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The Hidden Carbon Cost of AI: Data Centre Electricity Demand and Climate Implications for Sweden

by

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Abstract

The rapid growth of artificial intelligence (AI) has made data centres a significant and growing source of electricity demand. This study projects AI-driven data centre electricity demand in Sweden for the years 2022 to 2045, and further quantifies its implications for Sweden's 2030 and 2045 climate targets. Using a three-step methodological approach, the study constructs a total data centre electricity baseline, models enterprise AI adoption through a logistic S-curve with an infrastructure lag parameter, and calculates direct emissions and carbon opportunity costs across three competing industrial decarbonisation uses. Projected AI-driven electricity demand is expected to reach the equivalent of approximately 8 percent of Sweden's current total annual emissions by 2045 under the marginal carbon intensity scenario, while the carbon opportunity cost of AI further amplifies this tension. The central finding indicates that AI data centre growth will make the climate targets for Sweden meaningfully harder to achieve, a pressure that remains unaddressed in current Swedish climate policy.

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Table of Contents

1. Introduction.....	1
1.1 Research Problem	2
1.2 Aim and Scope.....	2
1.3 Outline of the Study	3
2. Context.....	3
2.1 Sweden's Electricity System	3
2.2 Sweden as a Data Centre Location	5
2.3 Sweden's Climate Policy Framework	6
3. Theory and Previous Research.....	6
3.1 Previous Research.....	7
3.2 Theoretical Approach.....	9
3.2.1 Technology diffusion and the logistic S-curve	9
3.2.2 Marginal emissions and the carbon opportunity cost	10
4. Data	11
4.1 Data Centre Electricity Baseline.....	11
4.2 Enterprise AI Adoption and Electricity Share	12
4.3 Emissions and Opportunity Cost	13
5. Methods.....	15
5.1 Step A: Constructing the Data Centre Electricity Baseline in Sweden (DCE_t)	17
5.2 Step B: Estimating the AI Share of Swedish Data Centre Electricity	19
5.2.1 Stage 1: The Enterprise AI Adoption Diffusion Curve	20
5.2.2 Stage 2: The Infrastructure Lag Parameter δ	22
5.2.3 Stage 3: Scenario-Based Electricity Share Mapping	24
5.3 Step C: Emissions and Carbon Opportunity Cost.....	25
5.3.1 Direct Emissions	26
5.3.2 Carbon Opportunity Cost.....	28
5.4 Limitations	30
6. Results and Analysis	31
6.1 AI-Driven Data Centre Electricity Demand	32
6.2 Direct Emissions from AI Data Centre Electricity Demand.....	33
6.3 Carbon Opportunity Cost.....	34
6.4 Discussion - Implications for Sweden's Climate Targets	35
7. Conclusions.....	37
Bibliography	39
Appendix A - AI disclosure	46
Appendix B - Model selection and worked example.....	47

Model Selection - Logistic over Alternative Diffusion Models	47
Parameter Estimation for k and τ	48
Worked Example for 2030 - medium scenario	49
Appendix C - Variable notation and sensitivity analysis	52
Variable and Notation Reference.....	52
One-at-a-time Sensitivity Analysis	53
Appendix D - Carbon opportunity cost derivations	56
HYBRIT.....	56
Heat pumps	56
Electric vehicles	57
Appendix E - Full model projections	58

List of Tables

Table 5.1: Overview of the three-step methodological approach	16
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List of Figures

Figure 5.1: Total Swedish data centre electricity use (DCE_t), 2022-2045	19
Figure 5.2: Infrastructure lag parameter δ across scenarios	23
Figure 5.3: Scenario parameters for s_t - the AI share of Swedish data centre electricity	25
Figure 5.4: The three displacement factors DF_j by competing decarbonisation use	29
Figure 6.1: Projected AI-driven data centre electricity demand in Sweden, 2024-2045	32
Figure 6.2: Direct emissions from AI data centre electricity demand, medium scenario	33
Figure 6.3: Carbon opportunity cost by competing decarbonisation use	34

1. Introduction

Artificial intelligence (AI) has become a central focus of economic policy in recent years. It has transformed the global economy and rapidly emerged as a major technological development. Recent advances of the technology have intensified expectations regarding the potential effects on long-term economic growth. For instance, experts believe that AI is to unleash the next wave of productivity, potentially adding trillions of dollars in value to the global economy (Chui et al., 2023, p.3). However, others argue that the aggregate productivity effects may be only modest (Acemoglu, 2024). Nevertheless, even moderate adoption of AI in the future may have other consequences for the world that extend beyond productivity and innovation.

As AI is rapidly expanding, a growing electricity demand is seen, with recent studies projecting a rapid increase in electricity consumption in the upcoming years. The International Energy Agency (2025) estimates that global data centre electricity consumption will double by 2030, with 70 percent coming from AI workloads (IEA, 2025, pp.63-64). With an accelerating electricity demand, the energy and climate implications of AI are becoming a concern.

Sweden sits at the centre of this tension. As one of Europe's leading data centre locations, the country has attracted major hyperscale companies driven by the characteristics of a cold climate and an almost fossil-free electricity system (Saunavaara et al., 2022). The country operates as one of the least carbon-intensive electricity systems in the world, with renewable energy accounting for approximately 90 percent of the generation mix (IEA, 2024, p.30). However, assuming that AI data centre growth in Sweden poses minimal climate risk for this reason is misleading. The reason lies in the fact that renewable energy is scarce, where new electricity demand might not be met by existing fossil-free generation. Instead, it is met at the margin by fossil-based power imported from continental Europe, which carries a carbon intensity approximately eighteen times higher than the average carbon intensity in Sweden (Dotzauer, 2010; Olkkonen and Syri, 2016, p.521; Ember, 2026). At the same time, the renewable electricity in Sweden is increasingly contested, as industrial decarbonisation is projected to be a major driver of electricity demand in the future, and will compete for the energy in the same way as AI data centres will. This is a national grid connection queue that is already taking place (IEA, 2024, p.40; Svenska kraftnät, 2024).

1.1 Research Problem

While there exists research on AI, energy, and its climate implications globally, no existing study has projected AI-driven data centre electricity demand specifically for Sweden or quantified its implications for the climate commitments of the country. The climate goals for Sweden are to have zero net emissions of greenhouse gases into the atmosphere by 2045, and a reduction of at least 63 percent by 2030 compared to 1990 levels. This is further under the Paris Agreement (Government Offices of Sweden, 2021; UNFCCC, 2015). Yet, the trajectory of the climate commitments of Sweden is already falling short (Klimatpolitiska Rådet, 2024), and the additional pressure from AI regarding electricity remains unquantified and unaddressed in Swedish climate policy.

This creates two research gaps that the present study addresses. The first one lies in the fact that there exists no projection on how AI-driven data centre electricity demand will develop for Sweden and how this will affect the climate targets. The second one lies in the methodology of how climate costs are estimated. While some existing research calculates emissions only through the average carbon intensity of a country, it understates the true climate costs for countries like Sweden with a grid predominantly fossil-free. Dotzauer (2010) establishes this as theoretically incorrect, motivating the present study to use a marginal carbon intensity and a carbon opportunity cost. This is something that no existing study has done for projecting AI data centre electricity use in Sweden specifically.

1.2 Aim and Scope

The aim of the present study is to project AI-driven data centre electricity demand in Sweden for the years 2022 to 2045, and further quantify its climate implications for Sweden's 2030 and 2045 climate targets. The present study addresses the following research question:

What are the climate implications of AI-driven data centre electricity demand growth in Sweden for the country's 2030 and 2045 climate targets?

The scope is limited to Sweden, and for the period of 2022-2045. The study covers projected enterprise AI adoption with 10 or more employees as the driver of electricity demand, projected total data centre electricity consumption in Sweden as the baseline, direct emissions under both average and marginal carbon intensity, and carbon opportunity costs across three competing

industrial decarbonisation uses. This includes HYBRIT green steel production, electric vehicles, and heat pump deployment. The present study does not model broader energy system expansion that Sweden would potentially need, does not evaluate whether policy solutions are realistic to implement or what these solutions could be, and does not prove that AI electricity demand will cause Sweden to miss its climate targets. However, as the study quantifies the scale of the tension between AI-driven electricity demand and Sweden's climate commitments, the present study does imply that AI data centre growth will make the climate targets for Sweden meaningfully harder to achieve. Further resolutions of this tension are left for policymakers and for future research.

1.3 Outline of the Study

The outline of the present study is structured as follows. Chapter 2 provides the contextual background on Sweden's electricity system, Sweden as a data centre location, and Sweden's climate policy framework. Chapter 3 reviews the previous research on AI and electricity demand, identifies the two research gaps the present study addresses in detail, and presents the two theoretical frameworks applied. Chapter 4 discusses the data sources used across the three methodological steps. Chapter 5 presents the three-step methodological approach in full. Chapter 6 presents the results and discusses its implications for Sweden's 2030 and 2045 climate targets. Chapter 7 concludes and discusses implications for policy and future research.

2. Context

The following chapter presents the context and background for the present study. Section 2.1 describes Sweden's electricity system, 2.2 discusses Sweden's broader emergence as a data centre location, and 2.3 presents Sweden's climate policy framework.

2.1 Sweden's Electricity System

The electricity system in Sweden is one of the least carbon-intensive in the world. The International Energy Agency (2024) reports that the electricity system is mostly fossil-free in Sweden. It is documented that the generation mix in 2022 consists of 40 percent from hydro, 30 percent from nuclear, and 19 percent from wind power. The remaining share comes from bioenergy and waste in cogeneration plants, with natural gas, oil, and coal only making up 0.7 percent of the generation

mix (IEA, 2024, p.30). By 2024, the generation mix had remained broadly stable.¹ The fossil-free characteristics of Sweden are not a recent development, but the outcome of a long-term energy transition of the country. Kander and Lindmark (2004) document that both energy consumption and pollution emissions declined relative to GDP over two centuries. Until 1970, both energy use and pollution increased in absolute terms, but started declining after (Kander and Lindmark, 2004, p.297). This is driven by the gradual shift away from fossil fuels toward hydropower and nuclear energy, explaining why the country today is one of the least carbon-intensive in the world.

The International Energy Agency (2024) further reports that the low-carbon-intensive generation mix in Sweden will be the cornerstone of its broader energy transition. Regarding exports of electricity, Sweden is one of the largest electricity exporters in Europe, however, Sweden is expecting a steep increase in domestic demand in the future (IEA, 2024, p.30).² This means that the current export surplus is expected to diminish significantly as domestic demand grows. Understanding Sweden's electricity system, the generation mix, and the pressure it faces from rising domestic demand is a fundamental context for the present study. The clean electricity supply determines both the carbon intensity of electricity consumed by AI data centres, but also explains why new electricity demand, such as from AI, competes for the same scarce clean electricity that decarbonisation pathways depend on. This tension is discussed through the methodology and results of the present study.

It is also important to understand how Sweden's electricity system is connected with the broader European market. The International Energy Agency (2024) highlights how the country is well-integrated with its neighbours. With interconnections to Denmark, Finland, Germany, Lithuania, Norway, and Poland, it is documented an interconnection capacity of 10.3 GW, equaling around 21 percent of interconnectivity, which is well above the EU 2030 target of 15 percent (IEA, 2024, p.32). This means that when Sweden increases domestic demand in the future, as projected from

¹ World Nuclear Association (2026) reports the generation mix for 2024, which shows 38 percent from hydro, 29 percent from nuclear, while wind power increased to 23 percent. It is further noted that the total electricity generation reached 172 TWh in 2024, while the net exports balance was 33.4 TWh. This includes 5.7 TWh of imports and 39.1 TWh of exports (World Nuclear Association, 2026).

² 19 percent of total electricity output, equivalent to 33 TWh, was exported in 2022. This is mainly through connections with Denmark and Finland (IEA, 2024, p.30). Electrification of end-use sectors is projected to drive electricity demand from 140 TWh in 2023 to 160-210 TWh in 2030 and 200-340 TWh in 2045. The main uncertainty of the forecast lies in Sweden's plans for decarbonisation, leading to the electricity demand by 2045 increasing anywhere between 40 percent and 140 percent (IEA, 2024, p.40).

expansions of AI data centres, the additional supply of electricity will likely not be met by Sweden's own fossil-free generation. As established in the methodology of the present study, the marginal source is coal-condensing power from continental Europe, which is underpinned by how well integrated Sweden's electricity system is with European countries.

2.2 Sweden as a Data Centre Location

Sweden has become a leading data centre location in Europe. Saunavaara et al. (2022) document that Sweden is the most recognized player in the international data centre market among the Nordic countries. It is established that the Nordic countries have developed into the largest European data centre market with live capacity of around 600 MW. Sweden has attracted major technology companies. Some of these include Amazon, which established its hyperscale data centre in Mälardalen, and Microsoft, which established data centres in Gävle, Sandviken, and Staffanstorps. Additionally, Google has acquired land in Avesta (Saunavaara et al., 2022, p.2). The key factors of why Sweden has become a data centre location lie in the low risk of natural hazards, as well as the cold climate that offers competitive advantages for smartly utilised free air cooling. Some other reasons are also a reliable power supply, international data connectivity, low energy prices, political stability, a business-friendly environment, abundant energy, and a competent workforce (Saunavaara et al., 2022, pp.1-2). Institutionally, 2017 marks the year when Sweden cut its electricity tax for data centres to the lowest level allowed by the European Union (Saunavaara et al., 2022, p.8). As a result, this significantly strengthened the competitive position of the country and accelerated investment and attraction for major technology companies.

Geographically, Sweden has advantages explaining why it is a major data centre location, directly relevant in understanding the scale of electricity demand that the present study projects. Regarding the cold climate of Sweden, Jerléus et al. (2024) report that free cooling can cover the entire cooling demand for data centres from a minimum of 93 percent and a maximum of 98 percent, depending on the region in Sweden (Jerléus et al., 2024, pp.12-13). Understanding why Sweden has attracted this scale of data centre investment institutionally and geographically is a necessary context as it explains why the present study focuses on Sweden rather than any other country.

2.3 Sweden's Climate Policy Framework

In 2017, the Swedish parliament decided to introduce a climate policy framework with a climate act for Sweden. Stated as the most important climate reform in Sweden's history, it sets out the implementation of the Paris Agreement. The climate reform includes important long-term goals. By 2045, Sweden has a goal to have net zero emissions of greenhouse gases into the atmosphere, meaning that greenhouse gas emissions should be at least 85 percent lower than in 1990. Other goals include a 63 percent reduction by 2030 compared to 1990 levels (Government Offices of Sweden, 2021). These goals are the two specific commitments that the present study addresses regarding the climate implications of AI-driven data centre electricity demand.

Despite these goals and a broader framework, Sweden already falls short of its commitments. Klimatpolitiska Rådet (2024) reports that the policy adopted in 2023 increased emissions, and it will further not lead toward the fulfilment of Sweden's climate goals and EU commitments. It is documented that the government's climate policy action plan does not live up to the requirements of the climate act, while it disregards the interim targets for 2030 set by Parliament, and largely lacks emission forecasts and timelines for policy implementation (Klimatpolitiska Rådet, 2024, pp.6-7). While the climate policy in Sweden is already under pressure, the present study quantifies the additional pressure that AI-driven electricity demand places on Sweden's ability to meet its 2030 and 2045 targets.

3. Theory and Previous Research

The following chapter presents the previous research and theoretical frameworks that the present study applies. Section 3.1 describes the previous research on AI. This includes the rapid expansion of electricity demand associated with AI and its climate implications, and presents two gaps that the present study addresses. Section 3.2 presents the theoretical frameworks applied in the present study. This is theory on technology diffusion and the logistic S-curve, and theory on the marginal emissions and the carbon opportunity cost.

3.1 Previous Research

Over the past decade, the literature on concerns regarding the energy and climate implications of AI has grown substantially. Among the first to quantify this tension systematically was Strubell et al. (2019). The finding included that the full development and tuning process for a single large natural language processing model can produce carbon emissions comparable to the lifetime emissions of five cars.³ It is further noted that these climate costs had been largely invisible within existing AI research. A further extension of this analysis was made by Patterson et al. (2021), reporting on the largest AI models available at the time. It is established that the model alone produced significant carbon emissions.⁴ Regarding infrastructure, Masanet et al. (2020) document that there existed a sixfold increase in global data centre workloads between 2010 and 2018, but note that the total electricity consumption grew only modestly because of efficiency gains in hardware and cooling. However, the conclusion of the paper warns that this efficient resource is approaching exhaustion, with data-intensive technologies, including AI, threatening to drive demand sharply higher in the future.

Building on this, an increasing amount of research regarding the rapid expansion of electricity demand associated with AI exists. For instance, Chen et al. (2025) highlight that there is a big contrast to traditional data centres, with AI data centres designed to optimize and execute large-scale workloads. It is noted that it raises challenges for electric power grids because of how AI data centers use energy-intensive hardware. Additionally, the International Energy Agency (2025) reported a projected global data centre electricity consumption to double by 2030, with AI workloads accounting for 70 percent of growth in server electricity demand over this period (IEA, 2025, pp.63-64).

Beyond the projected increase in electricity consumption, the climate implications of AI extend further. Xiao et al. (2025) raise sustainability concerns, as uncontrolled AI-related electricity growth may increase fossil-fuel reliance due to significant Scope 2 carbon emissions. Buffard et al. (2025) document that renewable energy alone can not meet AI-driven demand in the short term. This is because electricity systems need additional dispatchable capacity generation. Existing

³ Strubell et al. (2019) report the full training emissions as approximately 626,000 lbs of CO₂ equivalent.

⁴ Patterson et al. (2021) find that training the GPT-3 model consumed 1,287 MWh and produced 552 tCO₂e. The study further notes that model architecture, hardware, and geographic location could together reduce emissions.

research takes this further, highlighting the problems with embedded rebounds of AI. Nordgren (2023) reports that the technology causes multiple layers of emissions even before the electricity is used. Factory production of hardware, extraction of metals, and transportation are some of these rebounds, where, to the extent fossil fuels are used, each of these steps in the production chain leads to climate implications, which in the end is something that drastically increases the total emissions from AI. Taken together, the existing body of research establishes a clear global concern. It is known that AI is a significant driver of electricity demand, leading to meaningful climate implications in the world.

While the previous research provides a good overview of the AI implications for the world, it does not provide a country-specific projection on how this will go in Sweden and what it means for the country's climate commitments. Saunavaara et al. (2022) document on the national level of Sweden, highlighting Sweden's emergence as Europe's leading data centre country, and Jerléus et al. (2024) estimate the total electricity consumption of the Swedish data centre sector. However, none of these projects AI-driven electricity demand further, and does not connect this specifically to Sweden's 2030 and 2045 climate targets. This specialization on Sweden is the first gap that the present study addresses.

A second gap of the previous research lies in how the climate implications of AI are calculated. It is common that existing research calculates emissions by multiplying electricity consumption by the regional average carbon intensity. For instance, Strubell et al. (2019) use the US national average carbon intensity, and Patterson et al. (2021) do the same when calculating the carbon footprint for the model of GPT-3. That the electricity mix means different environmental outcomes is widely known, something that Melguizo et al. (2025) show through cross-country evidence.⁵ The findings include that AI's environmental impacts are non-linear across countries, with the emissions depending on the country's level of AI development. Implying that the consequences of AI likely depend on national energy-system characteristics is something similarly documented by Luccioni et al. (2023), finding that the carbon intensity of the grids used for AI models is the main factor influencing the final total emissions. However, this is a problem flagged by Dotzauer (2010), establishing that using the average carbon intensity is theoretically incorrect when calculating the total emissions. From a Swedish perspective, a mainly fossil-free electricity production does not

⁵ Melguizo et al. (2025) use a 23-country panel from 2019-2023.

show a true picture, with marginal calculations needing to be done instead. While no existing study has applied this framework to AI data centres for Sweden specifically, this is the second gap that the present study addresses.

3.2 Theoretical Approach

The first theoretical frameworks that the present study draws on include technology diffusion theory to model AI adoption and translate it into electricity demand. The second is regarding the marginal emissions and carbon opportunity cost framework to calculate and evaluate the climate implications of that demand.

3.2.1 Technology diffusion and the logistic S-curve

Projecting AI-driven electricity demand in the future requires a theoretical framework to model how enterprise AI adoption will evolve with time. The foundational theoretical argument comes from Rogers (1983), establishing the adoption of any new technology. It is documented that a technology will follow a cumulative S-shaped distribution, beginning with innovators and with time levelling off as the technology approaches market saturation. This theoretical framework reflects on how innovations spread through society, with different factors shaping the speed and ceiling of adoption.

For modeling this technology diffusion, different competing functional forms exist. Through empirical comparison of seventeen models across twenty-five telecommunications time series, Meade and Islam (1995) find that the logistic S-curve outperforms alternatives for technology forecasting. Meade and Islam (2006) further confirm that simpler models outperform more complex ones in out-of-sample forecasting, with better results the longer the projection is. This is directly relevant to the present study, which projects AI-driven electricity demand for over two decades. Bick et al. (2024) support that AI adoption will follow this logistic trajectory, documenting similarities between AI adoption and the PC, and Tankwa et al. (2025) confirm that the logistic S-curve robustly captures national-level diffusion in Information and Communication Technologies, a group of technologies AI is in. This is done across twenty-seven technologies in one hundred and sixty-one countries. Complementing this, Comin and Hobijn (2010) confirm that adoption measures capturing the extensive margin, the share of adopters, follow an S-shaped

curve. It is highlighted that this is one of the key findings of the empirical diffusion literature, something that their model is consistent with (Comin and Hobijn, 2010, p.2040). This is directly consistent with the logistic S-curve applied in the present study, motivating the choice of the functional form. The specific functional form and justification for choosing the logistic S-curve over alternative ones, as well as parameter estimations, are all developed in Stage 1, Step B of Chapter 5, with full derivations provided in Appendix B.

3.2.2 Marginal emissions and the carbon opportunity cost

Using average carbon intensity is something that Dotzauer (2010) establishes is theoretically incorrect for evaluating new electricity demand. Calculating AI emissions only on this would be theoretically wrong, as Sweden has a predominantly fossil-free generation mix and would show emissions close to nothing. However, this does not mean that average carbon intensity is without value. Dotzauer (2010) acknowledges that average emissions are appropriate for retrospective bookkeeping, meaning to describe the carbon profile of electricity already consumed. The present study, therefore, uses the average carbon intensity as a descriptive value for that purpose. Dotzauer (2010) further explains that the correct measure is marginal carbon intensity, capturing the actual generation source that responds to additional demand. The marginal intensity for Sweden is estimated at approximately 630 gCO₂/kWh by 2030 from Olkkonen and Syri (2016). This is approximately an eighteen-fold difference from Sweden's average intensity of approximately 35 gCO₂/kWh taken from Ember (2026). The full theoretical explanation and estimations are developed in Step C of Chapter 5.

The present study further introduces a carbon opportunity cost framework beyond direct and marginal emissions of AI. When a scarce resource is allocated to one use, the benefit of an alternative is gone. When applying this to Sweden's electricity system, clean electricity is a scarce resource with competing uses, with AI being one of them. As AI data centres absorb grid capacity in the electricity system, that electricity can not simultaneously enable industrial decarbonisation. The emissions reduction for industrial decarbonisation might therefore not be done, which is the carbon opportunity cost of AI electricity demand in Sweden. The International Energy Agency (2024) projects that industrial decarbonisation will be a major driver of the growth of Swedish electricity demand in the future (IEA, 2024, p.40) while Svenska kraftnät (2024) documents a national grid connection queue already taking place in Sweden, confirming this competition

happening in practice. This framework is applied across three competing decarbonisation uses, with the full explanation and estimations in Step C of Chapter 5.

4. Data

The following chapter discusses the main data sources used in the three-step methodological approach. The data sources are grouped by the role they have in the model, where reliability, representativity, and validity are discussed. Section 4.1 covers data sources for the data centre electricity baseline, 4.2 enterprise AI adoption and electricity share, and 4.3 emissions and opportunity costs.

4.1 Data Centre Electricity Baseline

The data centre electricity baseline in Sweden, denoted DCE_t , relies on three published sources across three time phases. The first time phase, phase 1, relies on RISE (2023). On a mission from the Swedish energy agency, RISE did a report on the energy consumption in data centres in Sweden, with a central goal of the Swedish government to better understand the energy usage in digital infrastructure. Regarding reliability, the method relies on a literature study, statistical data collection from different sources, and interviews with industry stakeholders, including Branschföreningen Svensk Datacenter, Business Sweden, and Vattenfall. The projections are therefore estimates rather than direct electricity consumption figures, which RISE acknowledges is necessary for projecting the future. Regarding representativity, RISE focuses only on Sweden and major data operators in the country. This makes it representative of the Swedish market for the period. However, RISE mentions that smaller data centres are difficult to fully capture. This affects the representativity and has an impact on the estimations. Regarding validity, the present study requires specifically what this source provides. The total data centre electricity consumption in Sweden is necessary for the method, making this data a valid primary source for Phase 1.

Phase 2 relies on Ember (2025) projecting that European data centre electricity demand will grow from 168 TWh in 2030 to 236 TWh in 2035. It is further projected that in Nordic countries, including Sweden, the growth could fivefold by 2035. Regarding reliability, the projections are estimates based on ICIS data rather than directly measured consumption. This brings an uncertainty around the pace of growth, which is acknowledged by Ember. Regarding

representativity, the report covers Europe broadly rather than Sweden specifically, which affects the representativity of the report. However, Sweden is highlighted as a part of the Nordic countries that Ember highlights. Regarding the validity, the report has data that the present study specifically needs to further estimate the total data centre electricity consumption in Sweden, making Ember a valid secondary source for Phase 2 despite the broader European scope.

Phase 3 relies on Energimyndigheten (2023), the Swedish Energy Agency, which publishes long-term electrification scenarios up to the year 2050. The report projects data centre electricity consumption in Sweden to reach 10 TWh in the lower electrification scenario and 21 TWh in the higher electrification scenario by 2050. Regarding reliability, the long-term projections are based on assessments from Svenska kraftnät with adjustments by Energimyndigheten, and it is stated that future data centre electricity use is difficult to project. This means that the data is estimates rather than direct electricity consumption figures. Regarding representativity, the report covers Sweden only, making it a good representative of the Swedish market for the chosen period. Regarding validity, the report provides long-term data centre electricity projections to 2050, which is what the present study needs, further making it a valid primary source for Phase 3.

4.2 Enterprise AI Adoption and Electricity Share

The enterprise AI adoption, denoted A_i , is the share of Swedish enterprises using any AI technology. This variable relies on SCB (2025) reporting four observations of this variable, including the years 2021, 2023, 2024, and 2025. Regarding reliability, the report draws on annual surveys named ICT usage in enterprises. This is aimed at describing the use of information and communication technology among Swedish enterprises. The survey simply asks the enterprises if they have used any of the eight different AI technologies named, where they are classified as using AI if reported using at least one of them. It is further noted a break in the time series of the year 2022, affecting the comparability of the statistics over time. Regarding representativity, the survey covers Swedish enterprises with 10 or more employees, excluding micro-enterprises with 0-9 employees. This is a minor representativity limitation, since the present study will not have data on micro-enterprise usage. Regarding validity, the data is directly relevant and needed for the enterprise AI adoption variable A_i used in Stage 1 of Step B in the method.

The AI share of Swedish data centre electricity, denoted s_i , relies on public estimates from the International Energy Agency (2025), facility-level validation from Meta (2025) and SVT Nyheter (2024), and calibrated assumptions. Regarding reliability, the International Energy Agency documents that 15 percent of total global data centre electricity demand in 2024 was accounted for by accelerated servers. The estimates of electricity consumption often rely on the electricity consumption of accelerated servers as a proxy for the share of AI in total electricity consumption from data centres. It is further stated an uncertainty around the exact share of data centre electricity of AI, which is why a proxy is used (IEA, 2025, p.56). The Meta and SVT Nyheter figure reports values from a single facility, which brings more direct observational data but lacks reliability beyond that facility.

Regarding representativity, the International Energy Agency (2025) provides a global value, which is then applied to a context in Sweden in the present study. This directly affects the representativity of the data, since the Swedish context is not addressed and, with most probability, differs from the global average. Meta (2025) and SVT Nyheter (2024) partially address this by looking at specific Swedish conditions, however lacks broader representativity since single facilities do not represent how the total Swedish market looks. Regarding validity, the International Energy Agency (2025) provides precisely the variable needed for the present study. The AI share of data centre electricity consumption is the definition of s_i , which is what is reported. No Swedish-specific published source reports this value directly, making this data source the closest available valid source for the present study. The Meta (2025) and SVT Nyheter (2024) data serve as a validation rather than primary measurement data, needed to validate how Sweden looks compared to the global value provided by the International Energy Agency (2025).

4.3 Emissions and Opportunity Cost

Regarding emissions, the present study uses data for two variables. This includes the average carbon intensity and marginal carbon intensity. The average carbon intensity of 35 gCO₂/kWh is taken from Ember (2026), which reports annual carbon intensity values for over 200 geographies. Regarding reliability, the data is collected from multi-country datasets, including sources such as EIA, Eurostat, BP, and UN, as well as national sources. The data is therefore direct evidence, making the reliability high. Regarding representativity, Ember reports data on carbon intensity per

country, including Sweden. The data is Sweden-specific, making it a good representative for the average carbon intensity for the country. Regarding validity, the carbon intensity value provided directly measures what the present study requires for step C of the method. Ember (2026) is therefore a valid primary source for this variable.

The marginal carbon intensity of 630 gCO₂/kWh is taken from Olkkonen and Syri (2016). This is a peer-reviewed study estimating marginal CO₂ emission intensities for electricity use in Finland, the Nordic countries, and the European energy system up to the year 2030. This was calibrated from data for the years 2009 and 2010, and further projected to 2030.⁶ The reliability is therefore moderate, as the data is estimated and derived from earlier conditions. For representativity, the study covers Sweden specifically, making the data representative for the grid conditions in Sweden, however, the marginal carbon intensity of 630 gCO₂/kWh is based on the 2030 projection from 2009-2010 data. Sweden may have changed the grid conditions since then, which would lead to a lower marginal intensity. Regarding validity, the source provides exactly the variable required for step C of the method.

Regarding the carbon opportunity cost, the displacement factor, denoted DF_j, is estimated for three competing uses. This includes fossil-free steel production through HYBRIT, electric vehicles, and heat pump deployment. Regarding reliability, the HYBRIT figures are taken from Pei (2024), documenting the electricity requirements and emission savings for the HYBRIT process based on engineering specifications. However, the figures are self-reported by SSAB, which limits the reliability. Regarding representativity, the figures are specific to SSAB's HYBRIT process rather than Swedish steel production as a whole. However, as stated in Pei (2024), HYBRIT is the primary clean steel initiative in Sweden, and SSAB is the dominant steel producer in Sweden, making the source representative for Sweden regarding the displacement factor. Regarding validity, the source provides the electricity consumption and emissions savings per tonne of crude steel, which is what the present study needs in step C of the method to derive the HYBRIT displacement factor.

⁶ Olkkonen and Syri (2016) use the EnergyPLAN model with an hour-by-hour energy system analysis to derive the marginal carbon intensity. It is further noted that the results are sensitive to assumptions, while results for specifically Sweden carry higher variability.

The displacement factor for electric vehicles relies on Morfeldt et al. (2021). Regarding reliability, the data source is peer-reviewed. The data on vehicle characteristics used for the present study come from modelled projections drawn from estimates of the International Energy Agency, as well as Swedish fleet statistics, rather than direct observed values. Regarding representativity, the data is specifically for Sweden, making the source a good representation of the Swedish EV context. Regarding validity, the data source provides the two variables needed for the present study to calculate the displacement factor. This includes electricity consumption per km for BEVs and CO₂ emissions per km for ICE vehicles, making the source a valid primary source for the displacement factor of electric vehicles.

Fossilfritt Sverige (2019) provides the displacement factor for heat pumps. The reliability is limited, since the data source reports values without documenting the underlying data sources. However, the source has high institutional credibility, since Fossilfritt Sverige is an initiative started by the Swedish government (Fossilfritt Sverige, n.d.). Regarding representativity, the data source provides data for the Swedish heating sector, making it a good representation of Swedish conditions. Regarding validity, the data source provides the variables needed for the present study to calculate the displacement factor for heat pumps. This includes the sectoral emissions and energy use, which are needed for Step C in the method.

5. Methods

In order to address the research question, a three-step methodological approach is used. The following chapter presents the methodological framework used to estimate AI-driven electricity demand for data centers in Sweden from 2022-2045, and further calculates the associated climate implications. The three-step methodological approach begins with Step A, constructing the total data centre electricity baseline in Sweden (DCE_t). This is done across three time phases, covering the years 2022-2030, 2031-2035, and 2036-2045. Each one of the three phases relies on published estimations. Step B develops a diffusion model to estimate the AI share of Swedish data centre electricity constructed from step A. Step B requires estimating three stages. Stage one fits a logistic diffusion curve to Swedish enterprise AI adoption data from SCB. This stage is projecting Swedish enterprise AI adoption beyond the observed data points. Stage two introduces the infrastructure lag parameter δ . This stage shifts the enterprise AI adoption signal backwards in time to account

for the time required to build and connect physical infrastructure, producing the lagged adoption variable I_t . Stage three applies a scenario-based electricity share mapping to convert the lagged adoption variable into the AI share of Swedish data centre electricity, denoted s_t . Step C calculates the direct emissions and carbon opportunity cost of AI electricity demand competing with industrial decarbonisation uses. Section 5.1 covers Step A, Section 5.2 covers Step B, and Section 5.3 covers Step C. Limitations are further addressed in Section 5.4. A fully worked numerical illustration of how the three stages combine to produce a single output value, the full parameter estimation for k and τ , and model selection, is all provided in Appendix B. Additionally, a summary of the variables used in the model and a one-at-a-time sensitivity analysis examining the isolated effect of each parameter on AIE are provided in Appendix C.

Table 5.1 presents an overview of the three-step methodological approach. This summarizes each of the steps, a description of them, the inputs, the data types, and the resulting outputs.

Table 5.1: Overview of the three-step methodological approach

Step	Description	Input	Data Type	Output
Step A	Constructing the Data Centre Electricity Baseline in Sweden (DCE_t)	Published projections across three time phases	Published estimates	DCE_t (TWh) 2022-2045
Step B Stage 1	The Enterprise AI Adoption Diffusion Curve	Four observed SCB data points. Saturation ceiling calibrated from cloud computing analogy	Observed data + calibrated assumption	Projected A_t across three scenarios (k, τ)
Step B Stage 2	Applying infrastructure lag δ to translate AI adoption into an electricity demand signal	IEA build timelines and Swedish grid constraints	Calibrated assumption	I_t - lagged adoption variable across three scenarios

Step B Stage 3	Mapping I_t to AI electricity share (s_t)	2024 anchor 15% from IEA, saturation ceilings 30%, 50%, 65%	Published estimate + facility level validation + calibrated assumption	s_t across three scenarios
Master equation	$AIE_t = DCE_t \times s_t$	Outputs of Step A and Step B	Derived	AIE_t (TWh) - AI-driven Swedish data centre electricity demand 2022-2045.
Step C.1	Direct emissions from AIE_t	Average CI = 35 gCO ₂ /kWh; Marginal CI = 630 gCO ₂ /kWh	Published estimates	E_t (thousand tCO ₂) under average and marginal intensity
Step C.2	Carbon opportunity cost across three competing uses	Displacement factors: HYBRIT 450,000 Heat pumps 30,000 EVs 632,000 tCO ₂ /TWh	Published estimates	OC_t (tCO ₂) per competing use across three scenarios

Source: Present study

5.1 Step A: Constructing the Data Centre Electricity Baseline in Sweden (DCE_t)

The total electricity consumed by data centres in Sweden in each year from 2022 to 2045 is denoted as DCE_t , measured in terawatt-hours (TWh). The construction of the variable is made in three phases, each drawing on published projections and estimates.

Phase 1: 2022-2030

The first period of 2022 to 2030 is taken from the RISE (2023) estimates. The central projections of Phase 1 are taken from the midpoints of the three published range values ⁷, and are used as the central estimates for Phase 1. The midpoints of the three published ranges give: 3.0 TWh in 2022, 4.2 TWh in 2025, and 4.8 TWh in 2030.

Phase 2: 2031-2035

For the second period of 2031 to 2035, DCE_t is estimated to grow by 5 percent per year. Ember (2025) projects European data centre electricity demand growing from 168 TWh in 2030 to 236 TWh in 2035, approximately a 7 percent increase per year to 2035. In Nordic countries, including Sweden, Ember projects that the growth could fivefold by 2035, highlighting the favourable conditions for expansion (Ember, 2025, pp.4-10). However, this projection reflects a scenario where expansion is primarily demand-driven.

In the context of Sweden, it is important to notice the electricity grid capacity. Svenska kraftnät (2024) documents that server halls among the significant electricity consumers face grid connection constraints. It is noted that local grid capacity is often inadequate and that it can take a long time to satisfy the desired grid capacity (Svenska kraftnät, 2024, p.12). This is further confirmed by SVT Nyheter (2025).⁸ Taken together, Sweden may follow the broader European trend provided by Ember, however, electricity consumption growth is likely to be constrained by infrastructure limitations. Further, this estimate carries uncertainty. If grid constraints ease faster than expected, growth could approach the Ember rate of 7 percent, and if constraints bind more severely, growth could be lower.

Phase 3: 2036-2045

DCE_t is projected to approximately 8 TWh in the lower electrification scenario and 16 TWh in the higher electrification scenario by 2045. This leads to a midpoint of 12 TWh by 2045, further

⁷ For 2022, RISE (2023) estimates that the total data centre electricity consumption in Sweden is 2.8-3.2 TWh. For 2025, the estimation is 4.0-4.4 TWh, and for 2030, the estimation is 4.4-5.2 TWh (RISE, 2023, pp.1-2).

⁸ SVT Nyheter (2025) reports that Microsoft stopped planned server hall construction in Sandviken, Sweden, because grid capacity could not be delivered within the required timeframe. It is noted that the company had reached the limit of what could be built with the current infrastructure in electricity.

implying a growth rate of approximately 7 per cent per year from the 2035 value of Phase 2. The third period of 2036 to 2045 is taken from Energimyndigheten's (2023) long-term scenarios for Swedish data centre electricity use (Energimyndigheten, 2023, p.64).⁹

Figure 5.1 presents the projection of total data centre electricity use in Sweden for each year from 2022 to 2045.

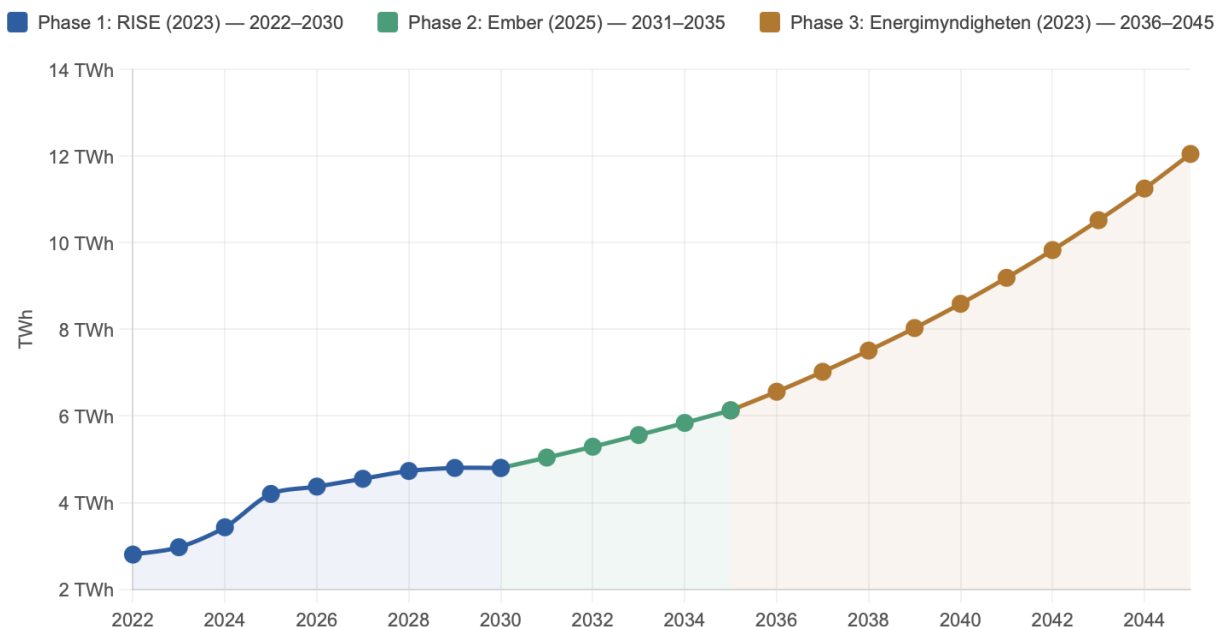


Figure 5.1: Total Swedish data centre electricity use (DCE_t), 2022-2045

Source: Present study

5.2 Step B: Estimating the AI Share of Swedish Data Centre Electricity

Step B estimates the AI share of Swedish data centre electricity, denoted s_t . This is through a three-stage process. Stage 1 estimates a logistic diffusion curve for Swedish enterprise AI adoption data. Stage 2 estimates an infrastructure lag parameter δ , which shifts the enterprise adoption signal backwards in time to produce the lagged variable I_t . Stage 3 applies a scenario-based electricity share mapping to convert I_t into s_t , the AI share of Swedish data centre electricity. A fully worked numerical illustration tracing a single year through all three stages to produce the final AIE output

⁹ The projection is taken from the DCE_t values projected to reach approximately 10 TWh by 2050 in the lower electrification scenario and approximately 21 TWh in the higher electrification scenario (Energimyndigheten, 2023, p.64).

is provided in Appendix B. The model output is AI-driven Swedish data centre electricity demand, where the master equation of the model is:

$$(1) AIE_t = DCE_t \times s_t$$

where AIE_t is AI-driven Swedish data centre electricity demand measured in TWh, DCE_t is the total electricity consumed by data centres in Sweden from Step A, and s_t is the AI share of Swedish data centre electricity measured in percentage from Step B.

5.2.1 Stage 1: The Enterprise AI Adoption Diffusion Curve

The enterprise AI adoption diffusion curve has a primary variable of Swedish enterprise AI adoption. Denoted as A_t , it is the share of Swedish enterprises with ten or more employees using any AI technology. SCB (2025) provides four observations of this variable.¹⁰ To further project the enterprise AI adoption beyond the observed data points of SCB, a logistic diffusion curve is fitted to the SCB observations. This follows the standard S-curve diffusion model established in earlier technology adoption literature.¹¹

Previous literature indicates that AI adoption will follow a S-curve framework. Bick et al. (2024) document that the work adoption of generative AI has been as fast as the personal computer, relative to both technologies' first mass-market product launch. It is noted that both technologies have very similar early adoption patterns (Bick et al., 2024, p.1)¹². Yang and Williams (2009) use the logistic S-curve function to characterize long-term trends in the generation of obsolete computers in the United States. It is documented that the function is found to empirically describe many cases of technology diffusion, and that the adoption and diffusion of innovations often follow an S-curve type behavior. Given that AI adoption matches the early trajectory of the personal

¹⁰ The four SCB (2025) observations are: 9.9 percent in 2021, 10.4 percent in 2023, 25.1 percent in 2024, and 35.0 percent in 2025. A methodological break in 2022 means earlier data points are not directly comparable.

¹¹ Rogers (1983) states the relative speed on which an innovation is adopted by members of a social system, specifically called the rate of adoption. The author establishes that new technology or an idea is plotted on a cumulative frequency basis over time, with the resulting distribution being an s-shaped curve. First, a few individuals, the innovators, adopt the innovation in each time period, which depends on the technology. As more and more individuals adopt, the diffusion curve begins to climb, however, the trajectory of the rate of adoption begins to level off with time, as fewer and fewer individuals remain who have not yet adopted. Finally, the s-shaped curve reaches its asymptote, and the diffusion process is finished (Rogers, 1983, p.23).

¹² Bick et al. (2024) used nationally representative U.S. surveys from over 10,000 respondents of generative AI use at work and at home.

computer, and that the technology diffusion of the PC is empirically documented to follow the logistic S-curve, the same diffusion pattern can be grounded for AI adoption.

The logistic functional form follows Meade and Islam (1995), who find that the model outperforms other growth curve models for technology forecasting, motivating the choice of the function.¹³ Furthermore, Tankwa et al. (2025) analyze 27 technologies across 161 countries to understand national-level technology diffusion. It is documented that the logistic S-curve is a robust, parsimonious model for capturing adoption patterns, and shown that technology adoption speeds have increased over time, specifically in Information and Communication Technologies (ICT), a group of technologies that includes Artificial Intelligence. Having empirical evidence that a logistic S-curve is a good approximation of technology diffusion at national levels is directly relevant for the present study, as it models a national level adoption of AI in Sweden.

The logistic adoption function is:

$$(2) A_t = M_u / (1 + \exp(-k \times (t - \tau)))$$

where A_t is the share of Swedish enterprises with ten or more employees using any AI technology, M_u is the saturation ceiling, k is the diffusion speed parameter governing the steepness of the curve, and τ is the inflection year at which adoption reaches $M_u / 2$.

Saturation ceiling M_u

The saturation ceiling M_u is set at 85 percent. To set a value for the saturation ceiling, an analogy with cloud computing adoption in Sweden has been used.¹⁴ Looking at enterprise cloud computing adoption, Eurostat (2021) reports a usage of 75 percent in Sweden in 2021. It is further reported a stagnation of the adoption, with Eurostat (2025) reporting a 72 percent usage in Sweden in 2025. This means that enterprise cloud computing is saturated in the 70-75 percent range. For the use of AI in Swedish enterprises, M_u is set at 85 percent. This is an estimation and is just above the

¹³ Meade and Islam (1995) conduct an empirical comparison of seventeen models to forecast the development of telecommunications markets across twentyfive time series. The logistic model is preferred over alternatives including the Gompertz, Bass, FLOG and GBM models, as simpler models outperform more complex ones in out-of-sample forecasting, particularly for long projections (Meade and Islam, 2006; Bemmaor and Lee, 2002). Full justification is provided in Appendix B.

¹⁴ OECD (2025) similarly uses AI adoption against cloud computing. This indicates that cloud computing represents the mature diffusion trajectory that AI follows. Bencivelli et al. (2026) further highlights that there are strong complementarities between AI and cloud computing.

observed Swedish cloud computing saturation level, reflecting the expectation that AI is a broader general-purpose technology and will therefore reach a higher enterprise saturation ceiling than cloud computing. Meade and Islam (2006) further reinforce this approach. It is documented that when time series data are limited, fixing model parameters from an analogous technology is a good and recognized methodological strategy.

Parameters k and τ

With establishing a value for the saturation ceiling, parameters k and τ are calculated from equation (2) with the two most recent SCB (2025) observations of A_t .¹⁵ Solving the calculation from equation (2) gives $k = 0.51$ and $\tau = 2026$. The full algebraic derivation of these parameter values is provided in Appendix B. Interpreting these results, the values indicate a steep diffusion curve with an inflection point in 2026, meaning that Sweden is currently in the steep acceleration phase of enterprise AI adoption.

Scenario parameter variants

Consistent with the International Energy Agency (2025), the present study uses scenario parameter variants. This is because there exists an uncertainty surrounding future data centre electricity demand. It is therefore required to use a scenario-based approach to explore alternative pathways and provide perspectives on timelines relevant to energy sector decision-making (IEA, 2025, p.50). The empirically derived baseline has both low and high scenario curves.¹⁶ The low scenario represents a slower diffusion with a later inflection point, with the high scenario representing a faster diffusion with an earlier inflection point.

5.2.2 Stage 2: The Infrastructure Lag Parameter δ

From the previous stage 1, enterprise AI adoption denoted as A_t gives the share of Swedish enterprises using any AI technology. However, when enterprises decide to adopt AI, it does not

¹⁵ The two observations used are 25.1 percent in 2024, and 35.0 percent in 2025. A methodological break in the SCB observations in the year of 2022 means that their earlier data points are not directly comparable. As a result, k and τ values are estimated from the 2024 and 2025 observations only.

¹⁶ The low scenario uses $k = 0.38$, calculated with a 25 percent margin from the baseline value, and $\tau = 2028$. The high scenario uses $k = 0.64$, also calculated with a 25 percent margin from the baseline value, and $\tau = 2024$.

immediately generate data centre electricity demand.¹⁷ This delay is formalised through the infrastructure lag parameter δ , which shifts the enterprise adoption signal backward in time. The infrastructure lag parameter is:

$$(3) I_t = A(t - \delta)$$

where I_t is the lagged variable, and $A(t - \delta)$ is the enterprise AI adoption rate from δ years prior.

While no existing study separates enterprise AI adoption from infrastructure electricity demand through a lag parameter, it is an original contribution of the present model. The central estimate of the variable δ is 2 years and includes scenario variants. In a Swedish context, the lag is grounded in concrete grid constraints.¹⁸ Building on this, the three scenario variants reflect the structural uncertainty in infrastructure deployment timelines. This includes a low scenario of 3 years and a high scenario of 1.5 years. Figure 5.2 presents the infrastructure lag parameter δ across the three scenarios.

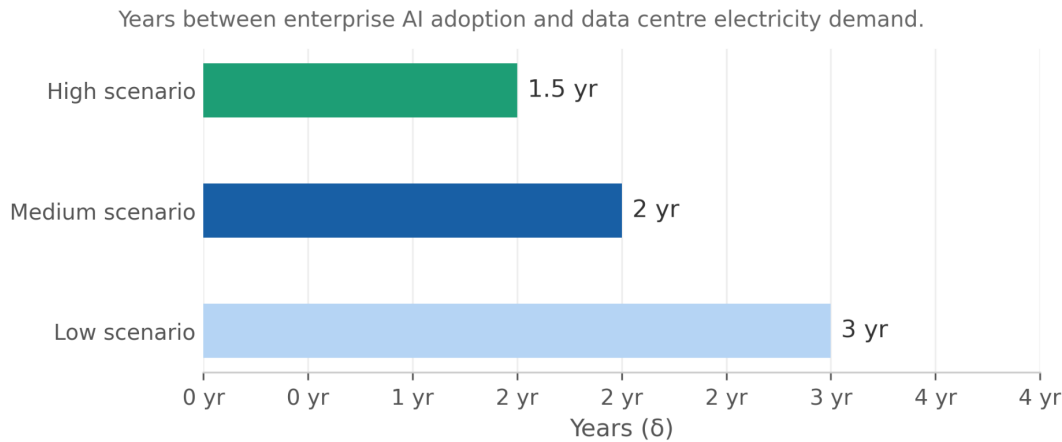


Figure 5.2: Infrastructure lag parameter δ across scenarios

Source: Present study

¹⁷ The International Energy Agency (2025) documents that the AI technology sector moves quickly, but can not be operational directly. It is noted that a data centre typically requires two or three years to be operational, because of broader energy systems requiring longer lead times to schedule and build infrastructure. This often requires extensive planning, long build times, and high upfront investment (IEA, 2025, p.50).

¹⁸ Svenska kraftnät (2024) documents that as the power demands increase, it has been difficult to connect them without undertaking grid reinforcement. In the end, it is highlighted that it can take a long time to satisfy the desired grid capacity, which indicates that Sweden has a delay. SVT Nyheter (2025) reports on this, noting that Microsoft stopped their planned server hall construction in Sandviken, Sweden, because of how the grid capacity could not be delivered within the required timeframe.

For the high scenario, $\delta = 1.5$ is implemented as the mean of adoption in years $t-1$ and $t-2$.¹⁹ For the earliest years of the projection where the lag parameter occurs with existing SCB data, I_t is anchored with fixed floor values.²⁰ After this, the infrastructure lag formula applies as data becomes available.

5.2.3 Stage 3: Scenario-Based Electricity Share Mapping

Stage 3 converts the lagged infrastructure variable I_t from the previous Stage 2 into s_t , the AI share of Swedish data centre electricity that enters the master equation 1. As I_t rises, s_t rises proportionally between the 2024 anchor and the saturation ceiling.

The function is:

$$(4) s_t = \text{MIN}(\text{ceiling}, \text{anchor} + (\text{ceiling} - \text{anchor}) \times \text{MAX}(0, I_t - I_{2024}) / (M_u - I_{2024}))^{21}$$

2024 anchor

The 2024 anchor value for Sweden is taken from the International Energy Agency (2025), documenting that 15 percent of total global data centre electricity demand in 2024 was accounted for by accelerated servers. It is noted that estimates often rely on the electricity consumption of accelerated servers as a proxy for the share of AI in total electricity consumption from data centres. However, to apply this global value to Sweden, facility-level evidence is needed, which implies that the data centre market in Sweden is dominated by hyperscale operators.²²

¹⁹ For the high scenario, $\delta = 1.5$ is implemented as the mean of the two nearest annual observations: $I_t = (A(t-1) + A(t-2)) / 2$. This approximates a 1.5 year lag using annual data.

²⁰ Floor values for I_t are 0.06 for medium, 0.05 for low, and 0.08 for high in 2022. The same values go for medium and low in 2023. These small values reflect that AI-driven data centre electricity demand was minimal in the early projection years, prior to the large-scale AI expansion from 2023 onwards.

²¹ Equation (4) is derived from the standard linear interpolation formula $y = y_1 + (x - x_1) \times (y_2 - y_1) / (x_2 - x_1)$. This is applied between two known points, including the 2024 anchor and the M_u ceiling. MIN and MAX operators are further added. This step is needed to ensure that s_t remains connected for all time periods the present study looks at. The formulation guarantees three properties. s_t equals the calibrated anchor in 2024, s_t rises consistently toward the ceiling as I_t approaches M_u , and the scenario ordering is preserved at all time periods. This is with the high scenario always exceeding the medium scenario, which in turn always exceeds the low scenario.

²² Meta (2025) documents 468,809 MWh (0.469 TWh) for their Luleå facility in 2024. SVT Nyheter (2024) documents over 500 GWh (0.5 TWh) for Microsoft's Gävle and Sandviken halls. Together these two operators account for at least 0.97 TWh, approximately 28 percent of Sweden's estimated 3.43 TWh DCE_i in 2024, confirming the Swedish market is dominated by hyperscale AI operators.

Saturation ceiling

The saturation ceiling is set at 30%, 50%, and 65%. With the estimated AI share of 15% in 2024, the International Energy Agency (2025) further projects that 70% of growth in electricity demand from servers will come from AI up to the year 2030, however, full saturation is constrained by the persistent need for non-AI workloads (IEA, 2025, p.64).²³ Figure 5.3 presents the scenario parameters for s_t , showing the 2024 anchor and saturation ceiling across the three scenarios.

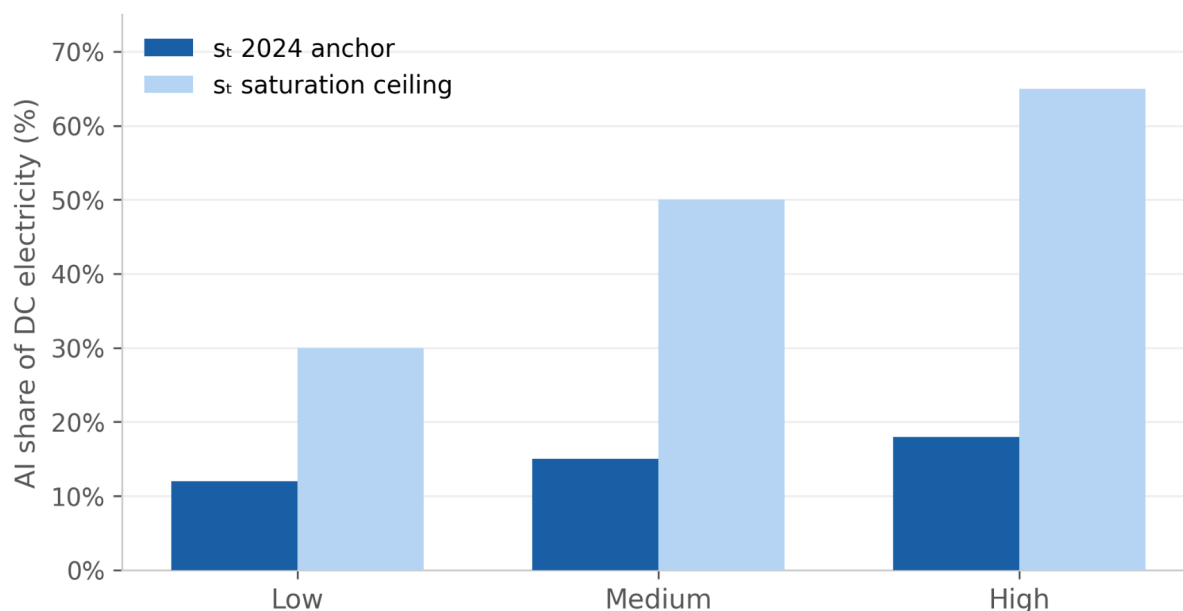


Figure 5.3: Scenario parameters for s_t - the AI share of Swedish data centre electricity (%)

Source: Present study

5.3 Step C: Emissions and Carbon Opportunity Cost

Step C takes the output from Step B and translates the AI-driven Swedish data centre electricity demand, AIE_t , into two climate implications for Sweden. Section 5.3.1 calculates the direct emissions from AI electricity consumption. Section 5.3.2 calculates the carbon opportunity cost. This arises from the competition for scarce clean electricity existing in Sweden, with AI data

²³ The 2024 anchor of 15% and the IEA (2025) projection of growth coming from AI means that AI is projected to grow much faster than conventional workloads, further implying that AI's share must increase substantially over time. However, AI can not fully use the total data centre electricity consumption due to the persistent need for non-AI workloads. Because of this, the estimated values are selected as representative points for a plausible range of future outcomes regarding the saturation ceiling.

centres competing with industrial decarbonisation uses. The two calculations finalize the method of the present study, as it takes the electricity demand projections of the previous steps A and B to raise the question whether the AI-driven data centre growth in Sweden will create a meaningful problem for the country's ability to meet its 2030 and 2045 climate targets.

5.3.1 Direct Emissions

Direct emissions are calculated as:

$$(5) E_t = AIE_t \times CI$$

where E_t is annual direct CO₂ equivalent emissions measured in thousand tonnes, AIE_t is AI-driven Swedish data centre electricity demand measured in TWh from Step B, and CI is the carbon intensity of Swedish electricity measured in gCO₂eq/kWh. CI has two values applied to the different calculations. This includes the average carbon intensity and marginal carbon intensity, which produce two emissions estimates for each scenario.

Average carbon intensity

Ember (2026) reports 35.26 gCO₂/kWh as the average carbon intensity in Sweden for the year 2025.²⁴ However, the carbon intensity is held constant at 35 gCO₂/kWh throughout the projection to the year 2045 of the present study. This assumption is conservative, as historical trends indicate that the average carbon intensity declines over time, but it is held as a published projection for the future Swedish value does not exist.

Dotzauer (2010) discusses the average carbon intensity of electricity in Sweden. It is mentioned that the calculation of this is simplified, using statistics and computing the average emissions.²⁵ Hence, direct AI emissions under the average carbon intensity are small, as Sweden's grid is among the least carbon-intensive in the European Union (Ember, 2026). This makes average carbon intensity a useful descriptive value for retrospective purposes. It shows what the footprint of AI

²⁴ Ember (2026) reports historic values for the carbon intensity in Sweden. This includes 38.71 gCO₂/kWh for 2020, 41.74 gCO₂/kWh for 2021, 41.03 gCO₂/kWh for 2022, 38.42 gCO₂/kWh for 2023, and 34.91 gCO₂/kWh for 2024.

²⁵ Dotzauer (2010) documents that direct average emissions are appropriate for what is termed as bookkeeping, meaning what the emissions outcomes were from looking back in time of the electricity already used. The average carbon intensity calculation in the present study therefore serves a descriptive purpose, showing the footprint of AI data centres under the current generation mix in Sweden.

data centres looks like under the current generation mix in Sweden. However, Dotzauer (2010) further implies that the average carbon intensity should never be applied when evaluating the impact of future changes in electricity consumption. Since AI data centres represent new electricity demand, the average intensity alone is methodologically insufficient for the forward-looking analysis of this study. This motivates the decision of a second value, marginal carbon intensity.

Marginal carbon intensity

The second value is marginal carbon intensity. This is used as a constant value of 630 gCO₂/kWh throughout the projection period of the present study, taken from Olkkonen and Syri (2016).²⁶ This is an estimation and conservative relative to any long-run decarbonisation in Sweden beyond 2030. Dotzauer (2010) documents this value, highlighting that for consequence analysis, meaning the evaluation of measures that affect future use of electricity, marginal calculations need to be done. It is noted that from a Swedish perspective, at first, it may look like power consumption will not contribute to a negative effect on the climate, since the production is mainly fossil-free in Sweden. However, this is not the case. The reason for this is how the Swedish electricity system responds to new electricity demand.²⁷ Dotzauer (2010) reports that the marginal source for Sweden is coal-condensing power from continental Europe.²⁸

The mechanism and effect of AI in Sweden are straightforward. Starting with how AI data centres consume additional electricity in Sweden, Swedish exports to Europe decrease. In turn, this forces other countries to increase their output to Sweden to compensate. Finally, Dotzauer (2010) highlights that the difference in emissions between average electricity and marginal electricity is large in Sweden, precisely because the country's average is low while the marginal source is fossil-based.

²⁶ Olkkonen and Syri (2016) report approximately 620 gCO₂/kWh in 2009, 660 gCO₂/kWh in 2010, and estimate 630 gCO₂/kWh by 2030.

²⁷ Dotzauer (2010) mentions that Swedish production consists mostly of nuclear, hydro, and wind power, which can not increase output in response to new electricity consumption. It is highlighted that hydro power and wind power depends on weather conditions and water supply rather than on the electricity consumption. Similarly, nuclear power is restricted by security conditions rather than by the electricity demand. This means that these sources can never be identified as marginal production, and can not respond to the additional demand created by AI data centres.

²⁸ Dotzauer (2010) documents that power production with fossil fuels, meaning coal and gas, will mainly constitute the marginal until 2050 in northern Europe, including Sweden.

5.3.2 Carbon Opportunity Cost

The second climate implication arises from the allocation of scarce renewable electricity, which might be taken to AI data centres rather than to industrial decarbonisation. The future climate goals of Sweden depend on available clean electricity, particularly important for the 2045 net-zero goal in the country. The International Energy Agency (2024) identifies Sweden's electricity system as the cornerstone of its energy transition plans. It is further projected that electrification of end-use sectors will increase electricity demand.²⁹ Industrial decarbonisation is a major driver of this growth. It is reported that the iron and steel industry is contributing to around 6 Mt CO₂ per year, with 85 percent of emissions coming from the conversion of iron ore using coal. Because of this, decarbonisation of steel is a top priority for industrial decarbonisation, and based on the target for fossil-free steel production by 2045, the transition to fossil-free hydrogen production is estimated to require up to 55 TWh of additional electricity by 2045 (IEA, 2024, pp.57-59). The problem becomes clear. When AI data centres absorb grid capacity in Sweden, they compete directly for the same scarce clean electricity that decarbonisation pathways depend on.

This problem arising is not hypothetical. Svenska kraftnät (2024) documents a national grid connection queue of approximately 20,500 MW, with local grid capacity described as often inadequate. (Svenska Kraftnät, 2024, p.12). The International Energy Agency (2024) similarly notes that Sweden faces a surge in grid connection requests from generation facilities, large industrial users, and data centres, with a pipeline exceeding 20 GW of capacity (IEA, 2024, p.53). Understanding this, electricity consumed by AI data centres carries an opportunity cost because of how the grid can not accommodate all competing users simultaneously.

The carbon opportunity cost formula is:

$$(6) OC_t(j) = AIE_t \times DF_j$$

where $OC_t(j)$ is tonnes of CO₂ not avoided in year t for competing use j , AIE_t is AI-driven Swedish data centre electricity demand measured in TWh from Step B, and DF_j is the displacement factor in tCO₂/TWh. This calculation is counterfactual, meaning it does not imply that AI will prevent

²⁹ Projected electricity demand is to increase from 140 TWh in 2023 to 160-210 TWh in 2030, and 200-340 TWh in 2045 (IEA, 2024, pp.5, 40).

these emission reductions fully in practice, but rather quantifies the implied carbon cost of a hypothetical scenario. Given the documented grid constraints presented earlier, the competition for scarce clean electricity is a real concern and a plausible outcome under continued AI-driven demand growth in Sweden.

The first competing use is fossil-free steel production through the HYBRIT process.³⁰ For every TWh allocated to AI data centres rather than HYBRIT, approximately 450,000 tonnes of CO₂ reduction is the opportunity cost. The second competing use is heat pump deployment to further replace fossil fuel heating in Sweden.³¹ For every TWh allocated to AI data centres rather than heat pumps, approximately 30,000 tonnes of CO₂ reduction is the opportunity cost. The third competing use is electric vehicles for transport decarbonisation in Sweden.³² For every TWh allocated to AI data centres rather than EVs, approximately 632,000 tonnes of CO₂ reduction is the opportunity cost. Figure 5.4 presents the three displacement factors.

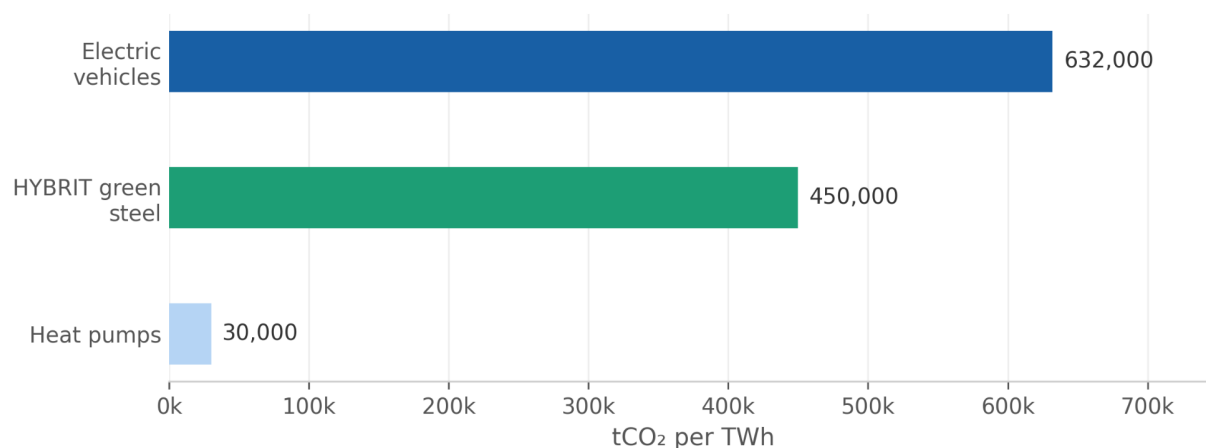


Figure 5.4: The three displacement factors DF_j by competing decarbonisation use

Source: Present study

³⁰ HYBRIT is a collaboration between SSAB, LKAB and Vattenfall aimed at eliminating CO₂ from steel production by replacing coal with fossil-free hydrogen (LKAB, 2024). Full derivation of the displacement factor of 450,000 tCO₂/TWh is provided in Appendix D.

³¹ Fossilfritt Sverige (2019) documents that the heating sector uses approximately 100 TWh in Sweden. Full derivation of the heat pump displacement factor of 30,000 tCO₂/TWh is provided in Appendix D.

³² Morfeldt et al. (2021) projects the energy use of electric vehicles to the year 2030. Full derivation of the EV displacement factor of 632,000 tCO₂/TWh is provided in Appendix D.

5.4 Limitations

Several limitations should be noted for the present study. A first limitation is regarding the AI electricity share s_t and AI-driven electricity demand AIE_t . These variables can not directly be observed today, as no published Swedish data source reports on the AI share of total data centre electricity consumption, resulting in estimations rather than observations. While this motivates the gap of the present study, the model relies on projections, global benchmarks, and calibrated assumptions to derive them, resulting in estimates that will always carry some part of uncertainty. However, the Swedish government has decided to implement the act (2025:570) on the Disclosure of Information on the Energy Performance of Data Centres. Already entered into effect in July 2025, it has required Swedish data centres with an installed IT power demand of at least 500 kW to report annual information on energy use to an EU database. The first reporting deadline covering the full year of 2025 is on May 15, 2026, which means that the data is not available at the time of the present study (Energimyndigheten, 2026). This data will strengthen Step A of the present study, as total data centre electricity consumption DCE_t will become directly observable from official sources rather than relying on published estimates and projections. However, this reporting does not identify AI workloads, meaning that the AI electricity share s_t and AI-driven electricity demand AIE_t will remain unobservable from official sources and will have to rely on estimations.

A second limitation is that the diffusion parameters k and τ from the logistic diffusion curve derived from Stage 1 are estimated from only two data points. This includes the SCB observations in 2024 and 2025, which are used because of a methodological break in the data in 2022 that hinders the comparability of using the data before. While the present study could estimate k and τ using least squares optimization including the year 2023, it would cost an exact analytical solution, which is why the two most recent data points are prioritized. However, deriving k and τ from two data points only carries uncertainty. Small changes in either observation would produce meaningfully different parameter values and projections. The full algebraic derivation is provided in Appendix B.

A third limitation is regarding the saturation ceiling. This is calculated with $M_u = 0.85$ by an analogy with Swedish cloud computing adoption. The true saturation level for enterprise AI adoption in Sweden is unknown, which means that the limitation lies in the assumption. A lower

or higher ceiling would shift all scenario projections in the present study accordingly. The fourth limitation is regarding the infrastructure lag parameter δ and the scenario ceiling values for s_t . Similar to the third limitation, these are also calibrated assumptions, which brings a limitation since the specific values carry uncertainty that the three-scenario approach only partially addresses.

The fifth limitation is regarding the marginal carbon intensity of 630 gCO₂/kWh. This is taken from Olkkonen and Syri (2016), who estimated the value for 2030 based on conditions in 2009 and 2010. The Swedish electricity system may have changed since then, with increased renewable capacity potentially lowering the marginal intensity over time. The limitation lies in the application of a constant value throughout the projection period, which is conservative and may overstate the true marginal emissions toward 2045.

A sixth limitation lies in how the opportunity cost calculation is counterfactual. The calculation is made under the assumption that clean electricity is scarce and competing uses can not all be accommodated simultaneously. Whether this assumption holds in practice depends on how quickly Sweden expands its electricity supply and resolves grid constraints. Moreover, if Sweden were to expand the supply fast enough, the actual opportunity cost may be lower than projected. Furthermore, the study covers three competing decarbonisation uses in the opportunity cost. All other electricity-intensive uses in Sweden are not included, which comes with a limitation that the exact and total opportunity cost could be understated.

6. Results and Analysis

Chapter 6 presents the empirical results of the three-step methodological approach developed in Chapter 5. Section 6.1 presents the projected AI-driven electricity demand across scenarios. Section 6.2 analyses the direct emissions implications under average and marginal carbon intensity. Section 6.3 presents the carbon opportunity cost across the three competing decarbonisation uses, including HYBRIT, heat pumps, and EVs. Section 6.4 discusses the implications for Sweden's 2030 and 2045 climate targets under the Paris Agreement.

6.1 AI-Driven Data Centre Electricity Demand

Figure 6.1 presents the results of the projected AI-driven electricity demand and total data centre electricity consumption across the three scenarios for the years 2024, 2030, 2035, and 2045 in the projection period. Total data centre electricity (DCE_t) shown for reference.

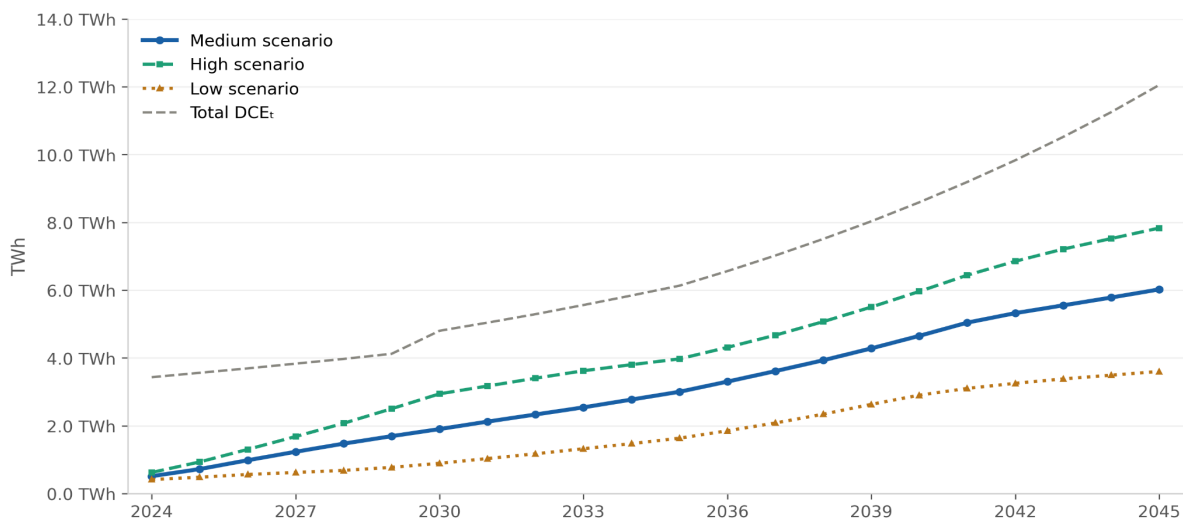


Figure 6.1: Projected AI-driven data centre electricity demand in Sweden, 2024-2045

Source: Present study

Interpreting the results, the total Swedish data centre electricity consumption, denoted DCE_t , grows from 3.43 TWh in 2024 to 12.05 TWh by 2045. In the medium scenario, AI-driven Swedish data centre electricity demand, denoted AIE_t , grows from 0.51 TWh in 2024 to 6.02 TWh by 2045, reflecting the accelerating enterprise AI adoption trajectory documented in SCB (2025) data and the corresponding infrastructure build-out captured through the lag parameter δ .

The low scenario, reflecting binding grid constraints and slower enterprise diffusion with $\delta = 3$ years, projects AIE_t reaching 0.89 TWh by 2030, 1.63 TWh by 2035, and 3.60 TWh by 2045. The high scenario, reflecting a faster infrastructure deployment with $\delta = 1.5$ years, projects 2.94 TWh by 2030, 3.97 TWh by 2035, and 7.83 TWh by 2045. By 2030, the difference between scenarios is 2.05 TWh, widening to 4.23 TWh by 2045. This spread reflects the genuine structural uncertainty in how quickly Sweden can resolve grid and infrastructure constraints documented by Svenska kraftnät (2024) and SVT Nyheter (2025). The medium scenario serves as the central

estimate throughout the analysis. The complete projection of DCE_t and AIE_t across all three scenarios for the full period 2022 to 2045 is reported in Appendix E.

6.2 Direct Emissions from AI Data Centre Electricity Demand

Direct emissions are calculated as $E_t = AIE_t \times CI$, where CI takes two values. This includes the average carbon intensity of 35 gCO₂/kWh and the marginal carbon intensity of 630 gCO₂/kWh. Figure 6.2 presents the results for the medium scenario across the years 2024, 2030, 2035, and 2045.

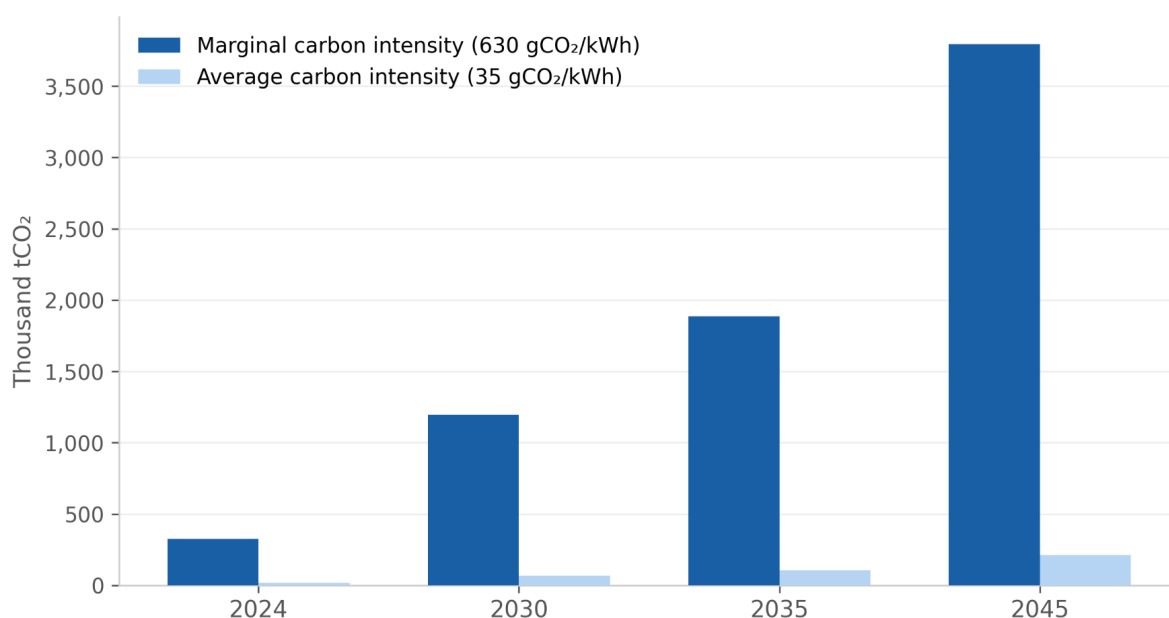


Figure 6.2: Direct emissions from AI data centre electricity demand, medium scenario

Source: Present study

Under the average carbon intensity, direct emissions from AI data centres in the medium scenario grow from approximately 18,000 tCO₂ in 2024 to 211,000 tCO₂ by 2045. While this increase looks big, it is small in absolute terms compared to Sweden's total territorial greenhouse gas emissions of 47.5 million tCO₂ equivalents (Naturvårdsverket, 2025). This equals 0.44 percent of Sweden's total emissions by 2045 in the medium scenario. However, as Dotzauer (2010) establishes, it is methodologically insufficient to look at the average carbon intensity for new electricity demand in the future. Instead, looking at the marginal carbon intensity gives a value of 630 gCO₂/kWh, which produces a substantially different result. In the medium scenario, marginal emissions grow from

324,000 tCO₂ in 2024 to 3,796,000 tCO₂ by 2045. This represents approximately 3.8 million tonnes annually, reflecting the mechanism further identified by Dotzauer (2010). Since Sweden's baseload generation from nuclear, hydro, and wind can not respond to new demand, each additional TWh consumed by AI data centres reduces Swedish electricity exports to continental Europe, where the marginal source is coal-condensing power. The emissions, therefore, happen abroad but are attributable to AI electricity demand growth in Sweden. Under marginal intensity, it represents approximately 8 percent of Sweden's current total annual emissions by 2045 in the medium scenario. This becomes a significant figure for a single sector. The complete direct emissions results across all scenarios and years are reported in Appendix E.

6.3 Carbon Opportunity Cost

Figure 6.3 presents the results of the carbon opportunity cost across the three competing decarbonisation uses. This is for the medium scenario across the years 2024, 2030, 2035, and 2045.

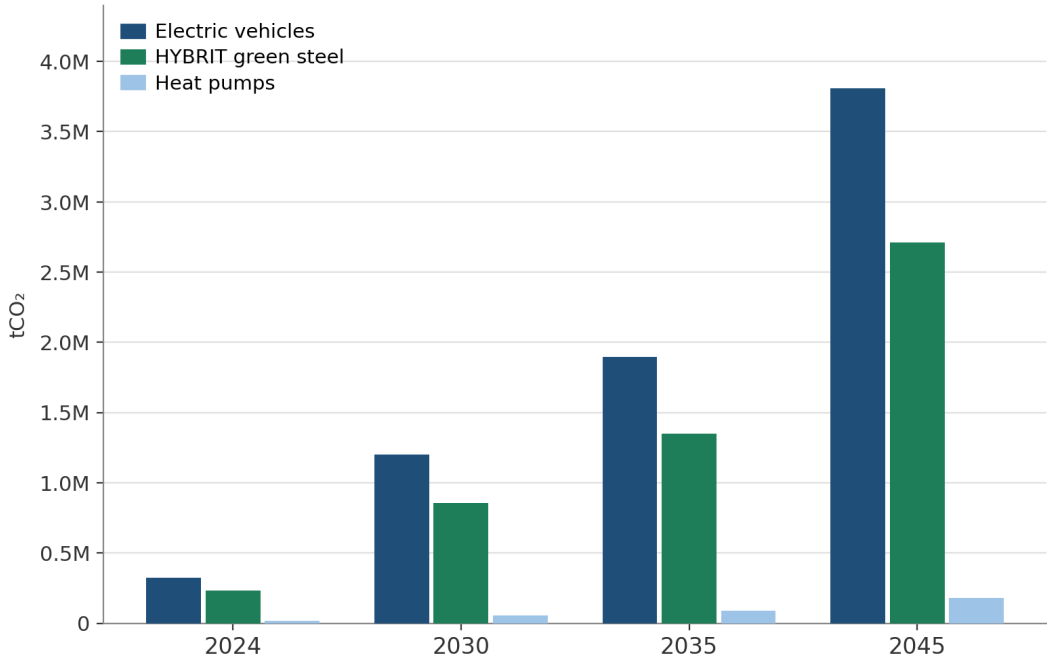


Figure 6.3: Carbon opportunity cost by competing decarbonisation use, medium scenario
Source: Present study

The results from the carbon opportunity cost vary across the three competing uses. The highest opportunity cost in the medium scenario is EVs, reaching 3.8 million tCO₂ by 2045. HYBRIT

follows at 2.7 million tCO₂ by 2045, while heat pumps show a lower opportunity cost of 180,741 tCO₂ by 2045. The three competing uses represent mutually exclusive counterfactuals. The same TWh absorbed by AI data centres can only crowd out one alternative use at a time, meaning that the opportunity costs should not be summed. Instead, each displacement factor defines the opportunity cost conditional on which use is foregone. The full opportunity cost results across all scenarios and years are reported in Appendix E.

6.4 Discussion - Implications for Sweden's Climate Targets

Under the Paris Agreement (UNFCCC, 2015), the Government Offices of Sweden (2021) report that Sweden has committed to having zero net emissions of greenhouse gases into the atmosphere by 2045, and a reduction of at least 63 percent by 2030 compared to 1990 levels. This study has aimed to quantify whether the AI-driven data centre electricity demand creates a meaningful tension with these climate commitments.

The direct emissions suggest a two-way picture. While the average carbon intensity shows that AI data centre emissions remain below 0.5 percent of Sweden's total territorial emissions by 2045 in the medium scenario, it is insignificant in absolute terms. However, the marginal carbon intensity shows that emissions reach approximately 8 percent of Sweden's current total annual emissions by 2045. This is a meaningful and significant value regarding the implications for the climate targets.

Looking at the carbon opportunity costs, the results become more significant. The net zero target by 2045 in Sweden requires all remaining territorial emissions of 47.5 million tCO₂ in 2024 to be gone (Naturvårdsverket, 2025). The results show that the opportunity cost of EVs in 2045 represents 8 percent of the total emissions, HYBRIT approximately 6 percent, and heat pumps approximately 0.4 percent. Since the three uses draw on the same scarce pool of electricity, these are mutually exclusive counterfactuals and should not be summed. Particularly significant is the HYBRIT result, given that Sweden has explicitly committed to fossil-free steel production by 2045, as reported by the International Energy Agency (2024). It is further estimated that this transition requires up to 55 TWh of additional clean electricity by 2045 (IEA, 2024, pp.57-59). Projecting AI electricity demand to 6.02 TWh by 2045 in the medium scenario, it represents approximately 11 percent of the 55 TWh that HYBRIT alone requires. While Svenska kraftnät (2024) documents a national grid connection queue of 20,500 MW of pending applications for

2024, it shows that the problem is not hypothetical. The problem becomes clear because data centres will compete for the same limited grid access. The present study does not determine the outcome of this competition. In other words, it does not answer who ultimately ends up securing the electricity, whether it is AI or industrial decarbonisation. Instead, it quantifies the scale of the tension that policymakers must resolve for Sweden to be able to hit its 2045 climate goal.

Important to note is that the present study does not imply that Sweden will fail to meet its 2045 net-zero target because of AI. Whether Sweden succeeds or not depends on factors outside the scope of this study. Some important questions about this are whether the total electricity supply expands fast enough to accommodate all competing users, or whether grid constraints are resolved in time. It is also important to ask whether the HYBRIT and EV deployment are actually delayed or prevented by AI competition, something that is not possible to fully determine now. These questions require broader energy system modelling beyond what this study provides.

What the present study does imply is that AI data centre growth will make the climate targets for Sweden meaningfully harder. Sweden's current climate planning does not fully take the AI expansion into account. Government Offices of Sweden (2026) documents that the use of AI will drive up demand for energy and cooling, and that environmental impacts need to be minimised, but a projection on how AI will actually complicate climate targets is lacking. The present study directly addresses this gap, and the quantified tension therefore remains unaddressed in current Swedish policy. Without policy intervention, one may say that a pathway toward net zero in 2045 will be hard to follow. This is further reinforced by the fact that Sweden is already behind on its climate goals. Klimatpolitiska Rådet (2024) documents that the Swedish government's climate policy is not reflected in action. The policy adopted in 2023 increased emissions, and will further not lead toward the fulfilment of Sweden's climate goals and EU commitments. It is further noted that the government's claim of reaching net zero by 2045 lacks analytical support. In this context, the quantifiable emerging and growing source of electricity demand from AI that the present study addressed represents a pressure that policymakers can not ignore.

7. Conclusions

The present study shows that the projected growth of AI-driven data centre electricity demand in Sweden creates a meaningful and growing tension with the country's 2030 and 2045 climate

targets. The present study makes two contributions to the existing literature. First, no existing study has done a projection of AI-driven data centre electricity demand for Sweden specifically, and further connecting this to the country's 2030 and 2045 climate targets. The methodological gap with existing research understating the true climate cost by only using the average carbon intensity is the second gap that the present study addresses. This is done by applying a marginal emissions framework and a carbon opportunity cost approach to AI data centres in Sweden. The central finding of the present study is that the climate implications of AI are systematically invisible under the average carbon intensity, but under the theoretically correct marginal carbon intensity, the results become significant and indicate a growing tension with Sweden's climate targets.

The carbon opportunity cost extends this further, showing that the climate implications of AI in Sweden are not limited to direct emissions but include the clean electricity that AI data centres absorb that can not be used for industrial decarbonisation. In the end, this leads to even more emissions as a consequence of AI data centre growth in Sweden, a finding that becomes particularly relevant since the country is already falling short of its climate trajectory. The additional pressure from a growing electricity demand of AI is real, quantifiable, and currently unaddressed in Swedish climate policy.

The limitations of the present study are notable. The most central limitation lies in the AI share of total data centre electricity consumption, the variable driving the entire model, which can not be directly observed from any published source and must be estimated from global benchmarks and calibrated assumptions. While this motivates why the study exists, it is estimations that always carry some part of uncertainty. This uncertainty is addressed by the three-scenario approach. Additionally, the marginal carbon intensity value is held at a constant value throughout the projection period, which may overstate or understate the true marginal emissions toward 2045. This depends on how Sweden will change its grid conditions in the upcoming years. Future research should address both limitations. On the data side, the future will have the Act (2025:570) on the Disclosure of Information on the Energy Performance of Data Centres in force. This will make the total data centre electricity consumption in Sweden directly observable for the first time. Future research should use this to strengthen the baseline. On the methodological side, the opportunity cost framework should be extended. The extension should include a broader set of competing decarbonisation uses, since the present study included three of them. Furthermore, the

infrastructure lag parameter should be empirically validated through primary data on actual build timelines in Sweden.

More broadly, the present study contributes to a growing body of research on AI and its climate implications. The climate implications extend well beyond what the average carbon intensity reveals. For Sweden, with an almost fossil-free grid, the true climate cost of new electricity demand is understated, and it is not a small difference. It is an eighteen-fold gap that makes the AI sector appear climate-neutral when it is not. In the future, as AI infrastructure continues to expand globally, this methodological distinction matters well beyond Sweden. The present study shows that the climate implications will not only matter for countries that have a high reliance on fossil fuels, but also for countries that are integrated with fossil-heavy grids at the margin. The tension the present study quantifies for Sweden is a warning that will apply to many countries in the future.

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Appendix A - AI disclosure

Tools

Claude, ChatGPT.

Degree of use

Claude and ChatGPT were used at several stages of the writing process.

In the early stages of the present study, ChatGPT was used for idea generation and research problem development. With a clear idea of the topic, ChatGPT was used to help identify the research gaps addressed in Chapter 1, as well as to explore how the methodological approach could be structured.

Claude was used mainly for the writing process, used occasionally as the editing tool across all chapters of the thesis. This included, for instance, highlighting where the grammar was wrong and could be improved. Furthermore, the tables and figures presented in the study were assisted by Claude. While the underlying calculations and data inputs were produced by the author, Claude helped in formatting and structuring the different figures presented throughout the paper in Chapters 5 and 6, as well as Appendix C and E. Furthermore, Claude was used during the development of the methodological approach in Chapter 5.

In the final stages, Claude was used to correct grammatical errors and to improve areas of the language throughout the thesis. This was used to spot any places that could be improved. The author takes full responsibility for the accuracy of all claims, citations, and results presented in the thesis.

Appendix B - Model selection and worked example

Model Selection - Logistic over Alternative Diffusion Models

The technology diffusion literature offers several competing models with alternative functional forms. Using logistic instead of other models merits explicit justification. Some important ones include the logistic, Gompertz, Bass, cumulative lognormal, Weibull, and more flexible extensions such as the Flexible Logistic (FLOG) and Generalised Bass Model (GBM) (Meade and Islam, 2006). Meade and Islam (2006) confirm that simpler models outperform the others. It is noted that for homogenous datasets, such as for SCB enterprise AI data in the present study, using simpler specifications tends to outperform more flexible alternatives in out-of-sample forecasting. This is further reinforced by Bemmaor and Lee (2002), who find that the forecasting advantage of more complex diffusion models over simpler ones becomes less effective the longer you forecast. This is directly relevant for the present study, as a projection of more than 20 years is being estimated.

Meade and Islam (2006) further note that the Bass model requires separate estimations of three parameters. This includes a coefficient of innovation (p) and coefficient of imitation (q), and market potential (m). The empirical evidence shows that even with full datasets, reliable estimations are problematic, further implying that the model is asking too much from too little data. Hence, these three parameters can not be reliably identified from the SCB observations available for the current study. For the Gompertz model, it is competitive in fit, however, more suited for technologies where the adoption peaks early relative to the saturation level. This is because it is asymmetric around its inflection point, occurring before diffusion has reached half the saturation level (Meade and Islam, 2006). The observed data of Swedish enterprises with ten or more employees using any AI technology shows 10.4 percent in 2023, 25.1 percent in 2024, and 35.0 percent in 2025 (SCB, 2025). This indicates that the growth remains in a phase of accelerating growth, with the inflection point not yet reached. The symmetric logistic places the inflection point at exactly half the saturation ceiling, which at $M_u = 0.85$ corresponds to 42.5 percent adoption. This is consistent with the observed data, which still has an increasing speed at 35 percent. In contrast, the Gompertz places the inflection point earlier, which, for the present study, would imply that growth has already peaked and is decelerating. This is inconsistent with

the observed acceleration in the SCB (2025) data, indicating that the chosen logistic model is not only simpler, but also the one that is most consistent with the data available.

Parameter Estimation for k and τ

With M_u fixed at 0.85, k and τ are estimated from the two most recent SCB (2025) observations. These observations include 25.1 percent in 2024 and 35.0 percent in 2025, giving $A = 0.251$ in 2024 and $A = 0.350$ in 2025. These two values are the only ones used because the methodological break in the SCB data before 2022 makes earlier observations not directly comparable.

The logistic formula from equation (2) is: $A_t = M_u / (1 + \exp(-k \times (t - \tau)))$

Plugging in the M_u value and 2024 observation into equation (2):

$$0.251 = 0.85 / (1 + \exp(-k \times (2024 - \tau)))$$

Rearranging this gives:

$$1 + \exp(-k(2024 - \tau)) = 0.85 / 0.251 = 3.386$$

$$\exp(-k(2024 - \tau)) = 2.386$$

$$-k(2024 - \tau) = \ln(2.386) = 0.870 \text{ (i)}$$

Plugging in the M_u value and 2025 observation into equation (2):

$$0.350 = 0.85 / (1 + \exp(-k \times (2025 - \tau)))$$

Rearranging this gives:

$$\exp(-k(2025 - \tau)) = 1.429$$

$$-k(2025 - \tau) = \ln(1.429) = 0.357 \text{ (ii)}$$

Subtracting (ii) from (i) gives:

$$-k(2024 - \tau) \text{ minus } -k(2025 - \tau) = 0.870 - 0.357$$

$$-k \times (2024 - \tau - 2025 + \tau) = 0.513$$

$$-k \times (-1) = 0.513$$

$$\mathbf{k = 0.51}$$

Substituting $k = 0.51$ back into equation (i): $-k(2024 - \tau) = \ln(2.386) = 0.870$

$$-0.51 \times (2024 - \tau) = 0.870$$

$$2024 - \tau = -1.70$$

$$\mathbf{\tau = 2026}$$

These are the two parameter values used throughout the model. It should be noted that deriving k and τ from only two observations means the results are sensitive to small changes in either value, which is acknowledged as a limitation in Section 5.4.

Worked Example for 2030 - medium scenario

To visually show how the complete three-stage model is done, this section shows how the 2030 medium scenario with the output of 1.90 TWh in Appendix E is produced. All inputs come directly from the assumptions established in Chapter 5.

Inputs for this example:

$$k = 0.51, \tau = 2026, M_u = 0.85$$

$$\delta = 2 \text{ years (medium scenario)}$$

$$s \text{ anchor in 2024} = 0.15 \text{ (15\%)}$$

$$s \text{ ceiling} = 0.50 \text{ (50\%, medium scenario)}$$

$$I \text{ in 2024} = 0.104$$

$$\text{DCE in 2030} = 4.80 \text{ TWh}$$

Stage 1 - Enterprise AI Adoption

To project enterprise AI adoption for 2030, stage 1 needs the adoption value for 2028. This is because the lag in Stage 2 is 2 years, reflecting that the electricity demand in 2030 is the adoption made 2 years earlier.

Using equation (2):

$$A_t = M_u / (1 + \exp(-k \times (t - \tau)))$$

$$A(2028) = 0.85 / (1 + \exp(-0.51 \times (2028 - 2026)))$$

Working through the steps:

$$2028 - 2026 = 2$$

$$-0.51 \times 2 = -1.02$$

$$\exp(-1.02) = 0.361$$

$$1 + 0.361 = 1.361$$

$$0.85 / 1.361 = \mathbf{0.625}$$

This means that in 2028, 62.5% of Swedish enterprises are using AI, according to the projection.

Stage 2 - Infrastructure Lag

Using equation (3): $I_t = A(t - \delta)$

The medium scenario lag gives $\delta = 2$ years. So the electricity demand signal in 2030 uses the adoption value from 2 years earlier.

$$I(2030) = A(2028) = \mathbf{0.625}$$

Stage 3 - AI Electricity Share

This stage converts the lagged adoption variable I into s , the AI share of Swedish data centre electricity.

To better understand how the logic works, the lagged enterprise AI adoption rate $I(2030) = 0.625$ from the previous step will grow from its 2024 value of 0.104 towards the ceiling of 0.85. In the same way, the AI electricity share (s) with a 2024 starting point of 15% will proportionally grow toward its ceiling of 50%. As I increase, s increases proportionally.

Using equation (4): $s_t = \text{MIN}(\text{ceiling}, \text{anchor} + (\text{ceiling} - \text{anchor}) \times \text{MAX}(0, I_t - I_{2024}) / (M_u - I_{2024}))$

Fitting the values for 2030:

$$s = 0.15 + (0.50 - 0.15) \times (0.625 - 0.104) / (0.85 - 0.104)$$

Working through the steps:

$$0.625 - 0.104 = 0.521 \rightarrow \text{how far (I) has travelled since 2024}$$

$$0.85 - 0.104 = 0.746 \rightarrow \text{the total distance (I) could maximum grow to reach } M_u$$

$$0.521 / 0.746 = 0.699 \rightarrow \text{(I) has completed 69.9\% of its journey toward } M_u$$

$$0.50 - 0.15 = 0.35 \rightarrow \text{the total distance (s) could maximum grow from the anchor to the ceiling}$$

$$0.35 \times 0.699 = 0.245 \rightarrow \text{shows (s) has also completed 69.9\% of its journey toward the ceiling of 50\%}$$

$$0.15 + 0.245 = \mathbf{0.394}$$

AI accounts for 39.4% of Swedish data centre electricity in 2030.

Master Equation

Using equation (1): $AIE_t = DCE_t \times s_t$

$$4.80 \times 0.394 = \mathbf{1.89 \text{ TWh}}$$
, which rounds up to 1.90 TWh as reported in Appendix E.

Appendix C - Variable notation and sensitivity analysis

Variable and Notation Reference

Table B1 presents a table of all variables and notations used across the three-step methodological approach. The table lists each symbol, its definition, the unit of measurement, and the step at which it is first introduced.

Table C1: Variable and notation reference

Symbol	Definition	Unit	First used
DCE_t	Total electricity consumed by all data centres in Sweden in year t	TWh	Step A
A_t	Share of Swedish enterprises with 10+ employees using any AI technology	%	Step B, Stage 1
M_u	Saturation ceiling for enterprise AI adoption	%	Step B, Stage 1
k	Diffusion speed parameter governing the steepness of the logistic curve		Step B, Stage 1
τ	Inflection year: year at which adoption reaches $M_u / 2$	Year	Step B, Stage 1
δ	Infrastructure lag parameter: years between enterprise AI adoption and data centre electricity demand	Years	Step B, Stage 2
I_t	Lagged adoption variable: enterprise AI adoption rate from δ years prior	%	Step B, Stage 2
I_{2024}	Value of I in the anchor year of 2024	%	Step B, Stage 2
s_t	AI share of Swedish data centre electricity in year t	%	Step B, Stage 3

anchor	2024 calibration anchor for s , set at 15% from IEA (2025)	%	Step B, Stage 3
ceiling	Long-run saturation ceiling for s across scenarios (30%, 50%, 65%)	%	Step B, Stage 3
AIE_t	AI-driven Swedish data centre electricity demand in year t	TWh	Master equation
E	Annual direct CO ₂ equivalent emissions from AI data centres	Thousand tCO ₂	Step C.1
CI	Carbon intensity of Swedish electricity	gCO ₂ /kWh	Step C.1
CI_{avg}	Average carbon intensity of Swedish electricity (Ember, 2026)	gCO ₂ /kWh	Step C.1
CI_{marg}	Marginal carbon intensity of Swedish electricity (Olkkonen and Syri, 2016)	gCO ₂ /kWh	Step C.1
OC(j)	Carbon opportunity cost for competing decarbonisation use j in year t	tCO ₂	Step C.2
DF_j	Displacement factor for competing use j	tCO ₂ /TWh	Step C.2

Source: Present study

One-at-a-time Sensitivity Analysis

The three-scenario approach in the present study uses the infrastructure lag δ , the diffusion speed k , the inflection year τ , and the s ceiling simultaneously. In order to improve transparency and to know which specific assumptions are driving the model output, this section does a one-at-a-time (OAT) sensitivity analysis. This sensitivity check has each parameter varied in isolation while all others are held at their medium-scenario baseline values, evaluating the model output at a low and high variant of a single parameter. The sensitivity analysis examines outputs of AIE, AI-driven

Swedish data centre electricity demand, in 2030 and 2045, corresponding to Sweden's long-term climate targets.

The medium-scenario baseline is: $k = 0.51$, $\tau = 2026$, $M_u = 0.85$, $\delta = 2$ years, s ceiling = 50 %. This produces AIE = 1.90 TWh in 2030, and AIE = 6.02 TWh in 2045 as reported in Appendix E. Values that differ from the baseline are shown in bold text.

Table C2: OAT sensitivity of AIE to individual parameter changes (TWh)

Parameter	Variant	Baseline 2030 (TWh)	AIE 2030 (TWh)	Baseline 2045 (TWh)	AIE 2045 (TWh)
s ceiling	Low: 30%	1.90	1.22	6.02	3.61
s ceiling	High: 65%	1.90	2.40	6.02	7.83
τ (inflection year)	Late: 2028	1.90	1.44	6.02	6.02
τ (inflection year)	Early: 2024	1.90	2.18	6.02	6.02
δ (infra. lag)	Slow: 3 yr	1.90	1.68	6.02	6.02
δ (infra. lag)	Fast: 1.5 yr	1.90	1.98	6.02	6.02
k (diffusion speed)	Low: 0.38	1.90	1.79	6.02	6.02
k (diffusion speed)	High: 0.64	1.90	1.98	6.02	6.02
M_u (sat. ceiling)	Low: 0.75	1.90	1.88	6.02	6.02
M_u (sat. ceiling)	High: 0.95	1.90	1.90	6.02	6.02

Source: Present study

Interpretation of the one-at-a-time sensitivity analysis

Interpreting the results of the sensitivity analysis, several findings emerge. Looking at the year 2045, the s ceiling, the long-run saturation ceiling of AI share of Swedish data centre electricity is the only parameter that meaningfully affects AIE at 2045. While the medium ceiling is 50 percent, shifting it to the low value of 30 percent shows AIE to reduce by 2.41 TWh, which is a reduction

of 40 percent. Raising the ceiling to 65 percent shows AIE to increase by 1.81 TWh, which is an increase of 30 percent. All other parameters produced no material change for AIE in 2045. This is because the logistic diffusion curve reaches the near-saturation ceiling by approximately the year 2040 under all parameter variants, meaning that enterprise AI adoption converges to the same level regardless of diffusion speed, inflection year, or infrastructure lag.

Looking at the year 2030, all parameters except the high value of the saturation ceiling M_u produce a change in AIE. Similar to 2045, the s ceiling produces the largest change, where the low variant of 30 percent shows AIE to reduce by 0.68 TWh, and the high variant of 65 percent shows AIE to increase by 0.50 TWh. The inflection year τ comes second, as the late inflection year of $\tau = 2028$ shows AIE to reduce by 0.46 TWh, while the early inflection year of $\tau = 2024$ shows AIE to increase by 0.28 TWh. The infrastructure lag δ produces a smaller change, as the slow variant of $\delta = 3$ years shows AIE to reduce by 0.22 TWh, and the fast variant of $\delta = 1.5$ years shows AIE to increase by 0.08 TWh. The diffusion speed k produces the smallest meaningful change, where the low variant of $k = 0.38$ shows AIE to reduce by 0.11 TWh, and the high variant of $k = 0.64$ shows AI to increase by 0.08 TWh. For the saturation ceiling M_u , it produces close to no change at all. The low variant of $M_u = 0.75$ shows AIE to reduce by 0.02 TWh, while the high variant of $M_u = 0.95$ produces no change from the baseline value.

Overall, the results of the one-at-a-time sensitivity analysis show that the saturating ceiling s is the most critical assumption driving the model output at both 2030 and 2045. The uncertainty this carries is discussed in Section 5.4 of the method.

Appendix D - Carbon opportunity cost derivations

HYBRIT

The first competing use is fossil-free steel production through the HYBRIT process. The HYBRIT initiative is a collaboration between the steel company SSAB, the mining company LKAB, and the energy company Vattenfall, launched to fundamentally change the iron and steel industry. The goal is to eliminate carbon dioxide emissions in the steel industry by replacing coal and coke in the production of iron with fossil-free hydrogen and electricity, which is expected to reduce Sweden's total carbon dioxide emissions by more than 10 percent (LKAB, 2024).

Pei (2024) documents that the conventional blast furnace process emits 1,600 kg CO₂ per tonne of crude steel, compared to 25 kg CO₂ per tonne that the HYBRIT process reduces this to. This is a saving of 1,575 kg CO₂ per tonne by substituting coal with hydrogen produced using clean electricity. However, this substitution demands more electricity. Pei (2024) further documents a requirement of 3,488 kWh of clean electricity per tonne of steel produced in the HYBRIT process, compared to 235 kWh of clean electricity per tonne of steel produced in the conventional blast furnace. The displacement factor, denoted DF_j , is therefore: one TWh of clean electricity enables the production of approximately 286,700 tonnes of green steel, each tonne avoids 1,575 kg CO₂ compared to conventional production, giving DF_j for HYBRIT approximately 450,000 tCO₂/TWh. This means that for every TWh allocated to AI data centres rather than HYBRIT, approximately 450,000 tonnes of CO₂ reduction is the opportunity cost.

Heat pumps

The second competing use is heat pump deployment to further replace fossil fuel heating in Sweden. Fossilfritt Sverige (2019) documents that the heating sector uses approximately 100 TWh in Sweden, half of which is district heating and half individual and small-scale heating. Direct emissions from district heating and own heating of homes and premises amounted to just under 3 Mtonnes CO₂-eq in 2019. This implies that the average electricity allocated to heat pumps rather than AI data centres therefore avoids approximately 30,000 tCO₂, giving DF_j for heat pumps

approximately 30,000 tCO₂/TWh.³³ This means that for every TWh allocated to AI data centres rather than heat pumps, approximately 30,000 tonnes of CO₂ reduction is the opportunity cost. However, this figure is conservative as Sweden's heating sector has already phased out fossil fuels and is targeting to be fully fossil-free by 2030 (Fossilfritt Sverige, 2019). This means that the real displacement potential declines over time. However, the value is held constant throughout the projection period for the present study.

Electric vehicles

The third competing use is electric vehicles for transport decarbonisation in Sweden. Morfeldt et al. (2021) project that an electric vehicle will require 201 Wh of electricity per km driven under real-world conditions in 2030, while a conventional internal combustion engine vehicle will emit 127 gCO₂ per km in 2030. This means that one TWh of clean electricity enables approximately 4,975,000,000 km of electric driving, each avoiding 127 gCO₂ compared to conventional internal combustion engine vehicles. This gives approximately 632,000 tCO₂ avoided per TWh. This means that for every TWh allocated to AI data centres rather than EVs, approximately 632,000 tonnes of CO₂ reduction is the opportunity cost.

³³ Dividing total emissions by total electricity use gives the displacement factor: 3,000,000 tCO₂ ÷ 100 TWh = 30,000 tCO₂/TWh.

Appendix E - Full model projections

Table E1: Full projection of total Swedish data centre electricity (DCE_t) and AI-driven data centre electricity demand (AIE_t) across three scenarios, 2022-2045

Year	DCE (TWh)	AIE Low (TWh)	AIE Med (TWh)	AIE High (TWh)
2022	3.00	0.36	0.45	0.54
2023	3.21	0.39	0.48	0.58
2024	3.43	0.41	0.51	0.62
2025	4.20	0.53	0.73	1.14
2026	4.31	0.57	0.90	1.61
2027	4.43	0.63	1.12	2.06
2028	4.55	0.70	1.38	2.44
2029	4.67	0.79	1.64	2.73
2030	4.80	0.89	1.90	2.94
2031	5.04	1.03	2.17	3.18
2032	5.29	1.18	2.41	3.38
2033	5.56	1.33	2.62	3.58
2034	5.83	1.48	2.81	3.77
2035	6.13	1.63	3.00	3.97
2036	6.55	1.81	3.23	4.26
2037	7.01	1.98	3.48	4.56
2038	7.50	2.16	3.73	4.88
2039	8.03	2.34	4.00	5.22

2040	8.59	2.53	4.29	5.58
2041	9.19	2.72	4.59	5.98
2042	9.84	2.92	4.92	6.39
2043	10.53	3.14	5.26	6.84
2044	11.26	3.36	5.63	7.32
2045	12.05	3.60	6.02	7.83

Source: Present study

Table E2: Full projection of direct emissions from AI-driven data centre electricity demand (AIE_t). Under average and marginal carbon intensity, 2022-2045

Year	Average CI - 35 gCO₂/kWh (thousand tCO₂)	Marginal CI - 630 gCO₂/kWh (thousand tCO₂)
2022	16	284
2023	17	303
2024	18	324
2025	26	463
2026	32	568
2027	39	706
2028	48	866
2029	57	1,034
2030	66	1,195
2031	76	1,364
2032	84	1,515
2033	92	1,650

2034	98	1,773
2035	105	1,888
2036	113	2,038
2037	122	2,192
2038	131	2,353
2039	140	2,522
2040	150	2,702
2041	161	2,893
2042	172	3,097
2043	184	3,314
2044	197	3,547
2045	211	3,796

Source: Present study

Table E3: Full projection of carbon opportunity cost by competing decarbonisation use, all scenarios, 2022-2045

Year	HYBRIT green steel (tCO₂) DF = 450,000 tCO₂/TWh			Heat pumps (tCO₂) DF = 30,000 tCO₂/TWh			Electric vehicles (tCO₂) DF = 632,000 tCO₂/TWh		
Year	Low	Medium	High	Low	Medium	High	Low	Medium	High
2022	162,000	202,500	243,000	10,800	13,500	16,200	227,520	284,400	341,280
2023	173,340	216,675	260,010	11,556	14,445	17,334	243,446	304,308	365,170
2024	185,220	231,525	277,830	12,348	15,435	18,522	260,131	325,164	390,197
2025	238,625	330,539	514,420	15,908	22,036	34,295	335,136	464,223	722,475

2026	258,659	405,959	723,678	17,244	27,064	48,245	363,273	570,146	1,016,366
2027	284,654	504,122	927,588	18,977	33,608	61,839	399,781	708,011	1,302,746
2028	317,016	618,847	1,098,232	21,134	41,256	73,215	445,232	869,136	1,542,406
2029	356,170	738,903	1,227,616	23,745	49,260	81,841	500,221	1,037,748	1,724,118
2030	402,422	853,587	1,324,762	26,828	56,906	88,317	565,179	1,198,815	1,860,555
2031	463,523	974,337	1,428,919	30,902	64,956	95,261	650,992	1,368,402	2,006,837
2032	529,727	1,082,322	1,522,376	35,315	72,155	101,492	743,972	1,520,062	2,138,093
2033	598,278	1,178,608	1,611,013	39,885	78,574	107,401	840,249	1,655,290	2,262,578
2034	666,663	1,266,239	1,698,602	44,444	84,416	113,240	936,291	1,778,362	2,385,592
2035	733,187	1,348,526	1,787,466	48,879	89,902	119,164	1,029,720	1,893,929	2,510,396
2036	812,318	1,455,474	1,914,821	54,155	97,032	127,655	1,140,855	2,044,132	2,689,260

2037	891,612	1,565,565	2,050,1 24	59,441	104,371	136,675	1,252,220	2,198,750	2,879,2 86
2038	971,609	1,680,486	2,194,3 50	64,774	112,032	146,290	1,364,570	2,360,149	3,081,8 42
2039	1,053,116	1,801,567	2,348,3 60	70,208	120,104	156,557	1,479,043	2,530,201	3,298,1 41
2040	1,137,034	1,929,900	2,512,9 74	75,802	128,660	167,532	1,596,902	2,710,438	3,529,3 33
2041	1,224,255	2,066,426	2,689,0 12	81,617	137,762	179,267	1,719,398	2,902,180	3,776,5 68
2042	1,315,614	2,211,997	2,877,3 16	87,708	147,466	191,821	1,847,707	3,106,627	4,041,0 31
2043	1,411,887	2,367,429	3,078,7 70	94,126	157,829	205,251	1,982,917	3,324,923	4,323,9 62
2044	1,513,795	2,533,530	3,294,3 07	100,920	168,902	219,620	2,126,041	3,558,202	4,626,6 72
2045	1,622,017	2,711,122	3,524,9 22	108,134	180,741	234,995	2,278,033	3,807,620	4,950,5 57

Source: Present study