Bachelor's Thesis Computing Science

The Potential Of Reducing Carbon Emissions By Demand Shifting In Dutch Data Centers

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Abstract

Data centers in the Netherlands account for more than 3% of the total power consumption, as of 2021. This research aims to estimate the upper bound to the potential demand shifting has in reducing CO_2 equivalent emissions to see if load shifting could contribute to carbon emission reductions in the Netherlands from within the IT landscape. A model is proposed which is solvable by linear programming and produces an optimized carbon-aware schedule for historical load and power breakdown data, resulting in a maximum potential of reducing CO_2 equivalent emissions of data centers. The model is evaluated using data about Dutch data centers and the Dutch electricity mix. It shows to what extent shifting workloads to time slots with lower carbon intensity can meaningfully reduce emissions by decreasing the demand for power from unsustainable energy sources. The observations from the modeled scenarios show that investigating more opportunities in the Dutch data center sector for utilizing carbon aware demand scheduling can save up to 29% carbon emissions in certain scenarios.

Contents

Chapter 1

Introduction

The advent of the computer in the 20th century has had a transformative impact on society and all kinds of devices containing computer chips can be found everywhere. Many applications and other software are being developed, to the benefit of our use of these devices. Although almost invisible, every bank account transfer or even typing words in an online word processor application, triggers the sending of API requests, requiring an active server to process them. The service providers therefore need hosting of (virtual) server space and cloud storage requires a lot of physical storage space and computing capacity, which is a solution data centers are providing. Along with other tasks for e.g. academic interest which may have a large computational effort, the demand for data centers has been increasing and is expected to grow in the upcoming years [1]. Resolving tasks requires energy for data centers and as the world is currently in an energy transition, researching options to reduce the emission of greenhouse gases is also relevant in the field of computing science and data centers.

This research explores the potential to reduce fossil fuel-based energy consumption in the Netherlands through demand shifting in data centers, with the aim of minimizing unsustainable electricity use. This can be measured by looking at the total energy consumption and associated greenhouse gas emissions (CO_2, methane, nitrogen compounds, etc., collectively referred to as CO_2 equivalents). The approach will be to utilize differences in the amount of green energy that is available at points in time, as the total consumption and generation rates are fluctuating. As statistics of individual data centers are difficult to obtain, the goal will be to find the reducing potential of time shifting for different circumstances in the Netherlands. By analyzing data centers, energy consumption and generation we will investigate what the potential for more sustainable demand processing in data centers is. We aim to develop a model that explores the benefits of shifting demand in time, although the same principles could be used to extend the model to geographic demand shifting. Given the variables and constraints defined prior to model development, the model is designed to approximate real-world conditions sufficiently to estimate an upper bound on the potential carbon emission reductions achievable through demand shifting. By applying this model, we aim to demonstrate the effectiveness of demand shifting as a mitigation strategy, thereby indicating the need for further research and development in this area.

This thesis focuses on demand shifting over time, using the Netherlands as geographical case study. However, the underlying model is theoretically applicable to other countries if sufficient data on emissions of electricity generation is available. We limit the scope of emissions to carbon emissions due to data availability. The method is applicable to other emissions if data is available. For data about electricity mix of the Netherlands (as well of most other European countries), Electricity Maps will be used as primary source [2]. It provides power and consumption breakdowns for energy sources and their carbon intensities per hour. Additionally, the carbon intensity factors for different power production types are given (as specified per country) [3]. As the possibilities for obtaining statistics of specific data centers is limited, the total consumption of data centers will be based on publicly available data.

The research contributes to scientific literature in relation to the fields of sustainability and data centers, leading to recommendations on future and more extensive research. We distinguish the following contributions:

1. Literature research is performed and an overview of collected data on data centers is given, especially in relation to demand shifting. Additionally literature is reviewed about modeling load shifting over time in relation with the electricity mix of the Netherlands. This forms a theoretical framework and context for the model and the obtained results. This contribution refers mostly to Chapter 2.

2. Criteria and conditions are defined for modeling demand shifting, among others the availability of green energy, import and export of energy in the region investigated and expected shifting proportions. These factors are decisive in the development of the model, and important to interpret the results as an upper bound to the potential in emission reductions. This relates to Chapters 3 and 4.

3. A model is developed to analyze how demand shifting can lead to reductions in carbon dioxide equivalent emissions and to estimate an upper bound on its potential. The model provides insights into when and to what extent demand shifting becomes effective, which are useful to data center system administrators and engineers performing research

in this field. This model is defined in Chapter 5

4. A case study is done in which we apply the model to data on Dutch data centers, and using data on emissions and electricity in the Netherlands. The results demonstrate how demand shifting could reduce carbon emissions in different modeled scenarios. This provides an interpretation of a theoretical upper bound by this model for the potential of reducing carbon emissions by demand shifting. The case study and its results are given in Chapter 6.

The code written for this thesis is published under an open source license.[1]

We begin by giving preliminary work relevant for this research (Chapter 2). Next, we present two conceptual demonstrations to visualize and motivate the use of properties of the electricity mix, particularly carbon intensity and its impact on the emissions (Chapter 3). We then address the properties of the model we will propose and the data set, which is data from Electricity Maps [2] covering a period of more than a year (containing parts of the years 2024 and 2025) (Chapter 4), as the second contribution mentioned above. Thereafter, we formulate a model which is solvable with linear programming, based on an objective, constraints and bounds required for such a model. We first compute the initial carbon emissions of data centers assuming data centers are powered solely by fossil fuel generators, without demand shifting. Differences in marginal carbon intensities based (primarily based on import and export of regional energy) are used to compute the gain from a shifting (Chapter 5). With this model, we do a case study for the Netherlands (Chapter 6). We use different sets of input parameters to explore multiple scenarios, showing how the potential varies under different conditions. We then present related work (Chapter 7) and end with our conclusions, where we summarize our main findings and give recommendations for future work (Chapter 8).

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[1] Robert van der Maas. *Code for bachelor thesis: The Potential Of Reducing Carbon Emissions By Demand Shifting in Dutch Data Centers.* 2025. v1.0. Licensed under the Apache License 2.0. URL: `https://gitlab.science.ru.nl/gmaas/the-potential-of-reducing-carbon-emissions-by-demand-shifting-in-dutch-data-centers`.

Chapter 2

Preliminaries

This chapter discusses several relevant topics that are useful and provide a theoretical background for the development of a model. In the first part the main data source, Electricity Maps, is covered. Then some key concepts are given about data centers, workload, jobs and scheduling as basis for the model.

2.1 Electricity Maps data

Electricity Maps [2] provides data about the electricity mix of regions, which can have the size of a full country or a part of it. Such zones or regions are not necessarily following borders (politically) but are defined as *"the physical grid on which consumers and producers are connected and which is controlled by a grid operator"* [3]. Among others, data about consumption and production of energy in these zones, import and export of energy between zones, the power generation and consumption data per hour including breakdown in sources and the carbon intensity of the consumption at each hour can be accessed. The consumption and production values are given in megawatts (MW). The intensities and intensity factors are given in g CO_2 equivalents per kilowatt hour (kWh) [2, 3, 4].

Power production and emission types

In the GitHub wiki of Electricity Maps [3], information about the method and a description of important concepts is given. Carbon intensity of consumed energy is the result of the emissions of the production and the amount of energy produced. Each energy source has a specific carbon intensity that can be computed as life cycle intensity (including fabrication, installation, demolition, etc.) or direct intensity (only operational emissions). Electricity Maps provides such factors for several zones, including the Netherlands

[2]. The data is the result of the work from Electricity Maps and based on other research and sources, such as Annex III from a working group that contributed to the IPCC Fifth Assessment Report published by the Intergovernmental Panel on Climate Change (IPCC) [5].

The emission factors and carbon intensity can be used to compute actual emissions in CO_2 equivalents. These equivalents can be other greenhouse gases than CO_2, but for which the amount is converted to its equivalent amount of CO_2, based on their global warming potential [6].

Electricity Maps [3, 4], makes a distinction between types of energy categories, specifically fossil fuel (coal, gas, oil and unknown sources), renewables (biomass, geothermal, hydro, solar, wind, hydro discharge and battery discharge) and low-carbon (or called fossil free or carbon free, which includes the renewables and furthermore nuclear energy).

Each of the power generation sources has its own emission factor, which can be different across regions and are shown for the Netherlands in Table 1 and Table 2 [3, 7]. Table 1 shows the emission factors of fossil fuel energy production sources and Table 2 shows the other low-carbon energy production sources. These factors are used in the model in Chapter 5 for computing emissions and marginal intensities (e.g. the intensity of all fossil fuel generators combined).

Production type	Coal	Gas	Oil	Unknown
Carbon intensity	859.37	524.39	1169.95	342

Table 1: Carbon intensity factors for lifecycle fossil fuel energy production types in the Netherlands in g CO_2 / kWh [7].

Production type	Wind	Hydro	Nuclear	Geothermal
Carbon intensity	12.62	10.7	5.13	38

Table continues...

Production type	Solar	Hydro discharge	Battery discharge	Biomass
Carbon intensity	36.5	301.11	301.11	230

Table 2: Carbon intensity factors for lifecycle non-fossil (low-carbon) fuel energy production types in the Netherlands in g CO_2 / kWh [7].

Production and consumption with import and export

Electricity Maps uses a difference between consumption and production [2]. Consumption indicates how much power is used. Moreover, energy can be imported from and exported to other countries, and affect the total carbon intensity of the power consumption of a region. The relation between consumption, production, import and export can be defined as [2]:

$$\text{consumption} = \text{production} - \text{export} + \text{import}$$

Although carbon intensities are often based on the consumption to indicate the polluting effect of the consumption pattern, we will also make use of intensities of production, both total (all production types) and marginal (a part of the production types). This allows us to obtain marginal intensities of power production sources mapped to data center consumption.

2.2 Modeling data center behavior

To explore the potential of shifting demand in terms of the sustainability of consumed energy, we need a model that simulates the behavior of a data center. Normally, scheduling is done with scheduling algorithms, which are also used in scheduling jobs for a single processor. An example is Earliest Deadline First (EDF) scheduling, where the tasks are prioritized based on the deadline [8]. However, our focus lies on finding an optimal schedule for a historical dataset. Hence we need an optimization method rather than an active scheduling algorithm for our model. This model must be defined in such a way that it reflects reality with sufficient completeness for the purpose of finding an upper bound potential. Section 2.2.2 about completeness discusses this.

2.2.1 Data centers and workload

Data centers are complex entities that consist of a large number of interacting hardware components. However, the focus will not be on the internal specifications and technical task handling. The purpose is rather to find how data centers behave from a regional perspective. This is influencing the choice of parameters and the units with which we compute and applies also to the data center workload.

First, it needs to be considered what type of unit will be used to model task sizes and data center capacity. Processing time would be a difficult unit to use as it would require a more detailed scope of data centers to find a relation between installed hardware and processing time and task parallelization. Another unit, which is also used often in related research on modeling data centers and demand shifting [9, 10, 11] is the amount of power required for the workload. Having task sizes as power consumption is reasonable for the scope of a full zone, as the total power consumption of data centers can be measured (see Data center consumption and capacity). Another advantage is that workload can in this way be mapped to emissions by carbon intensities as they are defined as the relation between emissions and power consumption (e.g. g CO_2 equiv. / kWh).

Data center characteristics

With a workload measured as power demand, we need variables for data centers to be able to process them. To provide enough detail for finding the potential, we need to control several variables which allow us to test and explore the saving of unsustainable energy in different scenarios. There are several studies on demand shifting where models of data centers are used.[9, 11, 10, 12] Some important specifications of data centers and task resolving are:

1. `capacity`: the load a data center can handle in a certain time unit. Is the same as the operation speed as a capacity given in MWh already relates time to power.
2. `parallelization-rate`: the extent to which we can parallelize the execution of tasks as N tasks per time unit with $N > 1$ (more relevant for individual data centers and when using time as unit).
3. `shifting-cost`: the cost to shift workload to another data center (only relevant if multiple data centers are involved in the simulator).

As here the focus is not on individual data centers, but a broad scale perspective, the most important property needed is the capacity as that limits the amount of workload can be handled per time unit and hence bounds the amount of workload that can be shifted to a time slot. Parallelization rate and shifting-cost are relevant factors when designing real-time scheduling algorithms for specific data centers.

Data center capacity and consumption

The capacity of a data center depends on its size and technical specifications and cannot easily be captured without access to the internal proprietary specifications of a data center itself. As our scope focuses on the region the Netherlands, the average capacity of data centers would provide a reasonable estimation which is sufficient for our research goal. The Dutch Data Center association claims to have an installed colocation data center capacity of 863 MW in the State of Dutch Data Centers 2024 [1]. As this data is primarily about colocation data centers, the total installed capacity (including private data centers) is likely higher. An article from RaboResearch from the Dutch bank Rabobank claims an installed data center capacity of 1000 MW in 2025 [13]. The consumption of data centers is related to the maximum capacity, as the consumption of data centers cannot exceed the capacity. With a given installed capacity, we could compute the consumption if we knew an average server utilization rate. Takci et al. [10] performed literature research on the utilization rate of servers in data centers, showing varying results ranging from lower than 20% to 80%. Due to this variation, using the utilization rate is not a very reliable factor when finding the consumption of a data center.

A more concrete method is to measure this consumption. The Dutch research institution Centraal Bureau voor Statistiek (English Statistics Netherlands) (CBS) has conducted a research of the total power consumption of data centers in 2021 [14]. This analysis states that data centers had a share of 3.29% of the total power consumption. Although this is a measurement from the year 2021, it gives an estimation that is usable for exploring (an upper bound to) the potential of saving emissions by demand shifting and not finding an exact optimal solution.

Task characteristics

Workload can be split up in separate tasks and we consider the following properties of importance to define when arguing about workload and shifting:

1. `size`: the computational effort of a task specified in MW.
2. `arrival`: at which moment in time t the task presents itself to the data center.
3. `deadline`: the deadline t before which it needs to be finished (`completion`), with $t \geq t_{\texttt{arrival}}$. This creates a time window for the task execution as: $\texttt{arrival} < \texttt{completion} \leq \texttt{deadline}$

A model of data center workload demand shifting should get these properties as input for each time slot of task execution, e.g. hours. When using a regional scope, this will be an estimation of arriving workload at each time slot. We leave scheduling out of scope since we use historical data, but otherwise a distinction between `arrival` and the `start` time could be given, being the time at which the task is scheduled [8].

Task size

The workload can be split up in separate tasks (especially relevant when analyzing individual data centers). Estimating the size and differentiation of tasks is not straightforward as it requires access to data centers statistics and some unit is required to compare them (using power consumption is less suitable for individual data centers as it can depend on the hardware and cooling systems etc.). Research was performed by Zaharia et al. [15] on Facebook servers and using local benchmarks to analyze the division of task sizes. The task sizes were mapped to the percentage of occurrence, of which the results are shown in Table 3. Task sizes can be useful when building a realistic and detailed scheduler, but as we are investigating what potential it has to shift demand, we will use an average and fixed workload per hour of which we can take different shiftable proportions to create multiple scenarios. This shiftable proportion is also input for the model. When exploring the potential, it is interesting to vary this proportion to get results for several scenarios.

# maps	1	2	3-20	21-60	61-150	151-300	301-500	501-1500	> 1501
percentage	38	16	14	9	6	6	4	4	3

Table 3: Number of job maps (per input block) compared to percentage of occurrence [15].

Task delaying

We also need a shiftable proportion of tasks that can be delayed. We can use the amount of delay-tolerant tasks for this, which can be found in related studies [10, 16, 17]. The remaining part of workload is considered to be delay-sensitive and cannot be shifted to a later period. Literature research in those studies showed findings for a delay-tolerant workload of 70% for Google workload analysis [17]. An analysis of Alibaba servers showed that over a period of 24 hours a considerable average amount of 90% of the workload was delay-tolerant, varying over different hours. [16]

2.2.2 Completeness

When creating a model as proposed in this thesis in Chapter 5, we need to create an abstraction of reality, which satisfies the required amount of detail for our research contributions, more specifically, to the level of finding an upper bound to the potential demand shifting has for reducing carbon equivalent emissions. In this chapter, topics have been discussed about the electricity data, data centers, workload and shifting, having the required level of depth to model this on a regional scale. When further researching demand shifting in detail, incorporating more (technical) variables is necessary to provide a level of accuracy suitable for that scope. To also cover the behavior and results of the model compared to reality (the soundness), we included validity sections in Chapters 4, 5 and 6 and we evaluated the model behavior in Section 6.3.

2.3 Optimization method

Finding a potential for reducing emissions of a data center requires a model that computes how demand should have been scheduled in a way that the carbon emissions would have been minimal, while respecting the constraints of workload, deadlines and capacities. It needs to check if scheduling a task later results in a reduction of carbon (equivalent) emission, with the constraint that it still meets its deadline, where shifting at a certain point may have implications for the optimal shifts later on. Therefore we consider this an optimization problem, specified to minimize the total carbon emissions resulting from data centers with flexible demand. There are some options to solve this minimization problem. A new specific algorithm can be implemented or existing methods can be used. There exist different approaches to address optimization problems [18]. A greedy algorithm can be used that gives an estimated optimal solution, but its accuracy is not guaranteed. It could be implemented by using a penalty for time slots where the carbon intensity of the available generated energy is high to create priorities or preferences for time slots. Another approach is using dynamic programming techniques to get an exact solution. However, the complexity of such an algorithm can get large [18].

Another possible method is to define the model as a linear problem that can be solved by linear programming [18]. Using the variables discussed in this chapter, we can construct a linear objective with the goal of minimizing emissions. The variables for data center capacity and the workload properties can be used to define constraints and variable bounds. An advantage of linear programming (LP) is the ability to solve the problem in polynomial time when using an interior-point algorithm to solve it [19]. Using the interior-point method is more efficient than using the simplex method, which is less efficient and can have in worst case exponential complexity [20]. To find an upper bound to the potential of minimizing emissions by demand shifting, and on the scale of a full region, LP will be used for our model. However, when requiring more detail or non-linearity, the use of LP will become unsuitable. The limitations of LP are also discussed in Section 5.3.

Chapter 3

Exploring demand shifting

This chapter contains two visibility studies, which show the properties and behavior the model uses to calculate emission savings. First, we plot the relation between renewable energy and carbon intensity over a 24-hour period. Second, we demonstrate demand shifting using a naive method to show its potential to reduce emissions.

3.1 Visualization of electricity production, consumption, carbon intensity and emissions

For the purpose of visualizing the relation between types of energy sources, we take a short time period (24 hours) of data from Electricity Maps, ranging from 01-26-2025 15:00 to 01-27-2025 14:00 (note that this is a different time range than used for the model evaluations) for the Netherlands zone [7].

The data were retrieved with the free tier `latest` request option, which retrieves the last 24 hours of data. Requesting a specific time range is possible with a paid tier [4].

In Figure 3.1, four lines are plotted: the consumption and carbon intensity (scaled by multiplying by a factor of 100 for visibility) on the left axis and the percentage of low-carbon energy in the energy mix and emissions on the right axis. The effect of a higher percentage of low-carbon energy is visible in the carbon intensity, as the lines roughly mirror each other. The carbon intensity drops when the low-carbon percentage increases, and vice versa.

We also notice that the effect of a lower carbon intensity is reflected in the emissions. The emissions first follow the increase in the demand (power consumption) starting approximately between 03:00 and 04:00, but at 07:00 the increase in emissions flattens out, as the carbon intensity of the consumed energy decreases.

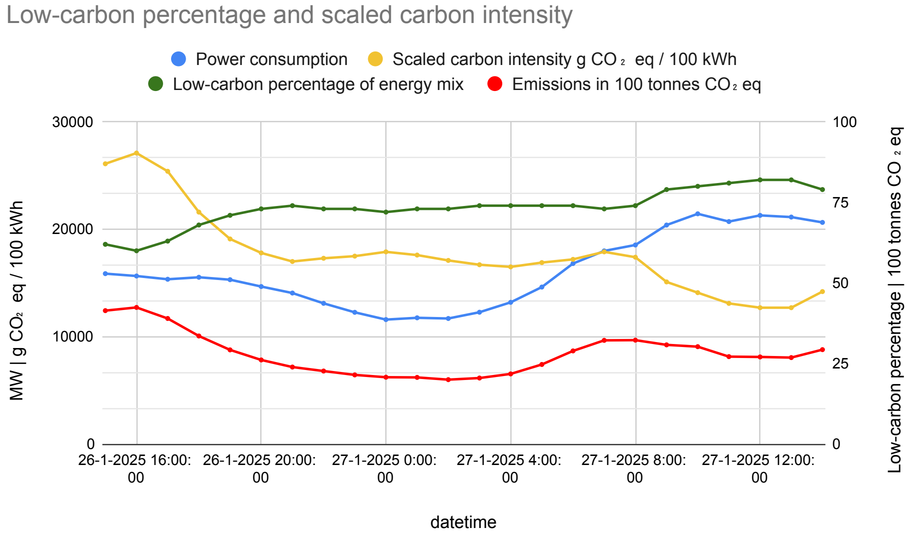

Figure 3.1: Low-carbon energy percentage set out against carbon intensity (multiplied by 100 for visual purposes), consumption and emissions over 24 hours (01-26-2025 15:00 to 01-27-2025 14:00).

Figure 3.1 furthermore shows that carbon intensity fluctuates, and that the differences can be significant (since the peak intensity is twice as high as the lowest point in this time plot). This supports the idea of modeling demand shifting based on the difference in carbon intensity, as consuming power at a time slot with a low carbon intensity will result in fewer emissions than consuming the same amount of power at a time slot with a higher carbon intensity.

3.2 Visualization of emission reduction using naive demand shifting

In the previous section we saw that the carbon intensity fluctuates, and we now explore how demand shifting can affect the emissions of data centers. We do this by simulating a hypothetical data center group that has a naive scheduling method. Consider the following specifications for the data centers and workload:

1. `capacity`: 500 MW
2. `Task size`: 500 MW
3. `shiftable proportion`: 0.25

4. `arrival`: $\forall t \in T((\exists s \in T(s_{\texttt{arrival}} = t_{\texttt{arrival}} - 1)) \vee t_{\texttt{arrival}} = 0)$

This means we have a data center (group) with a capacity of 500 MW. Each task has a size of 500 MW (the maximum size) and each hour exactly one task arrives. Furthermore, we assume the data center can naively shift 25% of its tasks to an ideal time slot with carbon intensity 0, or effectively remove them by shifting to a location out of scope, meaning one out of every four tasks is omitted. In the simulator, we define that each task at time t with $t \bmod 4 = 0$ is shifted away. The simulator takes the full hour to execute a task, and the cost of a task is therefore 500 MWh.

We use the same data as in the previous section (Section 3.1), so a short time period (24 hours) of data from Electricity Maps, ranging from 01-26-2025 15:00 to 01-27-2025 14:00 of the zone Netherlands [7]. We use the carbon intensity and task size to compute the emissions, because the carbon intensity is defined as emissions divided by power consumption. For each hour, the emissions E for hour t are obtained by multiplying the task size s by the carbon intensity I (which we need to multiply by 1000 to convert it from kWh to MWh): $E_t = I_t \cdot 1000 \cdot s_t$. The simulator tracks the total amount of emissions of this time period by adding all E_t to E_{total}. Similarly, it keeps track of the total emissions if shifting were applied. This results in the two lines that are plotted in Figure 3.2. The difference between those curves is the resulting reduction in emissions, or the gain, which is plotted in Figure 3.3. As follows from the naive scheduling, where we shift 25% of the tasks, the gain increases when more time passes, which is in this case every 4 hours.

The total gain is computed by subtracting the total shifted emissions after 24 hours from the value of the total emissions without shifting after 24 hours. This results in $2130 - 1578 = 552$ tonnes of CO_2 equivalent and a reduction in emissions of $\frac{552}{2130} \times 100\% = 25.9\%$. This indicates that the percentage of workload shifted can lead to varying emission reductions because carbon intensity is not constant. This illustrates that shifting tasks to hours with low carbon intensity can impact the emissions and is relevant for the development of the model in the following chapters, which aims to quantify such effects.

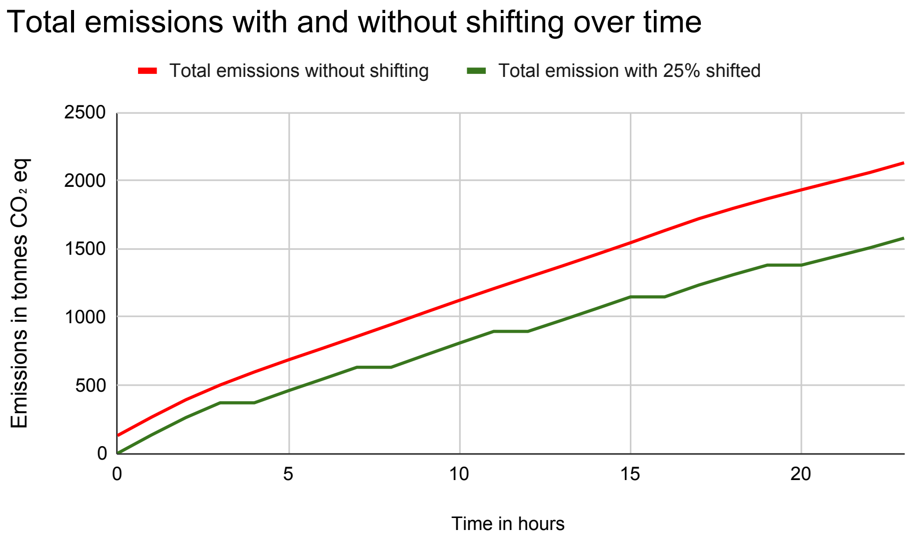

Figure 3.2: Total emissions after each hour without shifting and with shifting over 24 hours with an hourly workload of 500 MWh (01-26-2025 15:00 to 01-27-2025 14:00).

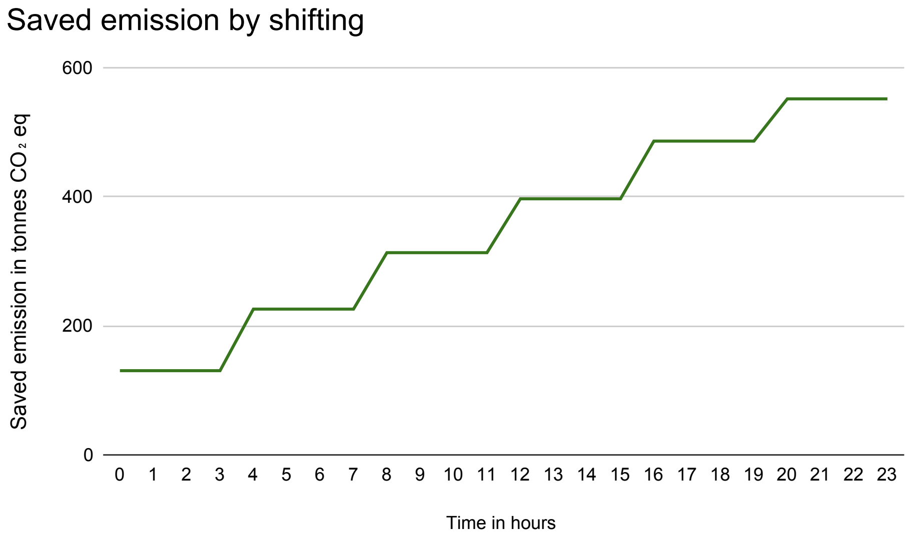

Figure 3.3: Gain in emissions obtained by naively shifting 25% of tasks over 24 hours (01-26-2025 15.00 to 01-27-2025 14.00).

Chapter 4

Properties

As seen in Chapter 3, naive scheduling results in a lower carbon emission. However, the approach used is naive and simple as we assume to shift the tasks out of scope. To answer to the goal of the research in this thesis, whether it is useful to exploit demand shifting to lower emissions by giving an upper bound to its potential, we need a more extensive model that is able to take data of a full year and provide it with parameters on the capacities of data centers. The model must compute the maximum savings based on these inputs.

4.1 Model type to find an upper bound

To analyze the potential of CO_2 equivalent savings, the model must be able to find upper bounds based on parameter settings. The model we propose needs to minimize the emissions caused by data centers. The model gives the maximum potential of (the upper bound for) savings, given a set of constraints. We call this an upper bound, since the assumptions imply we assume a perfect job schedule is possible in terms of carbon equivalent emissions. These assumptions and this line of reasoning lead to a set of constraints creating a search space in which a minimal solution can be found. It can be formulated in a linear way, which allows it to be solved using linear programming. Linear programming is less suitable for finding exact and realistic optimal solutions with fine-grained constraints due to its linearity limitation, but since we want to give an upper bound, using linear programming is an appropriate method for our research goals.

4.2 The dataset

The data used is a series of power breakdown data from Electricity Maps for the Netherlands region, from April 10, 2025, 09:00 to May 23, 2025, 06:00 [7]. This data is obtained from using Electricity Maps API, with the free-tier API calls

`"https://api.electricitymaps.com/v3/power-breakdown/latest?zone=NL"`

and

`"https://api.electricitymaps.com/v3/carbon-intensity/latest?zone=NL"`,

requiring an authorization key which is freely available after signing up. A specific datetime is also retrievable with a past or history request with a paid tier [4].

This data provides an hourly breakdown of production and consumption data. The production and consumption are broken down into separate resources, including nuclear, geothermal, biomass, coal, wind, solar, hydro, gas, oil, unknown, hydro discharge and battery discharge. Total consumption and production quantities are also provided [4].

In the data range we used, a of 328 hours are missing. An overview of the missing hours is given in Appendix A. The missing data is estimated by interpolating between the nearest previous and next available hour. The number of hours, including the estimated ones, sums up to a total of 9790 hours. We will from here on use the data set including the estimated hours by default, unless otherwise explicitly stated.

The model takes as input the power breakdown per hour and constants representing the lifecycle carbon intensity of fossil fuels (f) in the Netherlands. Power production types such as gas, coal, oil, and unknown sources are considered fossil fuels. The unknown power sources are considered fossil fuels as their origin cannot be reliably traced to low-carbon energy sources. The unknown energy has therefore an estimated constant for carbon intensity [3]. An overview of these constants for fossil fuels can be found in Table 1.

4.3 Method to find potential in carbon emission reduction

The linear programming model will generate shifting variables (p) for all possible slots. These slots are defined by the timeframe that is given as input to the model, which indicates the deadline for tasks available at time i. Thus, we obtain a list of variables $p_{i,j}$ indicating the workload shifted from i to j.

The difference in the carbon intensity of the power demand for data centers determines whether the shifting variable $p_{i,j}$ should be assigned a value greater than 0. So for each $p_{i,j}$ we use a precomputed value representing the difference in intensities between hour i and j.

4.3.1 The intensity of workload shifted away

At hour i, a certain amount of power is generated. Electricity Maps splits this up in fossil or non-fossil fuels. To estimate an upper bound on savings, we assume that all data centers are powered by fossil fuel generators. However, this does not reflect reality. For example, the Dutch Data Center Association published that 99.9% of the energy used by colocation data centers was green in 2024 [1]. However, the perspective of this research is only the total power and consumption breakdown, not how this is divided over individual regions, companies, or other instances. So if we shift demand (expressed as workload in MW) away, we assume a reduction in total power demand and therefore a reduction in the amount of power we need to generate by fossil fuel generators when non-fossil fuel generators are running short. So we compute the marginal intensity for workload to be shifted away as the intensity of emissions caused by fossil fuel generators.

4.3.2 The intensity of received workload

To determine whether shifting hours from i to j will have a positive effect, we need to know what carbon intensity the power generation for the extra workload has. We make a distinction between two cases: electricity is imported or electricity is exported.

If electricity is imported at hour j, or the net export is 0, there is apparently a shortage in the electricity production. Hence, additional energy needed will have to be generated by fossil fuel generators if it cannot be imported, which we assume, as our current scope is limited to the Netherlands zone. More precisely, we assume that the additional power generation comes from gas generators, as they are scalable in the Netherlands and have a large installed capacity that is often not fully utilized [2, 21]. Therefore, the carbon intensity of gas is used for computing emissions of the additional workload.

The other possibility is that there is a positive net export of energy at hour j, meaning there is an overproduction. So instead of exporting energy, we could use it to power the additional workload using the actual energy mix of that hour, which can have a lower intensity due to the lower carbon intensity of non-fossil fuel sources. So by doing this we steer the model to shift demand to such hours as it results in reductions in carbon equivalent emissions.

4.3.3 Shifting only forward in time

We explicitly make the assumption that we are shifting only forward in time, since data centers have at each hour an initial workload and it may also include tasks that are executed immediately. Therefore, we cannot assume that we can shift workload backward in time. The initial workload has to be seen as arriving tasks at that hour, which need to be scheduled between the arrival time and the deadline, and part of it probably must be executed immediately. For example, servers handling API requests must work in real-time and cannot be scheduled later, as that would result in downtime for the web service. Additionally, these servers may be scalable if the demand is predictable. For example, a server for a large web shop handling requests in a specific zone may receive more requests during daytime in that zone than at night or early morning.

4.4 Validity of the method in relation to the dataset

A number of hours are missing, which are all estimated by interpolation as explained in Section 4.2. This is about 3.4%, and may cause inaccuracies to the results of the model.

The potential saving of emissions could be further explored by taking other zones into account. Shifting workload to other regions could increase the potential because in zones have exploited other low-carbon resources as important power source besides wind and solar energy, which are important low-carbon energy sources in the Netherlands [7]. Data from Electricity Maps shows that in France nuclear energy has a large share in the energy mix, resulting in a low carbon intensity. And in the Scandinavian zones hydro energy forms a large part of the total production [7].

Related with this, is that the time shifting is based on the difference in carbon intensities of two time slots. In countries where the carbon intensity is almost always low or in countries where the carbon intensity does not differ much, the result of shifting demand over time only will hence be bounded by those small differences.

The data used contains fields for import and export, which allow calculation of the net export. When positive, it indicates actual export; when negative, it indicates import of energy during that hour. To better interpret the following part of the results, the data was analyzed to provide insight into energy import and export.

The model also relies on the scalability of gas power generators, which is a characteristic of the Dutch energy market, although the goal is to reduce the usage of gas [22]. The choice to use the gas intensity makes the model implementation suitable for zones where gas is an important fossil fuel energy source. However, it could be expandable by using a different method as long as this fits within the possibilities of linear programming, see Section 5.3.

Finally the model has the main goal to evaluate historical data to provide insight into the degree of possible emission reduction. The goal of the model is not to be a real time task scheduler, as that would require a much more detailed model involving extensive data center specifications. It would also involve predicting carbon intensities of upcoming time slots, but short term predictability of weather is a limitation, since low-carbon energy sources as wind and solar energy can heavily influence the carbon intensity in a short period [2].

4.4.1 Occurrences of import and export

- For 4532 hours in the dataset energy was imported to the Netherlands.
- For 5234 hours in the dataset energy was exported from the Netherlands.
- For 24 hours the net export was 0.

Average net export
The average net export (sum of total export minus total import divided by all hours) is 482 MW.

Highest import and highest export

- The peak occurrence for imported energy was 5539 MW.
- The peak occurrence for exported energy was 8284 MW.

Import and export quantities

- For the hours energy was imported, the average amount of energy imported was 1243 MW.
- For the hours energy was exported, the average amount of energy exported was 1978 MW.
- For 1196 hours, the amount of exported energy was lower than 577 MW. This is relevant, as a capacity of 1000 MW and a initial workload of 423 MW will be used and (1000 - 423 = 577), see Section 6.1.3.

Chapter 5

Model

Based upon the description of modeling data centers in the Preliminaries and the method in Chapter 4, we define a linear programming model that finds what would be the optimal shifting schedule based on the constraints and the given input.

5.1 Mathematical model definition

First, we give a mathematical definition of the model, starting by giving some variables and sets that are used, followed by the model objective, constraints, and some computations that can be used to evaluate and check the model result.

Let T be the set of hours t included in the time set defined as

$$T = \{t \mid t \in \mathbb{N} \text{ and } 0 \leq t \leq 9789\}$$

Let D be a time frame in hours in which a task needs to be completed, where D is the utmost deadline, which is given as input to the model.

Let W be the base workload of a data center in MW, which is given as input to the model and is assumed to be equal for each hour.

Let C be the maximum capacity of data centers in MW, given as input to the model and assumed to be equal at each hour.

Let s be the constant determining the proportion of workload that can be shifted, given as decimal number with $0 \leq s \leq 1$. When 0, no shifting is possible and when 1, the workload can be shifted completely.

Let $P_f(t)$ be the power generated by a fossil fuel power generator f at hour t in MW, which can be expressed in MWh as the power generation is over the period of an hour.

Let I_f be the carbon intensity of fossil fuel source f in g CO_2 / kWh.

Let $E_f(t)$ be the emitted amount of CO_2 by fossil fuel generator f (multiplied by 1000 to convert it to kWh) and $E_{\text{fossil}}(t)$ the sum of all fossil fuel generators at hour t in g CO_2 given as:

$$E_f(t) = P_f(t) \cdot 1000 \cdot I_f$$
$$E_{\text{fossil}}(t) = \sum_f E_f(t)$$

Let $P_{\text{fossil}}(t)$ be the total amount of power generated per hour by fossil fuel generators in MWh, given as

$$P_{\text{fossil}}(t) = \sum_f P_f(t)$$

We assume initially that all energy consumed by data centers comes from fossil fuel generators, since reducing the amount of energy required for data centers can be translated into a reduction in total power demand and an optimal gain if we reduce the fossil fuel generation, as also described in Section 4.3.1. So, when we shift workload away we can reduce the emissions by using the marginal intensity of fossil fuel generators.

Let $M_f(t)$ be the marginal intensity at hour t in g CO_2 / MWh, given as:

$$M_f(t) = \frac{E_{\text{fossil}}(t)}{P_{\text{fossil}}(t)}$$

However, when we shift to hour t we need to use a different way to calculate the intensity of the receiving time slot as also is described in Section 4.3.2, where a distinction between two cases was made:

1. Net, energy is exported at hour t. In this case, we assume that we can use the exported energy to power the data centers. That means we can use the normal total intensity at hour t of all power sources combined. Based on the total power production $P_{\text{total}}(t)$ and its emissions $E_{\text{total}}(t)$ (which are calculated in the same way as P_{fossil} and E_{fossil}, but include all production types at time t (see Table 2 for the intensity factors of non-fossil fuel)) we define the total marginal intensity at hour t $M_{\text{total}}(t)$ as:

$$M_{\text{total}}(t) = \frac{E_{\text{total}}(t)}{P_{\text{total}}(t)}$$

Electricity Maps also provides data on the total carbon intensity of a zone, but that is the intensity of the total consumption in the Netherlands [2]. We require the emission and intensity of the regional produced energy (as the net export is positive) so we cannot use this intensity, but need to compute it with this formula.

2. Net, energy is imported at hour t. In this case, we would need extra energy generation to power the extra work that data centers need to do. Because renewable energy is often limited to external factors such as the intensity of the sun and wind strength, renewable energy sources are hard to scale. However, in the Netherlands gas generators are scalable as was described in Section 4.3.2. Therefore in this case the intensity of gas will be used in g CO_2 / MWh, which we denote by $I_g \cdot 1000$ and is constant as can be found in Table 2.

In short, the marginal intensity for outgoing load $M_I(t)$ can be formulated as:

$$M_I(t) = \begin{cases} M_{\text{total}}(t), & \text{if net export at } t \\ I_g \cdot 1000, & \text{if net import at } t \end{cases}$$

Let the variable $p_{i,j}$ be an amount of workload in MW shifted from hour i to hour j with $i, j \in T$ and $i < j$ and $0 < j - i \leq D$. The result of $p_{i,j} \cdot (M_I(j) - M_f(i))$ is then the saved emission for this shifting slot, if $M_I(j) - M_f(i)$ is negative (the intensity at the receiving hour j is lower than the intensity at the sending hour i). If this value is positive, the value of the shift results in extra emissions.

Model objective

A linear programming model requires an objective function, which needs to be minimized (or maximized). In this case, the amount of CO_2 equivalents saved by shifting workload should be maximal. We express this objective as follows, where we sum all shiftings and minimize it (allowing negative values):

$$\text{minimized} \sum_{i,j} p_{i,j} \cdot (M_I(j) - M_f(i)) \text{ for all } i \text{ and } j$$

In this way, we get the maximum amount of saved emissions, because the higher the difference in intensities, the lower the value of $p_{i,j}$ will be. By expressing the marginal carbon intensity difference as $(M_j - M_i)$ the amount of carbon saved is $-(M_j - M_i)$. So minimizing this objective means that the saving is maximized.

Model constraints

The model has to take into account the following constraints to satisfy the formulated problem.

- Each hour can only shift the maximum amount of shiftable load:

$$\sum_{i<j} p_{i,j} \leq W \cdot s \text{ for each } i$$

- Let $k \in T$, $k > j$ and $0 < k - j \leq D$, and $p_{j,k}$ be the workload shifted from j to k. We define a constraint ensuring that each hour cannot accept more load than its maximum capacity as follows, where the difference between incoming and outgoing workload at hour j may not exceed the difference between C and W:

$$\sum_{i<j} p_{i,j} - \sum_{j<k} p_{j,k} \leq C - W$$

  The goal is that the capacity is never exceeded. Initially the incoming load may not exceed the difference between the capacity and the initial workload. However, workload that is shifted away creates space for additional workload.

Variable bounds

The amount shifted from i to j cannot be negative. If a shifting $p_{i,j}$ has a negative value, it would imply an actual shifting from j to i which is a shifting backward and is not expected behavior as was explained in Section 4.3.3.

$$p_{i,j} \geq 0$$

5.1.1 Model evaluation

Before shifting, the data centers are assumed to have an equal consumption each hour, defined as the initial workload W in MWh. We can compute the total amount of carbon equivalents emitted by fossil fuel generators E_{before} for this consumption as:

$$E_{\text{before}} = \sum_{t} W \cdot M_f(t)$$

After solving the LP problem and finding the maximized saved emission, each variable $p_{i,j}$ stores the amount of workload (in MWh) that was shifted from hour i to j, which enables us to compute the total emission by data centers from fossil fuel generators.

To formalize this, we need to make a distinction first on the net shifting at each hour. If there is more incoming than outgoing demand, meaning the net shifting (Δp_t) at t is positive, then there is extra workload to the initial load and we need to look at the net export with which intensity we need to compute the emissions. In case the incoming workload is less than the outgoing workload, the remaining workload at time t can be computed with the marginal fossil intensity $M_f(t)$.

First, we define Δp_t as the sum of all incoming demand for t minus the sum of all outgoing demand at t:

$$\Delta p_t = \sum_i p_{i,t} - \sum_j p_{t,j} \text{ for all } i \text{ and } j$$

If $\Delta p_t > 0$, we need to compute this extra workload with the intensity based on the net export. This results in the same marginal intensity as we already declared as $M_I(t)$, which value is based on the net export.

For E_{after} the final resulting definition:

$$E_{\text{after}} = \sum_t \begin{cases} (W + \Delta p_t) \cdot M_f(t), & \text{if } \Delta p_t \leq 0 \\ W \cdot M_f(t) + \Delta p_t \cdot M_I(t), & \text{if } \Delta p_t > 0 \end{cases} \quad \text{for all } t \in T$$

The final result, in g CO_2, which is the upper bound on the savings possible by shifting demand in the full dataset is then computed as:

$$\text{Upper bound emissions saving} = E_{\text{before}} - E_{\text{after}}$$

While the linear program's objective function

$$\text{minimized} \sum_{i,j} p_{i,j} \cdot (M_I(j) - M_f(i)) \text{ for all } i \text{ and } j$$

correctly captures the theoretical carbon saving potential for each individual shift (as it tries to shift as much as possible, which is the behavior we are looking for to get an upper bound on savings), it will overestimate the savings if we take into account the assumption that the initial workload is powered by energy from fossil fuel generators. This is due to the assumption that all incoming shifted workload contributes to emission savings, without distinguishing whether that load replaces the initial workload W or adds to it. In contrast, the E_{after} formula evaluates this behavior in line with the assumption: when the total received workload exceeds W ($\Delta p_t > 0$), the first part of the shifted value is used to compensate for the part of W that is shifted away with fossil fuel power consumption, and the remainder, Δp_t, is treated as additional load and computed using $M_I(t)$, which is either the total intensity or gas production intensity depending on the net export value. Therefore, the linear programming objective value should be interpreted as an optimistic upper bound. The actual upper bound savings are better captured by computing $E_{\text{before}} - E_{\text{after}}$, which accounts for capacity limits and realistic emission intensities for additional load and is in line with the goals and assumptions.

5.2 Model implementation and execution

The model above can be implemented in any programming language to generate a file that formulates the model objective, constraints and bounds for the input parameters and which be interpreted by an LP solver. In this case, the model was implemented in the Go programming language [23]. The way of implementing can be of choice, but the objective, constraints, bounds and eventually the evaluation methods must exactly and correctly implement the mathematical definitions as given in Section 5.1. The LP solver reads this file and solves it. In this case glpsol from the GNU Linear Programming Kit (GLPK) is used [24, 25, 26]. The solver produces a solution file, in which the variable shiftings $p_{i,j}$ are given as well as the optimal solution to the objective in g CO_2, which we do not use as our upper bound comes from the list of shiftings only, as was discussed in Section 5.1.1.

The used command of executing glpsol (embedded in the model command-line tool), where the `[input]` and `[output]` are just filenames that may be chosen to preference is:

```
glpsol --lp --interior [input].lp -o [output].txt
```

The `--lp` flag is used to solve the problem with linear programming and using the `--interior` flag configures the solver to use the interior-point method instead of the default simplex method [25, 26].

Our model implementation allows allows specification of the input as command line parameters. Consider the following input parameters:

$$\begin{aligned} C &= 530 \\ W &= 424 \\ D &= 24 \\ s &= 0.15 \end{aligned}$$

To run the model with this input, the following command needs to be executed:

```
./[analyzer] -maxDelay=24 -shiftableProportion=0.15 -maxLoad=530
 -initLoad=424
```

The name `[analyzer]` is here the name of the application and can vary, but in this case is built with name `analyzer`.

The data from electricity maps must be loaded by the program implementation and is not specified in the input.

The program outputs three files and a command line output after successful execution:

1. A file containing the LP problem formulation (the model with complete worked out terms) with extension `.lp`
2. A file containing the LP problem solution (with all shiftings) with extension `.txt`
3. An output file formatted as CSV which contains per hour the initial and new workload, initial and new emissions, marginal fossil intensity, marginal total intensity (the total production intensity), the initial total intensity (total consumption intensity) and the used intensity for that hour.
4. The following command line output (as well as logs of the execution process, which are here omitted):

   ```
   Total emissions of data center(s) before shifting:  2382194354336g CO₂
   Total emissions of data center(s) after shifting:  2286461329155 g CO₂
   Saved:  95733025181 g CO₂
   ```

5.3 Validity

The model is defined in a linear way, which makes it solvable by linear programming. Linear programming is working well for optimizing problems, however this puts restrictions on the possibilities of the model. An example is the use case referred to in 6.3, where at a certain time slot a higher gain would be possible if it could be decided whether shifting is beneficial from hours in which energy is exported. Some of such problems can possibly be addressed by mixed integer linear programming (MILP) as that introduces working with variables on which decisions can be made, but this makes the problem computationally harder (NP-hard) [27]. However, it would refine the upper bound and has features like including decisional options, which may be usable for example when dealing with import and export.

Chapter 6

Case study

With the model definition from Chapter 5, we are able to obtain an optimized scheduling based on the variable inputs to find upper bounds to emission reductions.

6.1 Input parameters

Our model has four types of input parameters: the capacity of the data center(s), a proportion of allowed shifting, a deadline to provide a time window and an initial workload. In this section, we describe which input values are used to obtain different scenarios.

6.1.1 Data center workloads and capacity

Our goal is to explore the potential of emission reductions on a regional level, using the zone Netherlands as scope. In section 2.2 about modeling data centers it was shown that data centers consumed 3.29% of the electricity in 2021, according to the CBS [14]. Although we are using a dataset from Electricity Maps of the years 2024-2025, we will use this percentage as it fits with the purpose of finding an upper bound to the potential, and not an exact solution.

From the data of our dataset [7], we can compute the total consumption of all hours. If we take 3.29% of this we get a total consumption of 4138.7 GWh. We divide this by the total amount of hours 9790, we get an average hourly consumption for data centers of $\frac{4138.7}{9790} \cdot 1000 = 422.7$ MW. We will use a fixed workload of 423 MW as initial workload W in our model evaluations.

As was stated in section 2.2.1, RaboResearch mentions an installed capacity of 1000 MW in a publication in May 2025 [13]. For our model evaluations we will therefore use a capacity of 1000 MW.

6.1.2 Shiftable proportion and time window

In Section 2.2.1 was discussed that different proportions for delay-tolerant tasks exist in literature [16, 10]. We will therefore use various values to create different scenarios for which we explore the effectiveness of demand shifting based on this proportion.

Also, for the time window defined by the deadline different values will be used in combination with the shiftable proportion to create different scenarios for demand shifting.

As inputs for the delay tolerant proportion of the total workload we will use the values $s \in \{0.1, 0.25, 0.5, 0.75, 1\}$. This includes both small proportions and a scenario in which the entire workload is shiftable.

As inputs for the deadline we use $D \in \{1, 8, 16, 24\}$. This covers delays from a short time window of 1 hour to a longer delay up to a full day.

6.1.3 Model input values and net export

As stated in Section 4.4 about net export data, there are occurrences where less than 577 MW is exported, which is the difference between the maximal capacity of 1000 MW and an initial workload of 423 MW. It can be the case that the model uses an hour with a low net export, and thus exceeds the net export value by shifting a load larger than the net export. This is also one of the reasons the result of the model has to be considered as an upper bound, and not an actual optimization result.

6.2 Model evaluation results

A model evaluation gives E_{before} (equal for all evaluations) and E_{after}. It also gives the saved emissions which are the result from $E_{\text{before}} - E_{\text{after}}$. This allows us to calculate the savings in percentages. Table 4 shows these percentage as results of evaluations with the input parameters $C = 1000$, $W = 423$, $s \in \{0.1, 0.25, 0.5, 0.75, 1\}$ and $D \in \{1, 8, 16, 24\}$, where the shiftable proportion is set compared to the maximum shifting delay.

	0.1	**0.25**	**0.5**	**0.75**	**1**
1	0.07	0.2	0.4	0.6	0.7
8	2.8	6.8	12.5	17.3	21.2
16	4.5	10.7	18.9	24.4	27.7
24	5.7	12.8	21.3	26.2	29.2

Table 4: The reduction in emissions of data centers given as percentage based on the shiftable proportion (columns) and time window (rows)

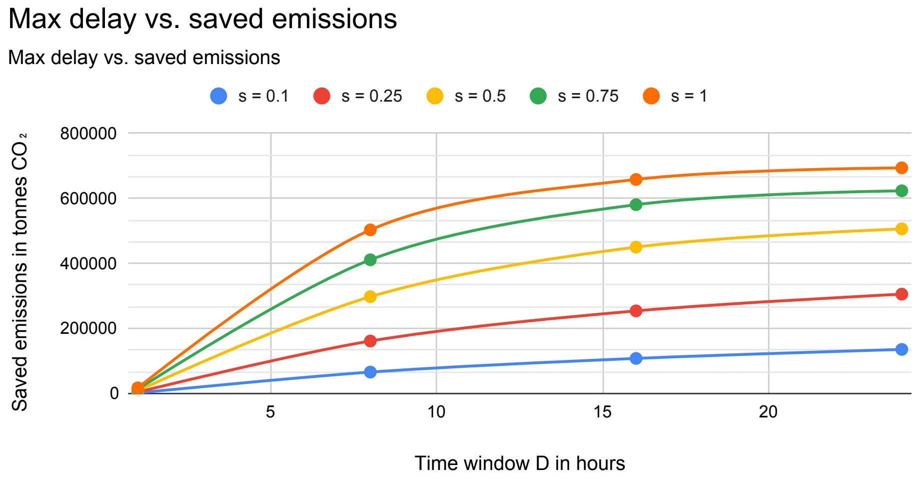

Figure 6.1: Total emission reductions in tonnes CO_2 per shiftable proportion set out against the maximum delay.

The relation between the maximum delay D and the saved emissions is shown in Figure 6.1, grouped per shifting proportion. It can be seen that the growth in effectiveness decreases when the time window becomes larger. The difference in saving between $D = 16$ and $D = 24$ is less significant than the difference between $D = 1$ and $D = 8$. In Figure 6.2 this is also clearly visible in the gaps between the plotted lines. These lines are also increasing and have also a flattening effect.

It is also interesting to see the effect of varying the capacity constraint. We used a fixed capacity of 1000 MW so far. If we compute the server utilization for this capacity, we get $\frac{423}{1000} \times 100\% = 42\%$. This percentage complies with the earlier discussed findings in section 2.2.1, although the range of utilization rates given there was wide. One might argue that bringing down the capacity may also increase the utilization rate. As we analyze the data on a regional level, it could be the case that these utilization rates differ for the data centers in this zone and that load shifting in a highly utilized data center is less effective than load shifting in a lower utilized data center. In table 5 below we provide an overview of some varying inputs showing the percentage of CO_2 eq emission reduction if the capacity was 530 MW, which is given the initial workload of 423 MW a utilization of 81%.

When comparing table 4 to table 5, it can be seen that the lower capacity has an effect on the effectivity of demand shifting. Where a small time window and shifting proportion have no visible effect, the values for higher time windows and shiftable proportions are significantly lower with a limited capacity. This is expected, since lower capacity restricts load shifting

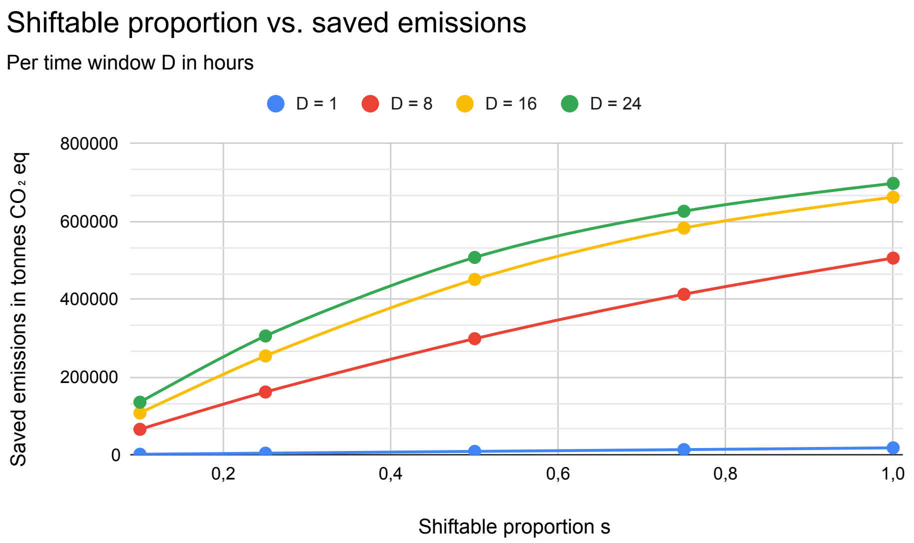

Figure 6.2: Total emission reductions in tonnes CO_2 per time window set out against the shiftable proportions.

$D = 1, s = 0.1$	$D = 1, s = 1$	$D = 8, s = 0.25$	$D = 8, s = 0.75$	$D = 16, s = 0.5$	$D = 16, s = 0.75$	$D = 24, s = 0.25$	$D = 24, s = 1$
0.07	0.2	4.5	6.0	6.0	6.2	5.6	6.3

Table 5: The reduction in emissions of data centers given as percentage for several time windows and shiftable proportions with a capacity C of 523 MW and initial workload W of 423 MW.

to optimal time slots. The capacity is therefore an important factor that bounds the maximum possible emission reduction of load shifting.

Overall, the results as shown in the figures and Table 4 indicate that there can be a potential (as upper bound), depending on the flexibility of the data centers. The more flexible and delay-tolerant the workload is and the more flexible the time window constraints are, the more emission savings are possible.

6.3 Behavior of the model

To show how the model behaves by shifting workloads, the first 24 hours of our dataset are displayed in Figure 6.3. The behavior of the model is illustrated in this figure by giving it extreme input values. The input parameters used are: $W = 423$, $s = 1$, $D = 24$ and $C = 1,000,000$. With this setting the model is able to shift all its load, without violating the capacity constraint. The figure shows the net load shift as bars. Time slots that have no net change therefore have no visible bar. This does not mean however that no shifting took place, in fact, load is shifted at every hour because the gas intensity for the target hour is always lower than for the sending hour in this time range. This is compensated in the post-processing of the model where it was defined that up to the initial workload W, the initial marginal fossil intensity $M_f(t)$ should be used. In this way, the result of the model is interpreted as if no shifting has taken place when the net shifting is 0. This has as side effect, which was mentioned in the validity section, that at some places a small setback in the result can occur. In Figure 6.3, the model shifts load from hour 16 to 17 (as hour 16 may not shift load to itself and 17 is also an hour with a net export of electricity). But from hour 17 load is shifted to hour 19, resulting in a net shift of 0 at hour 17. This implies it may be more efficient to either keep load at hour 16 or 17 in place, or shift both directly to hour 19, as then that amount of load is processed with a lower carbon intensity. However, this is a possibility our model does not account for.

The green line in Figure 6.3 shows the intensity that is used to compute the reduction (for negative net shift) or increase (for positive net shifting) in emissions. So for the hours where the net shifting is negative, the marginal fossil intensity $M_f(t)$ is used. The positive net shiftings only occur at export time slots, as they have an attractive low carbon intensity. At hour 5, the carbon intensity is lower (71938 g CO_2 eq / MWh) than the hours 16 (84694 g CO_2 eq / MWh) and 19 (90996 g CO_2 eq / MWh). It can be seen that the model favors the lowest carbon intensity to shift to, which aligns with the intended model behavior. The savings in carbon equivalent emission can be deducted from Figure 6.3 as follows:

1. The net emission change for hour t (with $t \in [0, 23]$) given as Δ_t^e can be derived from the net load shift S_t and intensity I_t: $\Delta_t^e = S_t \cdot I_t$.
2. The total gain Δ_E after applying this demand schedule is then the sum of those emission differences:

$$\Delta_E = \sum_t \Delta_t^e \text{ for all } t$$

3. The initial emissions cannot be directly derived from the figure as the

initial carbon intensity ($M_f(t)$) is not shown in the figure, but they are computed as:

$$E_{\text{initial}} = \sum_t W \cdot M_f(t) \text{ for all } t$$

4. The total new emissions E_{new} can be computed as:

$$E_{\text{new}} = E_{\text{initial}} - \Delta_E$$

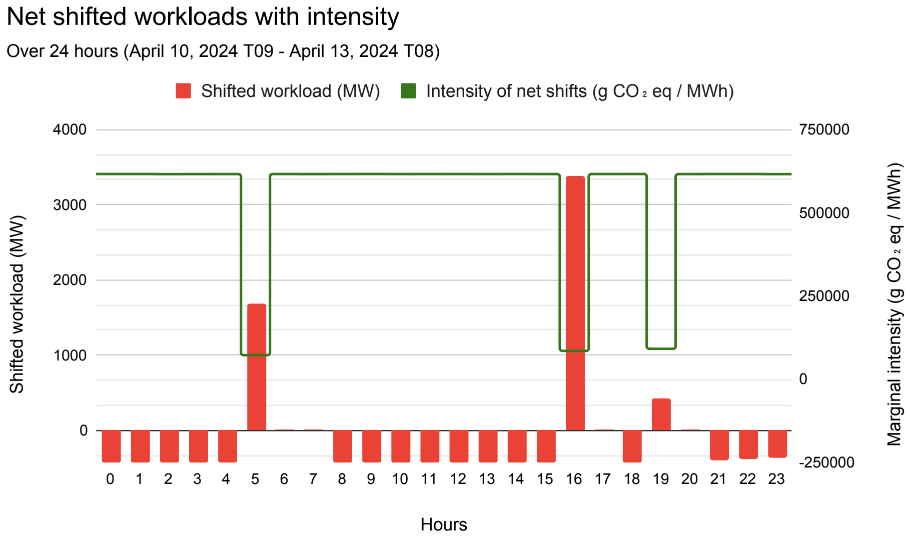

Figure 6.3: Net load shifts and the intensities of that shifts. The figure shows the first 24 hours of the used dataset (April 10, 2024 T09 - April 13, 2024 T08). The model execution has taken place on the full dataset, so the load shifted from the last 3 hours has a target time slot out of the scope of this figure.

6.4 Validity

Some of the choices and assumptions may influence the soundness or validity of the results, which is also a reason why the results are exploring upper bounds to the potentials instead of exact results.

First, the consumption rate used is from the year 2021 from the CBS [14]. The market of data centers in the Netherlands was still growing in 2024 compared to 2021 [1, 28], so the consumption rate has likely grown in these years. But since the value of 2021 is already significant (3.29% of the total consumption in the Netherlands) [14] and as it is uncertain how much the consumption would have increased, the decision was made to use the 2021 consumption rate. The capacity is also an estimation, based on the Dutch Data Center Association and RaboBank research [1, 13].

Furthermore, we have the uncertainty of time window sizes and the amount of delay-tolerant workload. Because of these assumptions, the model is not usable for finding realistic values in emission reductions, especially not for individual data centers. On the other hand, using this model design allows to easily vary with workloads and delays in a broader scope. The possibility to vary with these numbers on a broad scale is for finding and exploring the potential of demand shifting and giving upper bounds. We also use fixed values each hour for these variables, which also is the case for the initial base-line workload.

Another remark is that the carbon intensity of time slots is computed by analyzing the net energy export. An important assumptions is that in time slots with a net export of energy to other regions, the current energy mix (including both low-carbon and fossil fuel sources) can be used to compensate for the extra power demand, meaning that this model encourages using regional energy and improve the sustainability of available power sources. An overview of some relevant statistics on this net power export is given in the validity of Chapter 4 in Section 4.4.

Chapter 7

Related Work

Demand shifting is a topic that has already been researched in several studies and for different purposes. This underscores the relevance of this topic. The research about demand shifting can roughly be divided between economical or sustainable motivation. Economically driven research focuses on using the energy market to save costs on electricity. Fridgen et al. [29] researched the economical feasibility of spatial load shifting, considering the effect of power balancing, and found that this is indeed economically feasible.

A study by Wang. et al. (2023) [11] investigates the effects of demand shifting in data centers where an integrated energy system is used. Here, some specific factors are relevant, such as the cooling specifications and other variables on the internal systems of the power generator. The study aims to improve both economical performance and strives for a better sustainability. It shows that optimizing the performance of internal energy systems in data centers with demand shifting has benefits in energy usage, economic and environmental fields and shows that reductions in carbon dioxide are possible.

Another study by Tripathi et al. [9] is evaluating improvements in carbon intensities by rescheduling jobs of data centers where demand shifting is allowed. Different countries are compared by their carbon intensities based on a full year and a simulation model is presented with the aim of improving the carbon intensities for those countries. The model also takes carbon intensities into account and allows for demand shifting. The method used for their simulation is different from the model we presented in our research. They have a different way of making computations based on carbon intensities only, whereas in our model the actual reduction in carbon emissions is computed, on an hourly basis. The study of Tripathi et al. [9] makes use of forecasting intensities, SLA constraints and a scheduling algorithm in their simulation. They found a better carbon-aware schedule for the countries they investigated, which were France, Germany, Italy and the United Kingdom. The study of Tripathi et al. [9] differs from our research goal to find an upper bound on the saving potential, whereas we do not consider specific SLA constraints besides the time window. This research also focuses on the Netherlands as subject for the model and covers the usage of different power generation types. Although the background is similar, another method is presented in this research with another research scope, but the study of Tripathi et al. supports the concept of using demand shifting based on carbon awareness [9].

There are more studies about demand shifting, however many do use a different approach or model. The used methods differ often in the level of detail for data centers, tasks or the power grid, whereas our model is looking at data centers as one consuming body in the zone of the Netherlands, and has an explicit preference for time slots in which energy is exported in this region. In a study by Lin et al. [30], a virtual queue algorithm is proposed for carbon-aware load balancing control. They designed a detailed simulation with incorporating uncertainties for electricity price, fuel mix and renewable generation. Data from Australian states was used to evaluate their algorithm, showing that their model is economically and environmentally attractive. A study by Nkwawir et al. [31] used MILP to investigate carbon-aware load management on a small scale for a hypothetical Turkish data center, incorporating more technical specifications. Another study by Wang et al. (2022) [32] uses ILP for modeling spatial and temporal load shifting, finding both economic advantages and carbon reduction.

A study by Wiesner et al. simulated shiftable workloads using simulation software and two scenarios [33]. This study took into account more job specifications, such as execution time and interruptibility. They did not incorporate resource constraints on e.g. data center capacity. Another study by Piontek et al. [34] proposed a carbon aware scheduling algorithm for Kubernetes deployments. They make use of a greedy approach for making CO_2 decisions. When further investigating the implementation of a carbon aware scheduler for data centers, this research can be interesting as similar concepts are used here. Aksanli et al. [35] did a study where a short term prediction algorithm is proposed and evaluated to predict solar and wind energy production. The purpose is a better utilization of green energy, which is relevant in the context of demand shifting based on carbon intensities.

This thesis contributes to the existing literature by analyzing the emission reduction potential via demand shifting for the Netherlands. We do not take into account internal specifications of data centers such as cooling systems or hardware scaling and develop a model that gives an upper bound on the potential to reduce emissions caused by data centers using demand shifting as a method.

Chapter 8

Conclusions

This thesis designs and evaluates a model to assess the potential for reducing emissions through demand shifting in data centers. We validated this model using a case study on carbon emissions and data centers in the Netherlands.

First, a contextual framework is set up based on existing literature in Chapter 2. This background combines literature research, the Electricity Maps model, data centers, computational tasks and demand shifting, focusing on the Dutch electricity market and the role of data centers in the Netherlands. Statistical data on power consumption in the Netherlands is used to estimate their total power demand and capacity. This fulfills contribution 1.

From this theoretical framework, two exploratory studies are conducted in Chapter 3 to examine the relationship between electricity consumption, energy mix, and emissions. These studies demonstrate that temporal variations in carbon intensity can result in emission reductions, which is an important assumption in the proposed model. Furthermore, a simplified scheduling approach is applied to a short time interval, showing that emissions depend on both demand and carbon intensity. This, combined with the contextual background from the first contribution, is used to find properties of the data set, demand shifting and methodology for the model in Chapter 4, as contribution 2.

The model, which forms contribution 3, is introduced in Chapter 5, which evaluates carbon emission reductions over a longer time horizon. Linear programming is employed to efficiently solve the minimization problem in polynomial time, although this approach imposes limitations on the complexity of the model, which is explained in the validity sections of Chapters 4 - 6 and here below.

The model is evaluated under different input settings in a case study on Dutch data center and emission data in Chapter 6 as a result of contribution

4. Different scenarios are evaluated by varying the proportion of shiftable workload and the time window allowed. With a baseline server utilization of 42%, the model shows a small emission reduction potential (0.07%) under strict constraints (10% shifting with a time window of 1 hour). This potential increases rapidly when either constraint is relaxed. The most flexible setting tested (100% of demand shiftable in a time window of 24 hours) achieves up to 29% reduction. Both the shiftable proportion and time window significantly affect the potential of emission reductions. Other configurations yield results between these two extremes. It is also illustrated in Section 6.3 that the model shows the intended behavior by consistently shifting load to hours with lower carbon intensity. It further shows that lowering capacity or utilization limits the emission reduction potential.

The model is designed to be used on a regional scale, but the input settings can also be used by data center administrators or engineers at the level of individual data center(s) to analyze what emission reduction potential their subject has, provided that technical specifications are not required.

In general, we conclude after investigating the emission reduction possibilities, that significant reductions in carbon equivalent emissions are possible by shifting demand to time slots with lower carbon intensity, while we particularly focused on the Netherlands. These findings confirm that carbon-aware scheduling is a viable approach to reducing carbon emissions. We recommend further research to enhance the flexibility in data centers and scheduling techniques, to support the implementation of such schedulers and maximize the reduction in emissions.

Validity

A key assumption of the model is that it shifts demand only during hours when the Dutch energy market is exporting electricity (assumed to rely primarily on low-carbon energy sources rather than fossil fuels). This assumption simulates a scenario where reductions in workload lower fossil fuel usage first. These choices affect how emission reductions are interpreted and set an upper bound on what could theoretically be achieved under ideal shifting conditions. We also assume that gas will be the fossil fuel generator used when adding workload when low carbon energy is not available and we use historical data for our evaluations. These assumptions are explained in Section 4.4.

A limitation of the model is using linear programming for solving the minimization problem. Although it is a valid method, the scope depends on the complexity of the linear objective, constraints and bounds, for which the possibilities are limited when requiring linearity, as explained in Section 5.3.

Furthermore, historical data is used for data on electricity, emissions and data centers. Also, estimations of time windows and demand flexibility are made. We use variations of these variables to create multiple scenarios for our model evaluations, as has been worked out in Section 6.4.

Future work

To investigate demand shifting further and more technically, future work could explore the use of more sophisticated optimization algorithms such as MILP or a custom search algorithm which can be applied with specific constraints on data centers. Furthermore, the impact of scheduling algorithms should be included and evaluated in the model, to test their effectiveness in a flexible task environment. AI can contribute by the use of predictive models for forecasting advantageous time slots. Also, research on execution time windows, deadlines and priorities of data center tasks could explore the possibilities of making demand shifting more feasible. An experiment should be conducted in a real-world data center to test how a carbon-aware scheduler behaves and performs under realistic circumstances, as the energy mix can never be predicted exactly. Based on this experiment more research topics related to load shifting may be distinguished for future improvements.

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Appendix A

List of missing datetimes

The following hours in the data set from Electricity Maps are missing and are estimated by interpolation by averaging the data of the nearest earlier and next available hour.

1. 2024-04-12 hour 7
2. 2024-04-16 hour 17
3. 2024-04-18 hour 15
4. 2024-04-18 hour 16
5. 2024-04-18 hour 17
6. 2024-04-19 hour 13
7. 2024-04-19 hour 14
8. 2024-04-19 hour 15
9. 2024-04-19 hour 18
10. 2024-04-19 hour 19
11. 2024-04-19 hour 20
12. 2024-04-19 hour 21
13. 2024-04-19 hour 22
14. 2024-04-19 hour 23
15. 2024-04-20 hour 0
16. 2024-04-20 hour 1
17. 2024-04-20 hour 2
18. 2024-04-20 hour 3
19. 2024-04-20 hour 4
20. 2024-04-20 hour 5
21. 2024-04-20 hour 6
22. 2024-04-20 hour 7
23. 2024-04-20 hour 8
24. 2024-04-20 hour 9
25. 2024-04-20 hour 10
26. 2024-04-20 hour 11
27. 2024-04-20 hour 12
28. 2024-04-24 hour 3
29. 2024-04-24 hour 4
30. 2024-04-24 hour 5
31. 2024-04-24 hour 12
32. 2024-05-01 hour 23
33. 2024-05-02 hour 0
34. 2024-05-07 hour 16
35. 2024-05-19 hour 12
36. 2024-05-19 hour 13
37. 2024-05-19 hour 14
38. 2024-05-19 hour 15
39. 2024-05-19 hour 16
40. 2024-05-19 hour 17
41. 2024-05-19 hour 18
42. 2024-05-19 hour 19
43. 2024-05-20 hour 17
44. 2024-05-21 hour 2
45. 2024-05-21 hour 3
46. 2024-05-21 hour 4
47. 2024-05-21 hour 5
48. 2024-05-21 hour 6
49. 2024-05-22 hour 0
50. 2024-05-22 hour 1
51. 2024-05-22 hour 2
52. 2024-05-22 hour 3
53. 2024-05-22 hour 4
54. 2024-05-22 hour 5
55. 2024-05-24 hour 2
56. 2024-05-24 hour 3
57. 2024-05-24 hour 4

58. 2024-05-24 hour 5
59. 2024-05-24 hour 6
60. 2024-05-24 hour 7
61. 2024-05-26 hour 0
62. 2024-05-26 hour 1
63. 2024-05-26 hour 2
64. 2024-05-26 hour 3
65. 2024-05-26 hour 4
66. 2024-05-26 hour 5
67. 2024-05-26 hour 6
68. 2024-05-26 hour 7
69. 2024-05-26 hour 8
70. 2024-05-26 hour 9
71. 2024-05-26 hour 10
72. 2024-05-26 hour 11
73. 2024-05-26 hour 12
74. 2024-05-28 hour 2
75. 2024-05-28 hour 3
76. 2024-05-28 hour 4
77. 2024-06-03 hour 19
78. 2024-06-03 hour 20
79. 2024-08-28 hour 11
80. 2024-09-20 hour 15
81. 2024-09-20 hour 16
82. 2024-09-20 hour 17
83. 2024-09-20 hour 18
84. 2024-09-20 hour 19
85. 2024-09-20 hour 22
86. 2024-09-20 hour 23
87. 2024-09-21 hour 0
88. 2024-09-21 hour 1
89. 2024-09-21 hour 2
90. 2024-09-21 hour 3
91. 2024-09-21 hour 4
92. 2024-09-21 hour 5
93. 2024-09-21 hour 6
94. 2024-09-23 hour 3
95. 2024-09-23 hour 4
96. 2024-09-23 hour 5
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102. 2024-10-22 hour 23
103. 2024-11-01 hour 14
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111. 2024-11-01 hour 22
112. 2024-11-01 hour 23
113. 2024-11-02 hour 0
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125. 2024-11-02 hour 12
126. 2024-11-07 hour 20
127. 2024-11-07 hour 21
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129. 2024-11-07 hour 23
130. 2024-11-08 hour 0
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278. 2024-11-29 hour 17
279. 2024-11-29 hour 18
280. 2024-11-29 hour 19
281. 2024-11-29 hour 20
282. 2024-11-29 hour 21
283. 2024-11-29 hour 22
284. 2024-11-29 hour 23
285. 2024-11-30 hour 0
286. 2024-11-30 hour 1
287. 2024-11-30 hour 2
288. 2024-11-30 hour 3
289. 2024-11-30 hour 4
290. 2024-11-30 hour 5
291. 2024-11-30 hour 6
292. 2024-11-30 hour 7
293. 2024-11-30 hour 8
294. 2024-11-30 hour 9
295. 2024-11-30 hour 10
296. 2024-11-30 hour 11
297. 2024-11-30 hour 12
298. 2024-11-30 hour 13
299. 2024-11-30 hour 14
300. 2024-11-30 hour 15
301. 2024-11-30 hour 16
302. 2024-11-30 hour 17
303. 2024-11-30 hour 18
304. 2024-11-30 hour 19
305. 2024-11-30 hour 20
306. 2024-11-30 hour 21
307. 2024-11-30 hour 22
308. 2024-11-30 hour 23
309. 2024-12-01 hour 0
310. 2024-12-01 hour 1
311. 2024-12-01 hour 2
312. 2024-12-01 hour 3
313. 2024-12-01 hour 4
314. 2024-12-02 hour 4
315. 2024-12-02 hour 5
316. 2024-12-02 hour 6
317. 2024-12-22 hour 0
318. 2024-12-22 hour 1
319. 2024-12-22 hour 2
320. 2024-12-22 hour 3
321. 2024-12-22 hour 4
322. 2024-12-22 hour 5
323. 2024-12-22 hour 6
324. 2024-12-22 hour 7
325. 2025-05-23 hour 2
326. 2025-05-23 hour 3
327. 2025-05-23 hour 4
328. 2025-05-23 hour 5