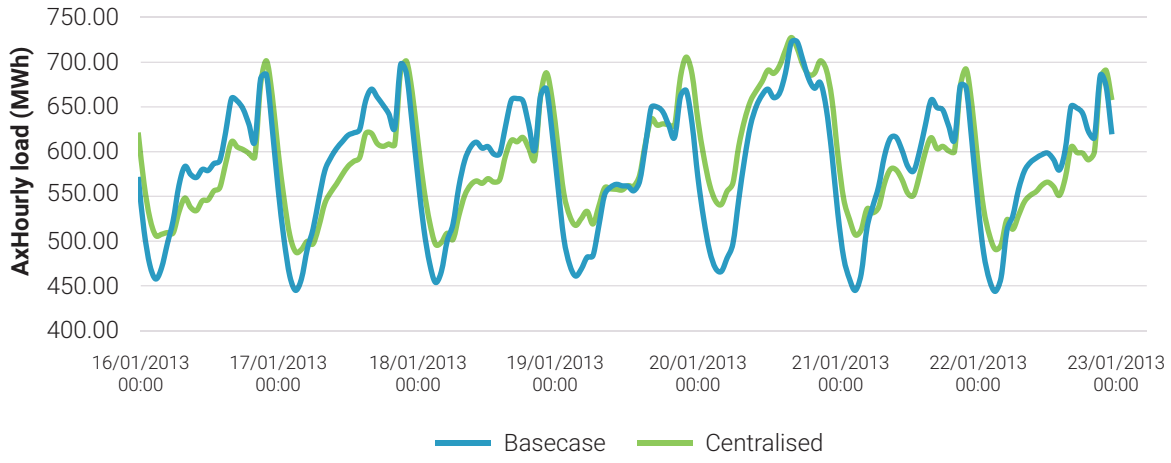
Figure 4.12. Comparison of hourly load shapes for the system: Adjusted shape to reflect 9% peak load reduction



Source: RAND analysis.

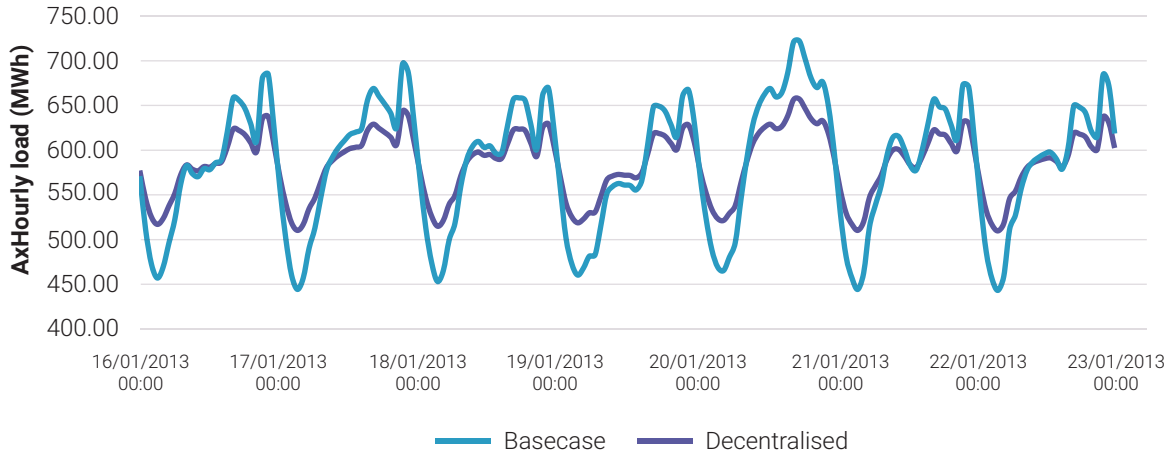
41 Bowler et al. (2020).

Figure 4.13. Comparison of hourly load shapes: Adjusted shape for centralised reduction versus decentralised reduction – centralised peak reduction for Albania



Source: RAND analysis.

Figure 4.14. Comparison of hourly load shapes: Adjusted shape for centralised reduction versus decentralised reduction – decentralised peak reduction for Albania



Source: RAND analysis.

Limitations

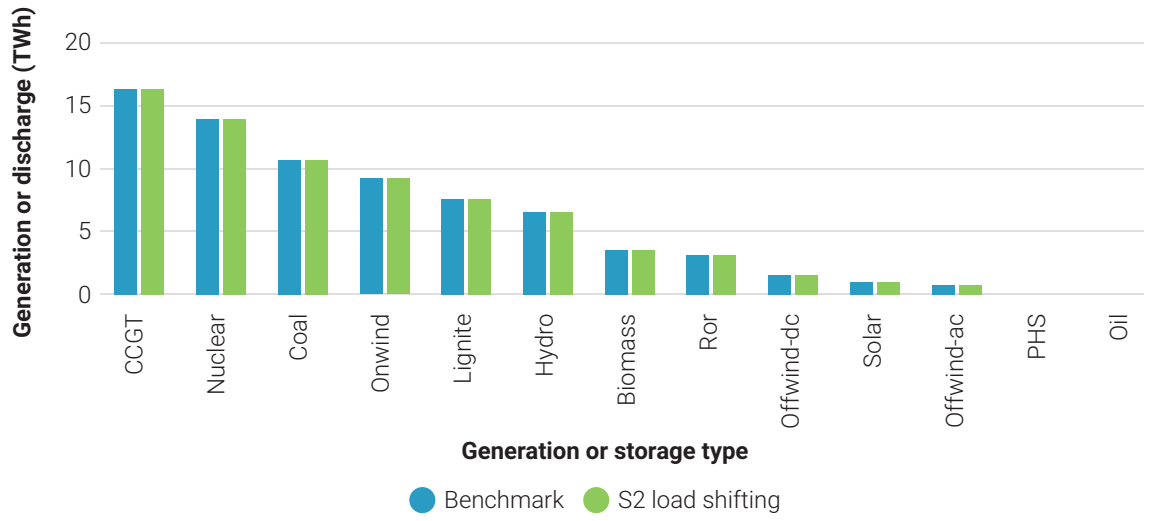
While our study provides a useful estimate of potential impacts that could be achieved through AI-driven load shifting, there are several limitations that should be considered when interpreting the results:

- We assume that each country load was shifted to reduce the European system peak. Achieving a particular load shape at the system level requires a high level of coordination among European countries, which may be difficult to achieve in the short term. AI applications are likely to be customised to provide building- or meter- benefits to end-user customers, which may not result in system peak reductions.
- We found literature discussing AI applications that can enhance the load management in real time if communication infrastructure and incentives exist.[42] In Europe, EU Directive 2019/944 enables dynamic price contracts for electricity end users who have smart meters, providing an opportunity to participate in the wholesale market. Customers can save on electricity bills by adjusting consumption in response to market price signals. However, the Council of European Energy Regulators (CEER) discusses several challenges to consumers realising such benefits – for example due to the complexity and unfamiliarity of wholesale markets, or not being able to adjust their behaviour to price signals to achieve desirable load shifting at the system level.[43]

Model results and comparison against benchmark

Figure 4.15. compares power dispatch from generation and storage resources in the benchmark and S2. S2 does not show significant differences in generation by source compared to the benchmark. There was a small but not significant reduction in CCGT and coal generation. This is because while the shape of the load flattened, total load did not change.

Figure 4.15. PyPSA output: Electricity generation/discharge by source for benchmark versus S2



Source: RAND analysis.

42 Wahid et al. (2019) ; Rocha et al. (2021).

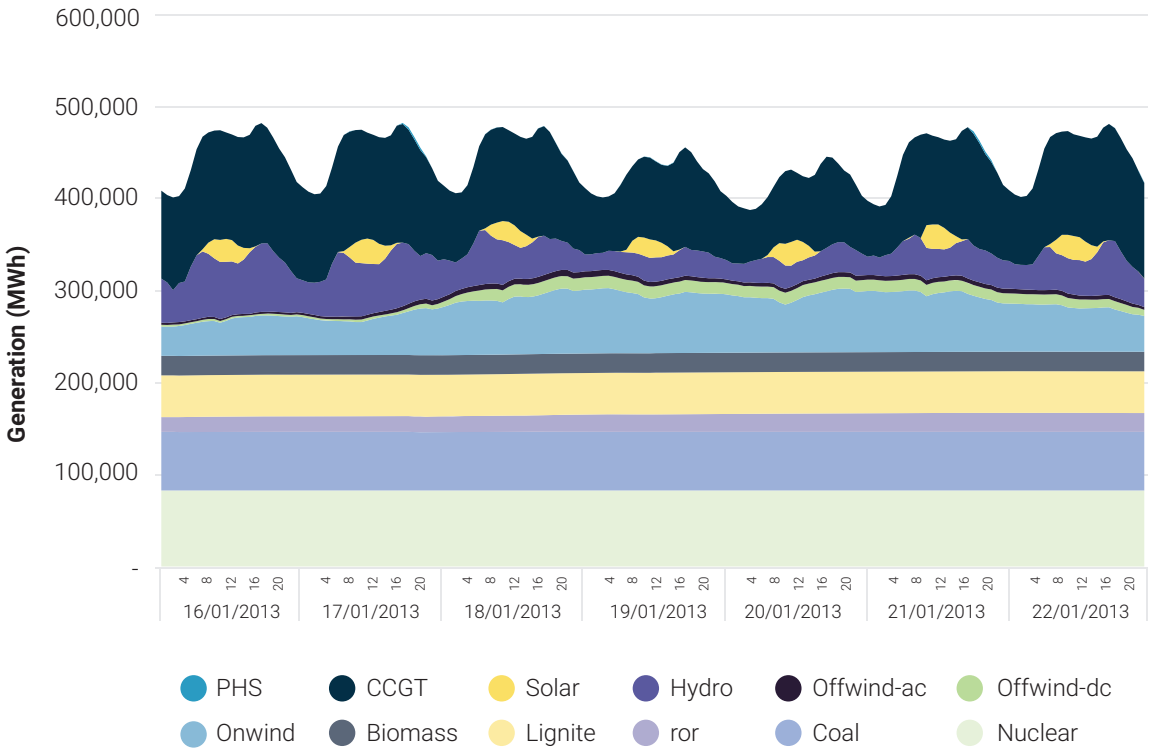
43 CEER (2020).

Figure 4.16. shows the hourly power generation dispatches for S2. Compared to the benchmark scenario, we can observe that the dispatch of CCGT has changed to meet the different load profile, while generation from the other sources remained the same. This is in line with our expectations, as CCGT is a dispatchable source of electricity.

Figure 4.17. represents the maximum LMP price by node, comparing the benchmark to S2. Most nodes show a reduction in maximum LMP, while some nodes have an increased price (ES1, ES4 and PT1).

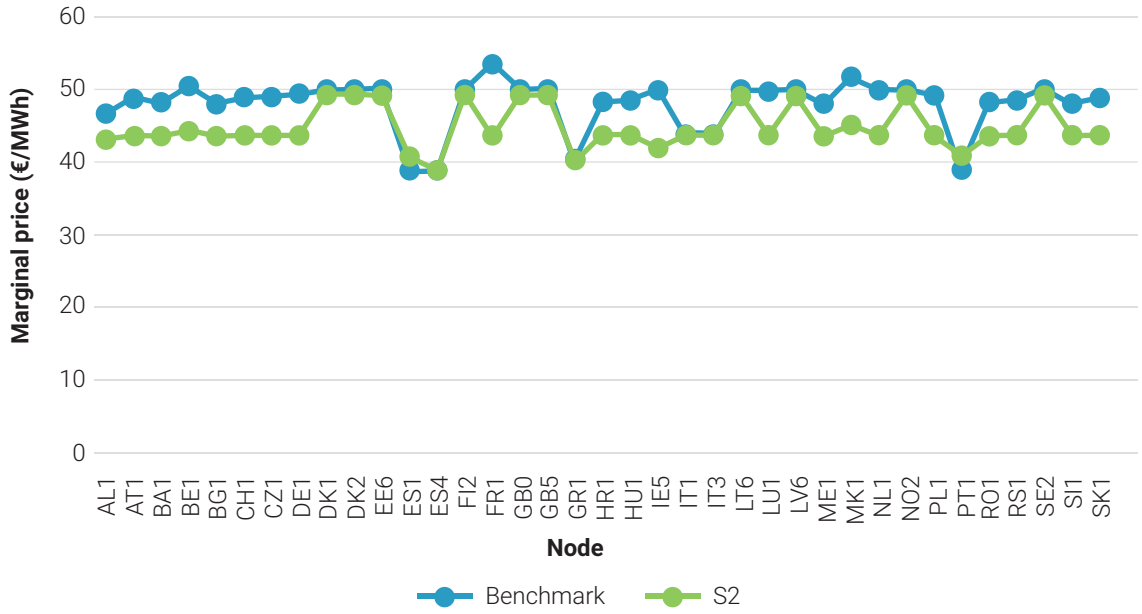
In summary, introducing AI-driven load shifting changes the dispatch profile of dispatchable generation, as reflected in changes in price compared to the benchmark. Overall, S2 leads to lower system-wide costs to meet demand.

Figure 4.16. PyPSA output: Hourly power generation by source for S2



Source: RAND analysis.

Figure 4.17. PyPSA output: Maximum LMP of electricity by node for benchmark versus S2



Source: RAND analysis.

Scenario 3 (S3): Wind wake steering

Assumptions and input parameters

In this scenario, we consider the IFOM impacts AI-driven applications could produce – for instance on the operation of wind energy resources. Wind turbine wakes result in significant energy loss during generation for the downstream turbines due to reduced wind speed. The magnitude of power loss due to the wake effect varies depending on the layout pattern and distance between turbines, but the literature reports that it could be as much as 23%.[44] Wake steering is a control strategy that misaligns wind turbines with wind direction, deflecting the wakes away from downstream turbines and improving the performance of wind farms. Companies such as Vestas have tested ML- and AI-based algorithms for optimal wake steering in actual power generation, resulting in performance improving by up to 13% and energy production improving by 3% to 5%. Meanwhile, the US National Renewable Energy Laboratory (NREL) reports a 3% gain in annual energy production from its simulation tool.[45]

We modified PyPSA-Eur parameters to reflect 3% improvements in wind-farm output from wake steering for both onshore and offshore wind. PyPSA-Eur utilises a parameter called a correction factor to account for the wake effects and array efficiency. A default correction factor value of 0.8855 was used based on a relevant study.[46] We used a correction factor of 0.9121 to reflect our assumption of a 3% improvement from AI/ML wake steering technology.

44 Adaramola et al. (2011); Choney (2022); Fairley (2019).

45 Harrison-Atlas (2021).

46 Bosch (2018).

Limitations

- The modification was applied to existing wind generation, which represents only a small share of generation capacity. As the grid continues to be decarbonised, the share of wind energy will grow, and the impact of this technology will be more significant.
- In the long term, wake steering strategies could also enhance wind deployment by helping to overcome land and layout constraints resulting from the wake effect. This will lead to a higher wind turbine density and higher power output. However, our study focuses only on short-term energy generation improvements as we are not modelling future expansion of the energy system.

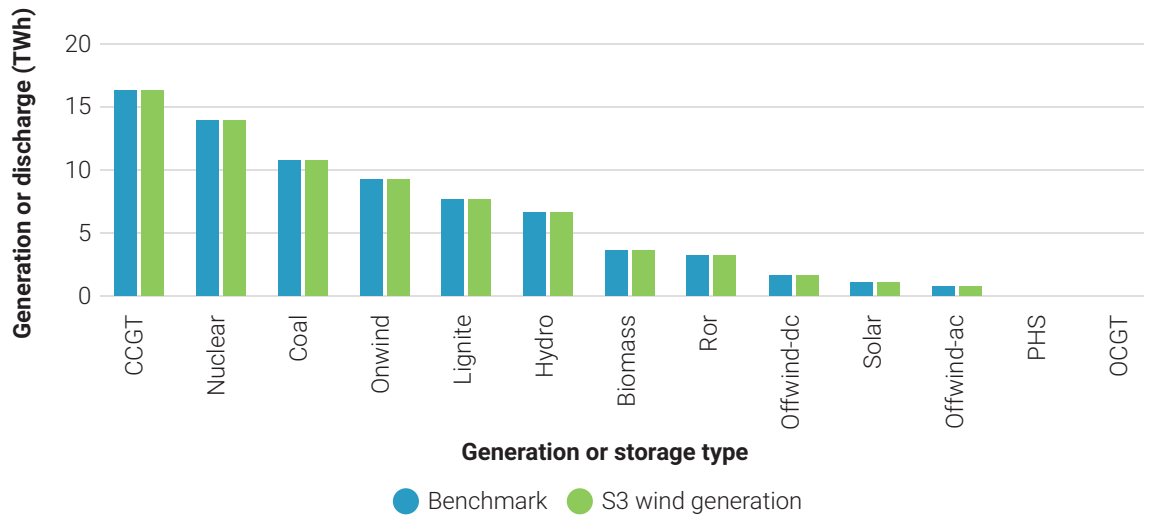
Model results and comparison against benchmark

Figure 4.18. compares power dispatch from generation and storage resources for the benchmark and S3. Compared to the benchmark, we see no significant differences for this scenario. This may be due to a small share of wind generation and relatively small improvement (3%) in wind energy output.

As with the Figure 4.18., we do not observe much difference on the portfolio of hourly generation (Figure 4.19.). Similarly, maximum LMPs for benchmark and S3 were almost identical (Figure 4.20.).

In summary, introducing AI-driven wind steering does not seem to produce enough change to significantly affect the performance of the energy system in the outputs considered.[47]

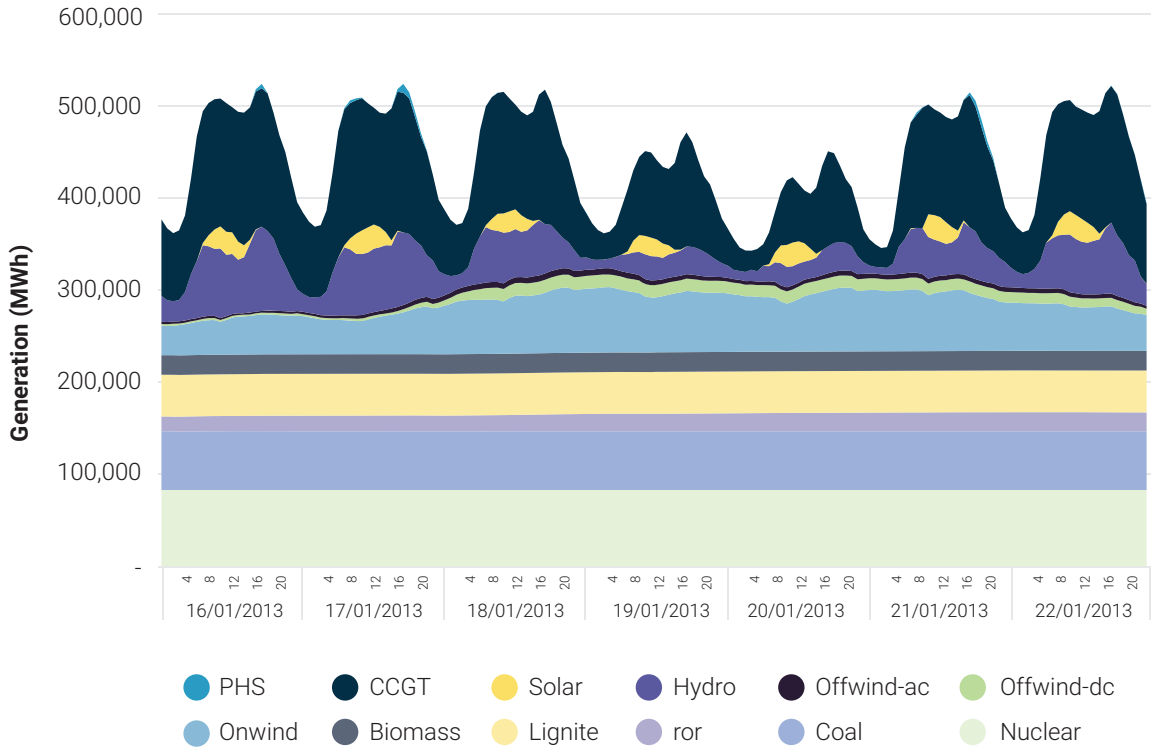
Figure 4.18. PyPSA output: Electricity generation/discharge by source for benchmark versus S3



Source: RAND analysis.

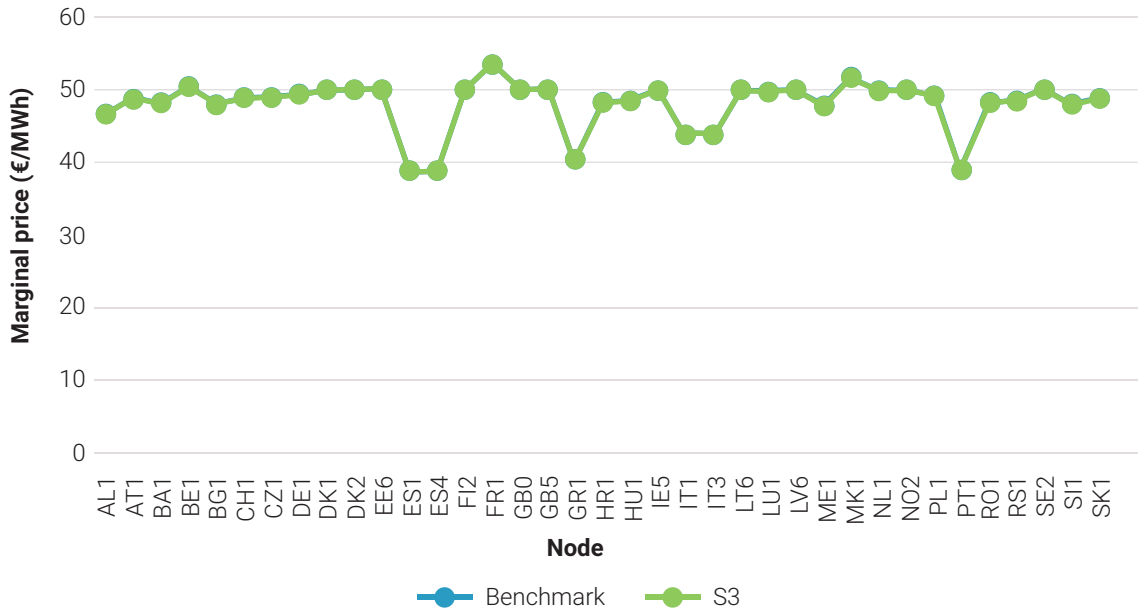
47 This conclusion may change as the share of wind in the energy portfolio increases.

Figure 4.19. PyPSA output: Hourly power generation by source for S3



Source: RAND analysis.

Figure 4.20. PyPSA output: Maximum LMP of electricity by node for benchmark versus S3



Source: RAND analysis

Scenario 4 (S4): All together

Assumptions and input parameters

We analysed the potential impact of all three AI technologies in the power system as if they were available simultaneously. We modified all input parameters discussed above, then optimised the system to evaluate changes in energy security metrics from the benchmark scenario.

Limitations

- Gradual rollout of AI applications may look very different from what we modelled. We assumed that each application's potential would stay the same, though in reality there may be differences in how countries roll out the technology.
- AI-driven load reduction and load shifting may interfere with each other, meaning that rolling them out in the additive way we assumed here may not be possible.

Model results and comparison against benchmark

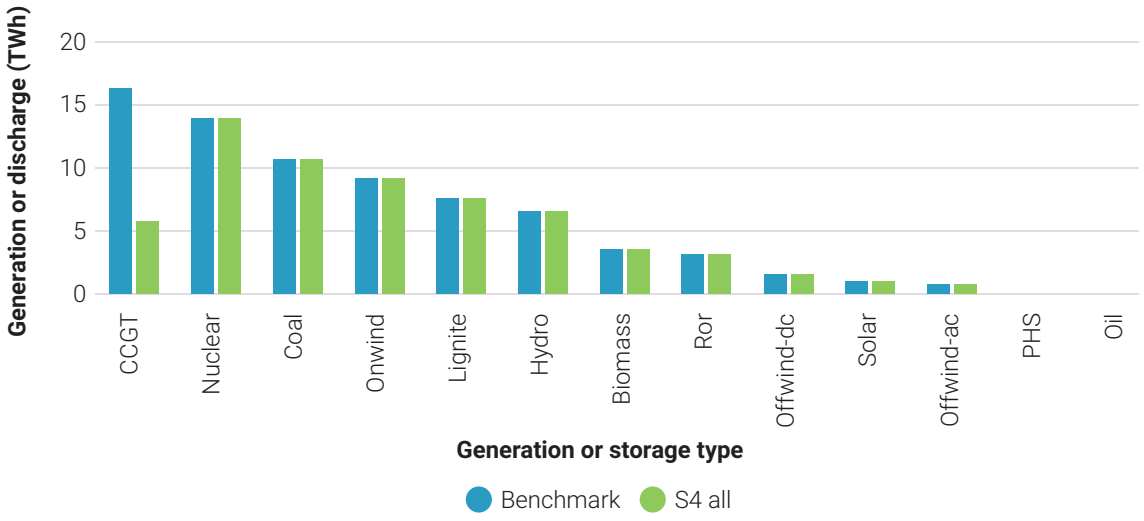
Figure 4.21. below represents a comparison of power dispatch from generation and storage resources between the benchmark and S4. We notice that CCGT generation in S4 is significantly lower than the benchmark, as it was in S1. Compared to S1, however, we found that CCGT generation is further reduced in S4, while PHS is not dispatched.

Figure 4.22. shows hourly power generation dispatches for S4. The dispatch profile looks very similar to S2 while the output of CCGT is significantly reduced.

Figure 4.23. represents the maximum LMP by node for S4, compared to the benchmark. We observe that at the price level, the combined impact of all AI applications is not necessarily additive across the whole system. For example, the maximum LMP for S4 is higher than for S1 for some nodes, especially LT6 (Lithuania) and LV6 (Latvia).

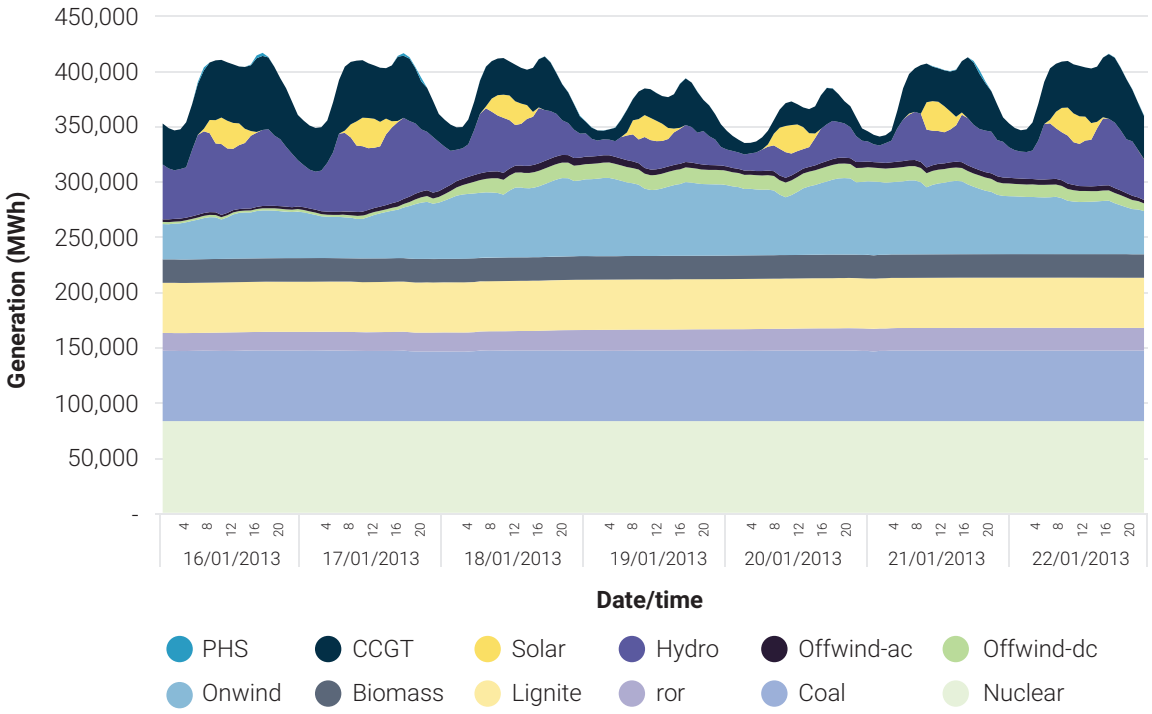
In summary, introducing several AI initiatives seems to have an additive impact on the overall system, but not necessarily at the node level. This could be further investigated. The reasons why the optimisations generated differentials in the results for some nodes are out of scope for this project.

Figure 4.21. PyPSA output: Electricity generation/discharge by source for benchmark versus S4



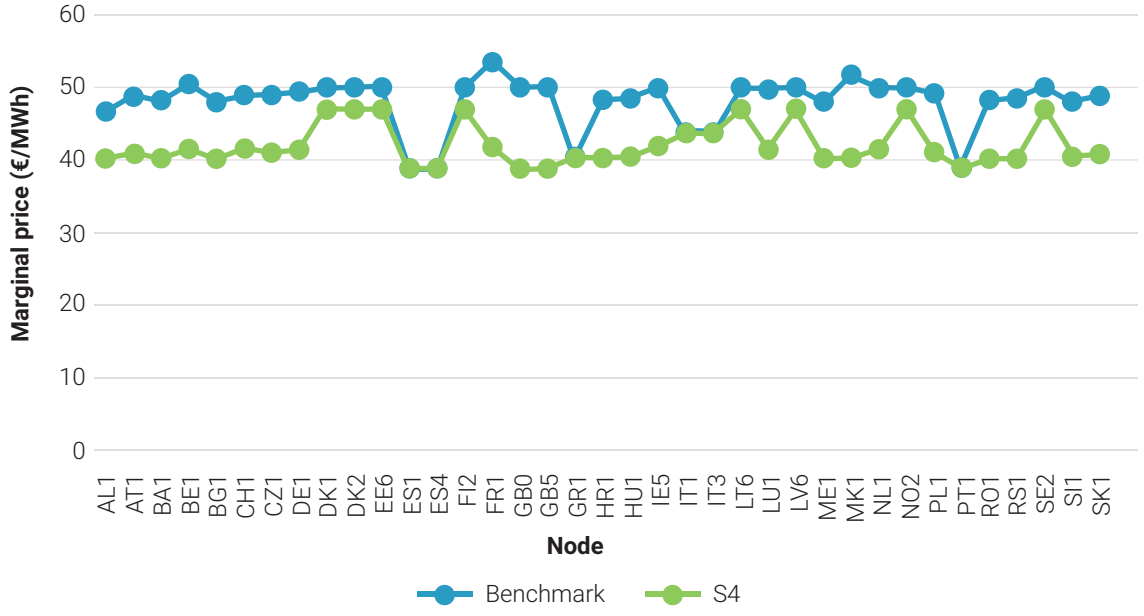
Source: RAND analysis.

Figure 4.22. PyPSA output: Hourly power generation by source for S4



Source: RAND analysis.

Figure 4.23. PyPSA output: Maximum LMP of electricity by node for benchmark versus S4



Source: RAND analysis.

Chapter 5.

FINDINGS AND DISCUSSION

This chapter presents our analysis of the impact of AI on energy security metrics for different scenarios and the benchmark. As discussed in Chapter 2, we developed methods to quantitatively estimate energy security attributes of availability/reliability, accessibility, acceptability and affordability. The aim was to evaluate the performance of each scenario and identify AI applications that can improve energy security. The energy security metrics considered in this analysis include fossil fuel dependency as a proxy for accessibility, CO_2 emissions as a proxy for acceptability, reserve margin as a proxy for availability/reliability and average LMPs and maximum LMPs as proxies for affordability.

Findings

Table 5.1. provides a comprehensive summary of the energy security metrics for all scenarios and the benchmark. Among the scenarios, S1 (load reduction) and S4 (all measures combined) exhibit improvements across all metrics compared to the benchmark. However, other scenarios demonstrate mixed results, with metrics improving while others maintain the status quo, as indicated in green below.

Table 5.1. Energy security metric comparison

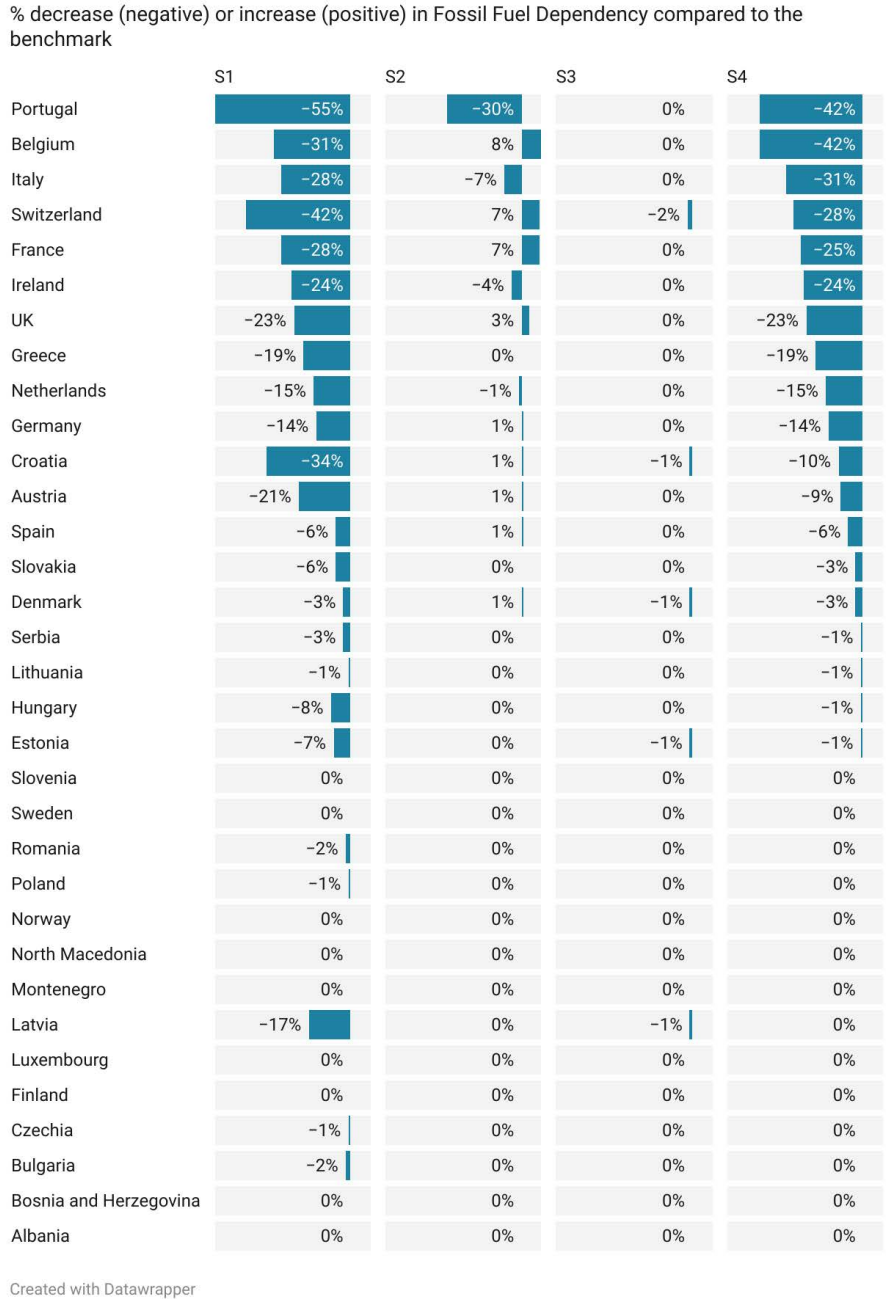
Energy security		Scenarios				
Category	Metric	Benchmark	BTM applications		IFOM applications	BTM and IFOM applications
			S1 Load reduction	S2 Load shifting	S3 Wind wake steering	S4 All combined (S1 + S2 + S3)
Accessibility	Fossil fuel dependency	46.5%	38%	46.6%	46.4%	38%
Availability	Reserve margin	21.0%	43%	32.4%	21%	57%
Acceptability	Kilotons of CO_2e emissions	10036	7970	10032	10022	7934
Affordability	Average LMP	€42,68	€38,36	€42,13	€42,66	€39,36
	Max LMP	€53,53	€45,89	€49,28	€53,54	€47,09

Source: RAND analysis.

Note: Green shades represent improvement from the benchmark.

Table 5.2. and Table 5.3. show how some energy security metrics are impacted across the different member countries in the European system by scenario. A quick glance at the graphs below indicates significant variability of impact. Also, in some scenarios, there are trade-offs between security metrics for some countries. We discuss each scenario in detail below.

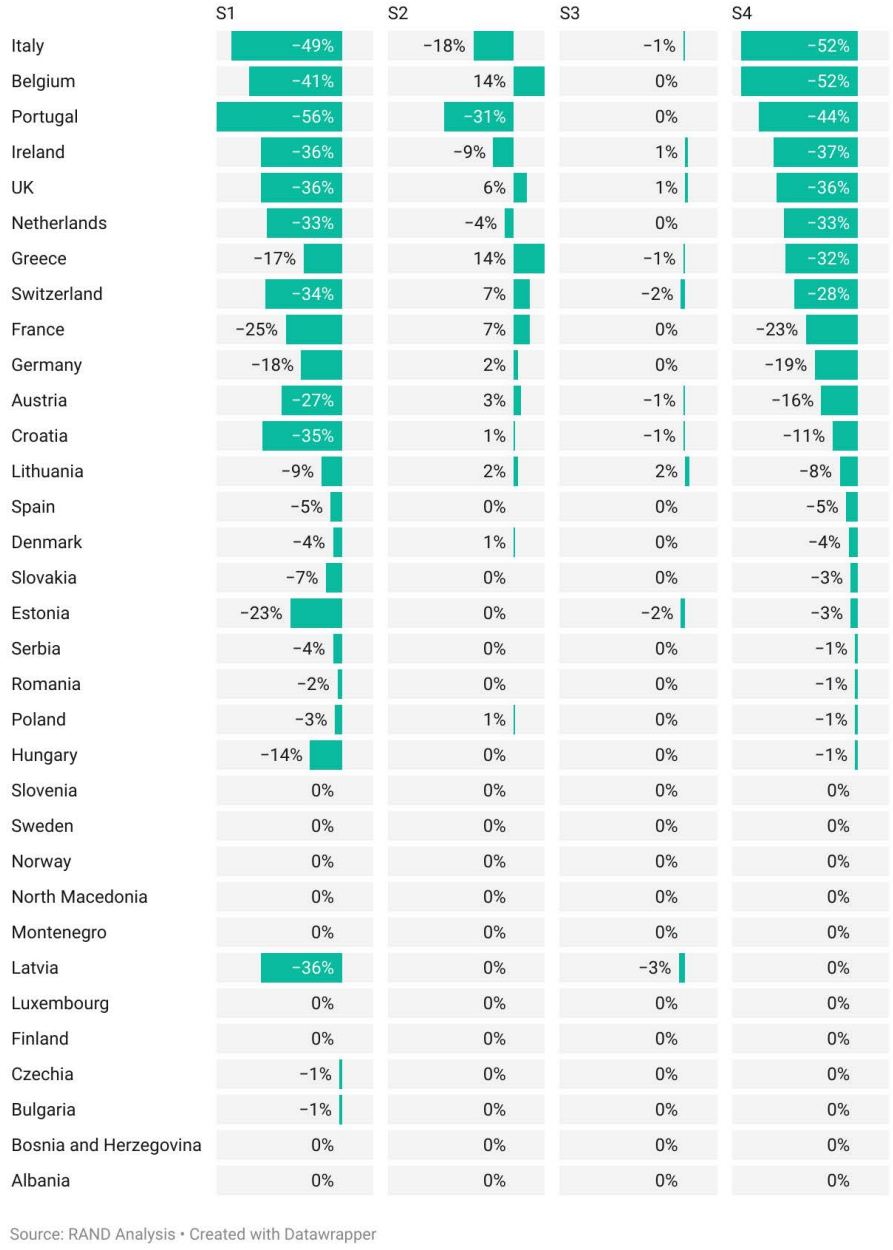
Table 5.2. Changes in accessibility by country and scenario



Source: RAND analysis
Note: Fossil fuel dependency is quantified in percentage change for each scenario in every country. Changes relative to the benchmark scenario are expressed as percentage change, determined by calculating the difference between two values divided by the value from the benchmark.

Table 5.3. Changes in acceptability by countries and scenarios

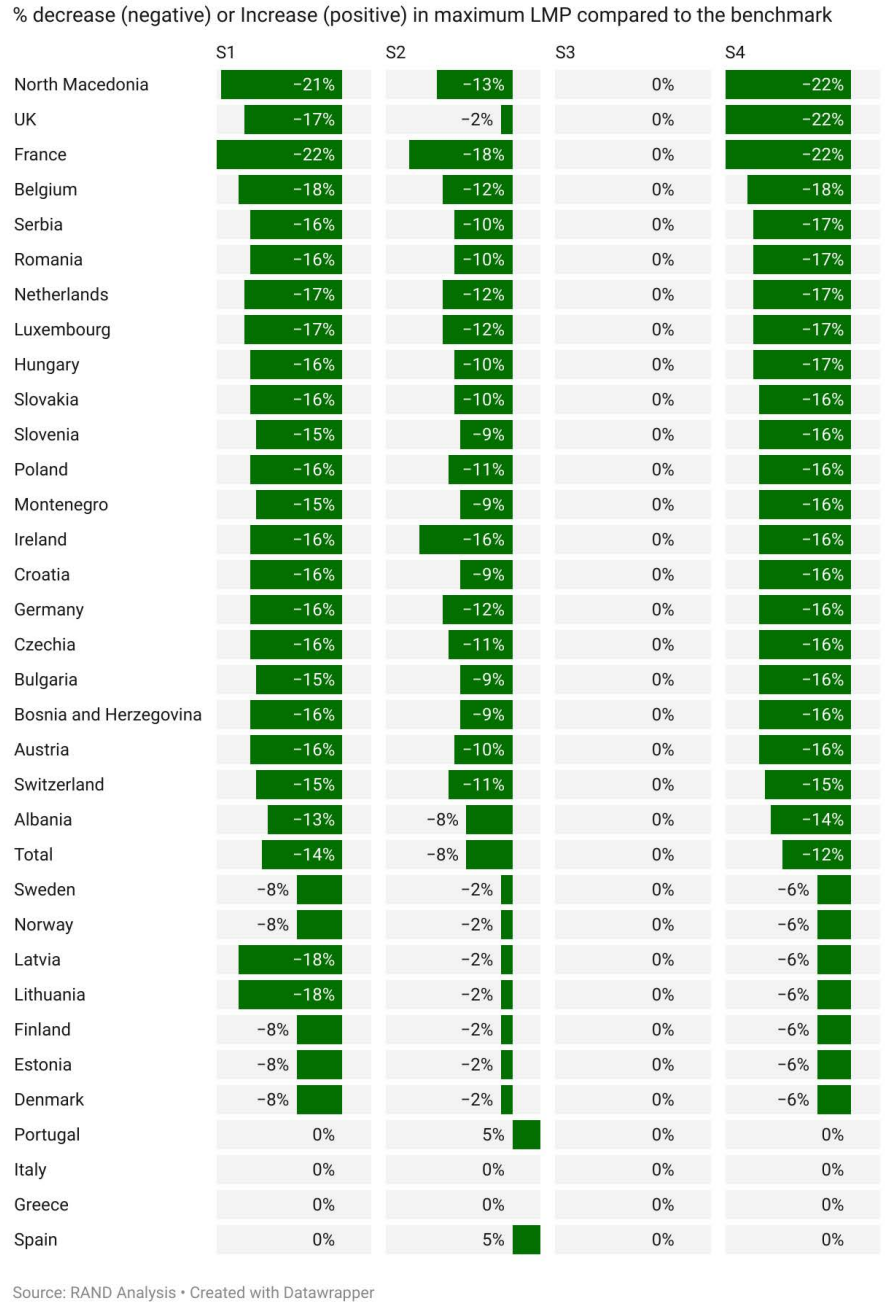
% decrease (negative) or increase (positive) in CO2 emissions compared to the benchmark



Source: RAND Analysis • Created with Datawrapper

Source: RAND analysis.
Note: GHG emissions are quantified in metric tons of CO_2e. Changes from the benchmark scenario are evaluated in terms of percentage changes.

Table 5.4. Changes in affordability by country and scenario



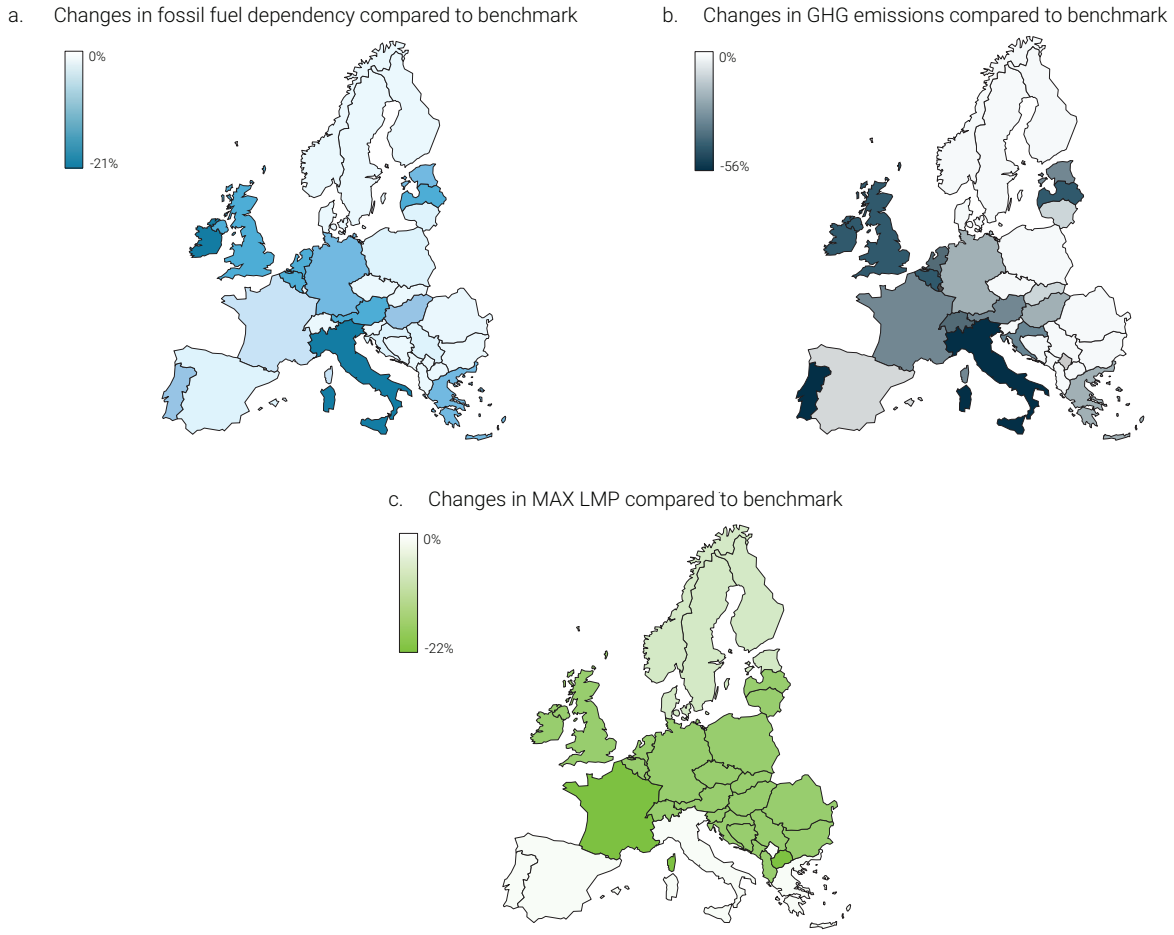
Source: RAND analysis.
Note: LMPs are expressed in $/MWh. Changes from the benchmark scenario are assessed based on percentage changes.

Discussion

S1 AI-driven load reduction: best performance

Conserving load provides benefits across all energy security metrics. The magnitude of the impact varies across countries, from more than 10% in some cases to negligible impact in others. Figure 5.1. illustrates changes from the benchmark for three energy security metrics: a. fossil fuel dependency; b. GHG emissions; c. max LMP for S1. Although at the system level all three energy security metrics improved compared to the benchmark, distributional impact on each country varied. While some countries showed more improvement than the system-wide reduction, others did not change at all. Portugal, for example, showed a 56% reduction[48] in GHG emissions, while Northern European countries did not change. For maximum LMP, France and the UK showed the biggest reductions from the benchmark, while Spain and Portugal did not change at all.

Figure 5.1. Distributional impact for S1 (load reduction) compared to benchmark



Source: RAND analysis.

48 Portugal's GHG emissions were reduced by more than 50% from the benchmark of 19 kilotons of CO_2e to 8 kilotons of CO_2e in Scenario 1. Fossil fuel dependency also decreased by over 50%, from 8% to 3%. However, these promising results should be carefully interpreted given the noted limitations of the modelling approach and the exploratory nature of the overall study.

We noticed that for S1 (load reduction), the countries experiencing greatest impact are not the same across all security metrics. One possible explanation is that countries with larger dispatchable fossil generation fleets are likely to benefit most from changes on dispatchable load profiles triggered by AI-driven load reductions. Both Germany and Italy – the biggest importers of gas in Europe – see significant energy security improvements in accessibility and acceptability. Our exploratory analysis does not allow us to explain particular relative differences between countries – for example, why Latvia sees significant improvement on affordability compared to Estonia, despite both being in the Baltic region. Teasing out this and other such differences requires more scenarios than we developed here.

In summary, our exploratory analysis has raised important insights at the European level but is more restricted at the national level, given the nature of the applied scenarios. Overall, however, AI-driven load reduction seems to have a positive impact across all the energy security metrics without significant trade-offs.

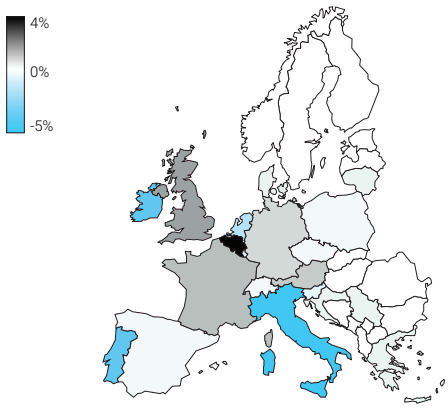
S2 Load shifting: Objective matters

The analysis reveals that S2 (load shifting) did not significantly alter fossil fuel dependency or GHG emissions compared to the benchmark. This can be attributed to the total amount of CCGT generation remaining unchanged. However, a positive development was observed in the reserve margin, which improved as the peak load was reduced. Additionally, average and maximum LMPs improved due to changes in marginal resources and load profiles due to a smoother, less peaked demand curve.

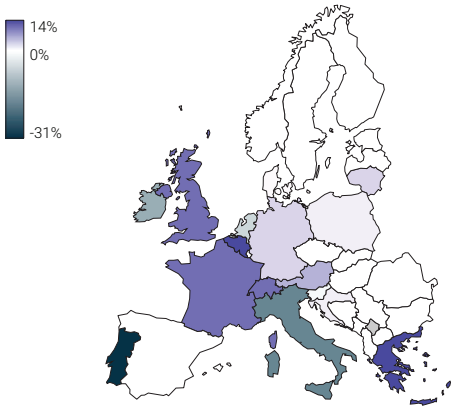
Figure 5.2. displays distributional changes from the benchmark for three energy security metrics: a. fossil fuel dependency; b. GHG emissions; c. max LMP for S2. Although at the system level fossil fuel dependency and GHG emission metrics did not change compared to the benchmark, the magnitude and direction of change varied by country. Some countries showed more improvement than the system-wide reduction, while others did not change at all or even worsened compared to the benchmark. For example, Italy's fossil fuel dependency showed a 5% reduction, while Belgium's increased by 4%. Regarding maximum LMP, France showed the most significant reductions from the benchmark, while LMPs for Spain and Portugal increased by 5%. This result further highlights trade-offs between countries and could be an area of further research.

Figure 5.2. Distributional impact for S2 load shifting compared to benchmark

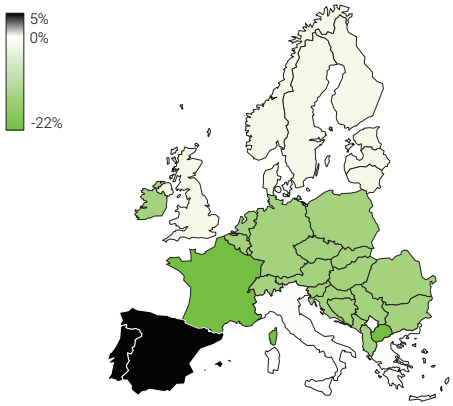
a. Changes in fossil fuel dependency compared to benchmark



b. Changes in GHG emissions compared to benchmark



c. Changes in MAX LMP compared to benchmark



Source: RAND analysis.

As mentioned above, we do not intend here to resolve the debate over the benefits of centralised versus decentralised markets. However, we decided to contribute to the discussion by examining the case of decentralised load shifting as each country reduces its peak load rather than contributing to system peak reductions. Table 5.5. compares the two cases (centralised/ decentralised) against the benchmark. In general, the impact on energy security was similar. The reserve margin was slightly higher for the centralised case, which makes sense as we are estimating the system-side reserve. On the other hand, CO_2 emissions and LMPs performed better for the decentralised case. This may be due to the scenario's impact on alleviating localised constraints.

Table 5.5. Energy security metric comparison between centralised and decentralised load shifting

Energy security		Scenarios		
Category	Metric	Benchmark	BTM Applications	
			S2 Load shifting (centralised)	S2a Load shifting (decentralised)
Accessibility	Fossil fuel dependency	46.5%	46.6%	46.6%
Availability	Reserve margin	21.0%	32.4%	32.2%
Acceptability	Kilotons of CO_2e emissions	10,036	10,032	10,032
Affordability	Average LMP	€ 42.68	€ 42.13	€ 42.04
	Max LMP	€ 53.53	€ 49.28	€ 49.06

Source: RAND analysis.
Note: Green shades represent improvement from the benchmark.

S3 Wind wake steering: incremental progress

In contrast to the other scenarios, S3 (wind generation efficiency) did not display significant differences from the benchmark across all metrics. The magnitude of improvement observed was minimal. Nonetheless, it is crucial to acknowledge that the impact of wind generation efficiency is expected to grow as the grid undergoes decarbonisation and incorporates new wind developments.

S4 All combined

The results of S4 (all combined) yielded unexpected findings. Initially, we anticipated that this scenario would outperform all others. However, only the reserve margin metric exhibited the highest performance, while the average and maximum LMPs were worse than those in S1 (load reduction). Other metrics remained on par with S1. This outcome can be attributed to the predetermined load profile strategy, which focused on reducing the peak load. While successful in improving the reserve margin, it neglected optimisation around the price signal after load reduction. This serves as an important reminder of the complexity of optimisation and highlights the need for careful consideration of interactions between applications to avoid adverse impacts on the system.

Chapter 6.

POLICY IMPLICATIONS AND FURTHER RESEARCH

Drawing on the findings and discussion, we have identified a number of insights for policymakers in Europe and beyond when considering potential system-wide AI applications in energy. We also propose several further areas of research that could build on this exploratory study in the future.

Policy insights

Our analysis of energy security metrics offers valuable insights into the performance of different AI expansion scenarios compared to a status quo benchmark. It underscores the positive impact of strategies such as AI-driven load reduction across multiple energy metrics. However, it also emphasises the need for careful consideration of the impact of AI applications across different countries and across different security metrics. We present below a set of potential policy implications for AI on the ENTSO-E grid.

1. Each of the AI scenarios leads to improvement in at least one of the energy security metrics, although the magnitude varies between scenarios different metrics. Our study implies that some AI deployments generate trade-offs between energy security metrics. For instance, in S2 (load shifting), AI implementation led to improvements in availability and affordability but not accessibility and acceptability. This implies that polices supporting AI should align with the security metric of greater saliency (accessibility, availability, acceptability, affordability) for the policymaker.

2. The impact of AI applications across countries would likely depend on the energy market rules governing the electricity system. Our research indicates AI's role in the grid should be part of the current policy discussions on market decentralisation that should govern ENTSO-E. For instance, S2 showed different levels of impact on energy security metrics under centralisation and decentralisation.

3. When different AI technologies are implemented together, interactions between the applications may result in adverse effects on energy security. For instance, AI applications that reduce peak load may reduce the share of CCGT in the energy portfolio as they are dispatched to cover peak load without changing the participation of dirtier coal-fired baseload power plants. Policymakers should recognise that AI impact on energy security is not necessarily additive and there could be trade-offs.

4. Our results indicate that AI applications aimed at load reducing behind the meter have significant positive impacts on all four energy security metrics (e.g. >10% on accessibility). Given the technological readiness of this approach, our results support policies that incentivise the use of:

    a. AI HVAC control technology for buildings

    b. Smart metering

    c. VPP and distributed energy resources.

Future research opportunities

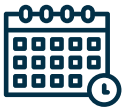
We identified several major opportunities that can be built upon the research conducted using PyPSA. The identified expansions are as follows:



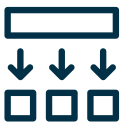
Expanding the time horizon to long-term future: Expanding the time horizon from short-term (<5 years) to long-term (>5 years) will allow for the inclusion of AI technologies at a lower level of technological readiness than those considered in this research.



Expanding the scope to include other energy sectors: Expanding the scope to include other energy sectors such as primary fuel sources and transportation would help to address a broad energy system question, such as navigating through climate policy and energy system transition. The PyPSA tool already has these features that can be adopted without extensive time or resources.



Testing for a longer period time: We were only able to assess the energy system for a week given computational and solver constraints. Including a longer assessment period would allow researchers to examine the system more holistically as demand and supply vary seasonally, especially to account for a grid with high penetration of intermittent renewable energy whose generation may vary and be uncertain based on weather conditions.



Allowing additional levels of granularity in the optimisation: Given computational constraints, the research was limited to a one-node-per-country for most countries. This limitation was due to the use of a solver that, although available at no cost, has limited power. Additional funds can be allocated to allow for additional levels of granularity in the optimisation, which will help to assess more distributional impact and better represent the actual system.



Exploring other geographic regions: There are many projects[49] underway that are using open data to construct energy system in various regions. This expansion will open up the possibility to explore energy policy problems on a global scale.[50]

49 For an application in India see Spencer et al. (2021).

50 PyPSA meets Earth (2022).

Chapter 7.

OPEN-SOURCE MODEL DISCUSSION

One of the ancillary objectives of this research was to gain experience with open-source power flow modelling. In this section, we share some of the insights the team gained from this exercise that can guide future deployment of AI in the electricity system.

Benefits and challenges

In recent years, open-source tools and open data have become increasingly popular in clean energy transition research, due to improved computing capabilities and the need for lower-cost entry solutions for non-industry use cases, such as for researchers, policy analysts and others.

PyPSA is a mature open-source tools and has functions comparable with commercial and proprietary tools.[51] It is intuitive and easy to learn. However, during our use of PyPSA, we encountered several issues that impeded our progress in conducting research.



Operating system issues with installation: The first issue we encountered was related to the installation process. The core function and its dependencies require a Linux system and do not work with Windows. This presented a challenge for us, as we were using Windows, and had to switch to Linux to use PyPSA. This resulted in additional time and effort being expended on the installation process.



De-bugging and error handling: We found that de-bugging and handling errors were not intuitive and required us to rely on open discussion forums for answers. This process was unreliable as we sometimes received answers in a matter of days, but at other times we did not receive any response at all. Having to wait to resolve errors before we could continue our work slowed the progress of our research.



Deviating from basic set-up: Another issue we encountered was that deviating from the basic set-up, such as choosing a different year to study, required additional processes and runtime. We often faced errors that prevented us from completing the run. As a result, we had to change the plan and limit the project scope to the data and set-up available to us.



Frequent updates: We found that PyPSA had frequent updates, with a new version release almost every month. When there was a major update to the tool, we had to configure the tool again, as a significant amount of the workflow was modified or merged with other functions. This resulted in additional time and effort spent re-doing work we had already completed.

51 Groissböck (2019).

Lessons learned

Our experience using PyPSA revealed several issues, such as difficulties with installation, error handling and deviations from the basic set-up, as well as frequent updates that required us to redo work. Through our PyPSA experience, we learned the inherent trade-offs between using open-source and commercial tools. While open-source tools like PyPSA offer extensive capabilities and cost-effectiveness, they can also present unique challenges such as system-specific requirements, less intuitive debugging and frequent updates that necessitate reconfiguration. Our experience highlighted the importance of factoring these considerations into the project timeline, especially when facing tight deadlines.

Despite these challenges, the understanding of the tool we gained through the project will be valuable for future undertakings. The lessons learned from this research is testament to the evolving nature of power system modelling, where the balance between functionality, ease of use and cost-effectiveness is key.



Chapter 8.
CONCLUSIONS

Our exploratory results suggest that AI applications tackling the efficiency and optimisations of demand (BTM) may have a significant positive impact on energy security metrics. The impact varies according to the attribute of demand targeted (e.g. average demand versus peak demand). In addition, our results also indicate significant variability of impact between countries, with some benefiting more than others.

Our results should be caveated by the exploratory nature of our analysis, its short-term horizon as well as the limited AI applications/scenarios analysed. We conclude our report with a list of lessons learned on the use of open-source power flow modelling techniques, which we think are worth highlighting as a result of this research.

GLOSSARY

BTM	Behind-the-meter (BTM) refers to resources typically owned and operated by the customer and used to offset their energy consumption from the grid.
Correction factor	This factor represents wake losses for wind energy production in PyPSA-Eur model.
IFOM	In-front-of-the-meter (IFOM) refers to the part of the grid owned and operated by utilities or other grid operators, including power plants, transmission lines and distribution networks that deliver electricity to end users.
Load scaling factor	This factor allows users to linearly scale the load in PyPSA-Eur model.
Reserve margin	Reserve margin refers to the amount of excess capacity available in a power system to meet unexpected increases in demand or unexpected outages of power plants or other energy resources.

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