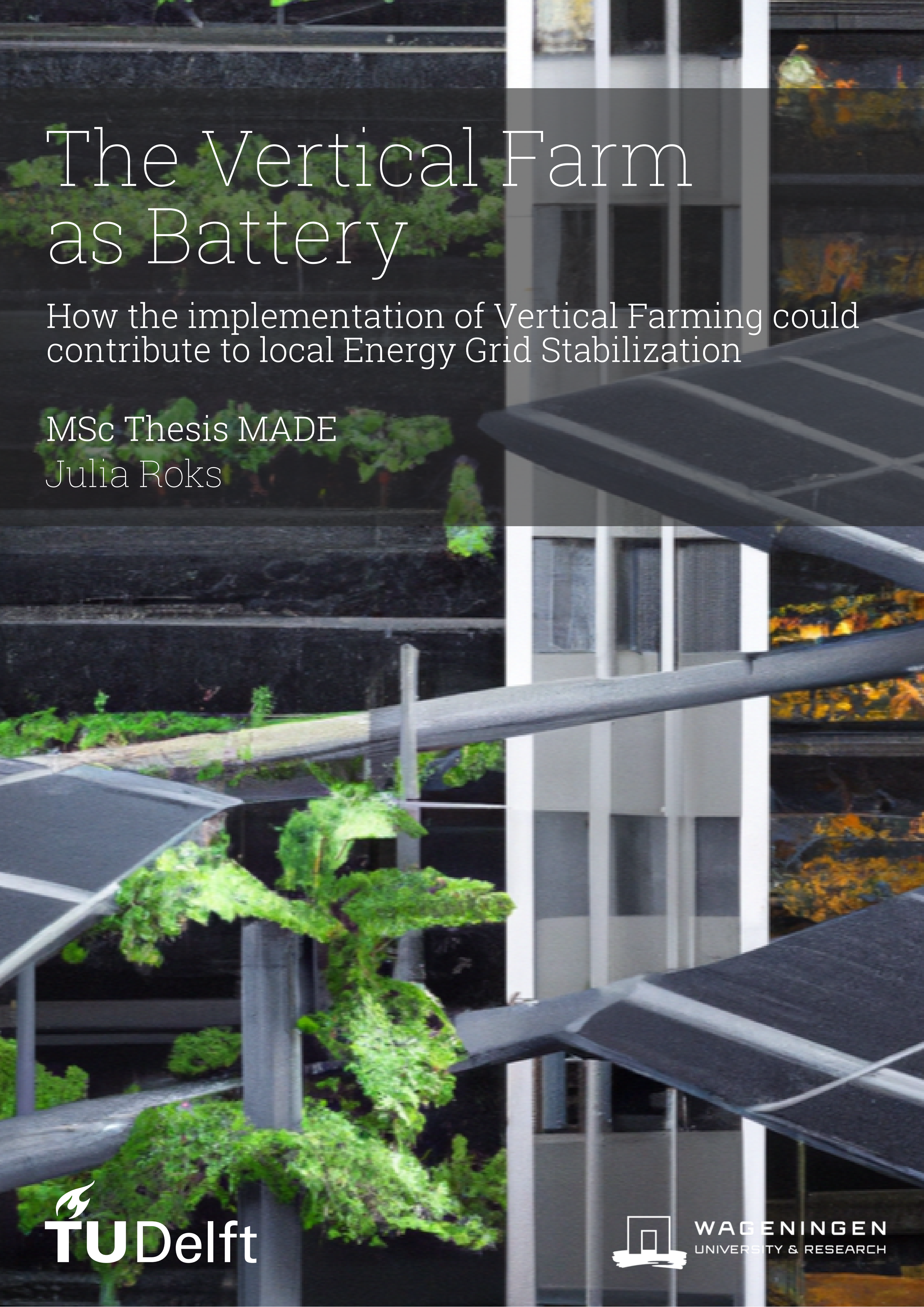
The Vertical Farm as Battery

How the implementation of Vertical Farming could contribute to local Energy Grid Stabilization

MSc Thesis MADE

Julia Roks



TU Delft

WAGENINGEN UNIVERSITY & RESEARCH

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How the implementation of Vertical Farming could contribute to local Energy Grid Stabilization

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Abstract

The global challenge of food shortage, exacerbated by population growth, climate change, and economic disparities, demands innovative agricultural solutions. Vertical farming (VF) emerges as a promising alternative, offering higher yields, efficient land use, minimal water and nutrient usage, and the potential for urban integration. However, VFs face significant barriers, primarily due to their high energy demands for artificial lighting and climate control. This study investigates how vertical farming can contribute to local energy grid stabilization through optimized energy management strategies. Focusing on a case study in Zeeland, Netherlands, an area with significant grid congestion, this research develops a Mixed-Integer Linear Programming (MILP) model to dynamically adjust energy consumption based on real-time data from photovoltaic (PV) panels, battery storage, and grid prices. The primary objective is to minimize energy fed back to the grid, while a secondary objective is to reduce operational costs. Results indicate that optimized energy management can significantly reduce costs and impact on the grid. Flexible light schedules, aligned with periods of low energy costs and high solar PV generation, enhance grid stability and economic viability. This study highlights the potential of vertical farms to support the energy grid, contributing to the broader goal of a sustainable and resilient food system.

Keywords: Vertical Farming, Energy Management, Grid Stability, Optimization, Mixed-Integer Linear Programming

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Acronyms

VF	Vertical Farming
DSM	Demand-side Management
DSR	Demand-side Response
DSO	Distribution System Operator
LP	Linear Programming
MILP	Mixed-Integer Linear Programming
PV	Photovoltaic
RES	Renewable Energy Sources
TSO	Transmission System Operator
VF	Vertical Farm

1 Introduction

1.1. Background

Food shortage remains a global challenge [1] intensified by factors such as population growth [2], changing dietary patterns and economic disparities [3]. Climate change further intensifies this issue by altering weather patterns, degrading soil quality, and increasing the frequency of extreme weather events, all of which affect agricultural productivity [4]. Traditional farming practices struggle to adapt to these changes, leading to concerns about long-term food security [3].

In response to these challenges, vertical farming provides an alternative to conventional agriculture around the world [1, 4]. Vertical farms (VFs) involve growing crops in vertically stacked layers in controlled indoor environments with artificial light [5]. Researchers highlight several advantages, including efficient land use [6], higher yields [7], minimal water and nutrient usage, reduced dependency on pesticides and herbicides [8], and the ability to locate farms within or near urban areas to meet local food demand [4].

Vertical farming presents an interesting opportunity for Europe, which aims to be a climate-neutral continent by 2050 [9]. One of the EU's key goals is reducing the environmental and climate footprint of the EU food system and strengthening its resilience, ensuring food security in the face of climate change and biodiversity loss[10]. Key action points include reducing the use of and dependency on pesticides, minimizing excess nitrogen, and protecting land, soil, and water. Additionally, the transition to sustainable food systems is seen as a significant economic opportunity [10]. Zooming in from the EU level to the national context, the Netherlands presents a unique case study for vertical farming with its high urban density [11] and, most importantly, the Dutch agriculture sector facing a significant challenge: the local nitrogen crisis [12]. This environmental issue, caused by high manure and fertilizer outputs from traditional farming, leads to pollution in soil and water and affects biodiversity. The situation has led to strict regulations and a reassessment of farming practices within the region [13].

Vertical farming presents itself as a solution with the potential to mitigate some aspects of the nitrogen crisis. By transitioning to controlled, soilless growing environments, vertical farms (VFs) can significantly reduce the runoff of nitrogen fertilizers, thus mitigating one of the primary sources of excess nitrogen [14, 13]. In this way, vertical farming not only contributes to the EU goal of being the first climate-neutral continent by 2050 [8, 1, 4, 10], but also offers a response to a local crisis faced by the Netherlands.

Nevertheless, the economic feasibility of a VF remains uncertain [15] and vertical farming faces several barriers to widespread adoption [7]. One of the most significant ones is the high energy demand associated with artificial lighting and climate control systems, which are required for optimal growing conditions [7]. This energy-intensive nature affects the sustainability and economic viability of VF operations, particularly in regions where electricity costs are high. To mitigate electricity costs, strategies such as employing energy-efficient LED lighting and using renewable energy sources have been suggested, which would decrease energy expenses and enhance efficiency [8, 5]. Additionally, it has been proposed to incorporate VF systems within urban settings, including industrial sites and renewable energy production facilities, to develop closed-loop systems that can reduce shared expenses [16, 17].

In the EU, integrating vertical farming in urban settings and implementing renewable energy to mitigate the costs [5] presents significant challenges. With ambitious EU climate targets for 2050, one of them is reducing greenhouse gas emissions by 55% by the year 2030 through enhanced energy efficiency and the integration of new renewable sources [18]. The shift towards renewable energy sources is expected to substantially increase from 2020 to 2050, with the share of electricity from wind generation increasing from 15% to 57% and from solar generation from 5% to 19% of total gross electricity production [19]. As these energy sources also introduce production profiles which are variable by nature, the intermittency of such energy resources implies significant systemic requirements for flexible solutions. The intermittent nature of VRE (variable renewable energy) sources and the resulting dynamics of the residual load create a need for flexibility ranging from short-term to seasonal time scales [20, 19].

In particular, Koolen et al. [19], assessed flexibility requirements across three timescales (daily, weekly, and monthly) for EU countries. One of the member states that stood out was the Netherlands. Because of the largest market share of solar and wind energy relative to total demand, the country will face the most substantial flexibility requirements (compared to other European countries) across all three timescales. The variability and uncertainty of power generation through VRE sources and the consumers' increasingly proactive role in the power system operation, complemented by their expanding technology options (e.g., solar PV, plug-in electric vehicles, etc.), drive the need for system flexibility [20]. The limited capacity of the Dutch grid infrastructure, coupled with the inherent variability of renewable energy sources, often results in grid congestion [21]. The situation arises when the electricity supply and demand, particularly during peak periods, surpass the grid's capacity, resulting in congestion [18]. Grid congestion remains a significant barrier that impedes the shift from traditional energy sources to renewable alternatives. As a result, it slows down the overall energy transition [22], making it more difficult to achieve the EU climate target.

As a potential solution to the energy and environmental challenges, the Netherlands is looking towards innovative, flexible, and interconnected energy systems. These systems are important for a cost-effective transition to a low-carbon economy [23]. Additionally, non-firm ATO contracts are implemented which allow temporary disconnections during peak loads, these contracts help to prevent grid congestion and enhance grid stability [24]. Blom et al. [17] explore the concept of energy flexibility in the vertical farming sector, theorizing that flexible energy usage, especially through renewable energy sources, could significantly reduce operational costs and lessen the pressure on local electricity grid infrastructures[22]. By adjusting energy consumption in response to the electricity price, VFs could play an important role in enhancing grid stability and facilitating a more sustainable integration of renewable energy sources [25] .

1.2. Research Aim

By developing an energy management strategy that optimizes energy usage in VFs by dynamically adjusting energy consumption based on real data from photovoltaic (PV) panels, battery storage, and grid prices, this study aims to bridge the gap between theoretical potential and practical application of vertical farming within the Dutch energy landscape.Central to this research is the identification and selection of a vertical farm (VF) situated in an area experiencing significant congestion challenges, which consequently faces specific energy issues [26]. The chosen VF is located in Zeeland, a province in the southwest of the Netherlands known for its substantial renewable energy generation [27]. By examining the VF's energy management system and consumption patterns, this research aims to uncover practical methods through which vertical farming systems can contribute to enhancing grid stabilization in the Netherlands. Such a strategy is essential not only for reducing operational costs but also for enhancing efficiency and sustainability [5]. Furthermore, VFs could in that way contribute to stabilizing the grid in transitioning to renewable energy sources [23], which helps in achieving the EU climate targets [9]. Therefore, the objective of the research is to optimize energy consumption, particularly in the operation of lighting systems, to enhance grid stabilization and cost-effectiveness for vertical farming operations.

Subsequently, the following research question is formulated to achieve the objective:

How can the energy management of a vertical farm be optimized using data from PV panels, batteries, and grid prices to contribute to grid stability while lowering costs?

With sub research questions:

1. What are the current energy management strategies employed by vertical farms and how can these be modeled?
2. To what extent can an optimized energy management strategy reduce operational costs and impact on the grid for vertical farms?

The rest of the thesis is structured as follows, chapter 2 provides a literature study on VRE Integration, Demand Side Management, Price-Based Energy Flexibility, and Flexibility in Vertical Farming. In Chapter 3, the case study is presented and the model is formulated. The results of the proposed model are presented in Chapter 4. Subsequently, Chapter 5 discusses the results, followed by the conclusion in Chapter 6.

2 Literature Review

This literature review aims to explore the intersection of vertical farming, energy management, and grid stability within the context of the Netherlands, a country facing significant challenges in integrating VRE sources. To address these issues, the review will focus on demand-side management (DSM), and energy optimization strategies specific to vertical farming. The search terms used for this literature review include ”grid stability”, ”VRE”, ”flexibility”, ”demand response”, ”demand-side management (VFs)”, ”energy management (VFs)”, and ”optimization (VFs)”. These terms were selected to cover the critical areas of energy flexibility, demand-side management, and the specific application of these concepts in vertical farming within the context of the Dutch energy landscape.

2.1. Demand Side Management

Wind and solar power, classified as VRE sources, depend on weather conditions for their power output. This contrasts with conventional dispatchable power plants which adjust their output based on market demands [28]. The intermittent nature of VRE sources poses challenges for grid stability, requiring innovative approaches to effectively balance supply and demand. From 2020 until 2050, the contribution of VREs to total electricity generation will rise from 15% to 57% for wind and from 5% to 19% for solar [19]. For this research, one of the European member states that stood out was the Netherlands, with the largest projected relative share of solar and wind to the total demand in 2030, it showed the highest flexibility requirements for the near future.

Furthermore, the increasing role of consumers who use emerging technologies such as solar photovoltaics (PV) and electric vehicles also demands greater flexibility in the power system [20]. These technologies enable consumers to become ’prosumers,’ actively participating in the energy market by producing and consuming electricity, which adds a new layer of complexity to the grid. This need spans from short-term adjustments to seasonal shifts, reflecting the complex dynamics of integrating renewable energy sources into existing grids [19]. According to Lund et al. [29], energy flexibility can be defined as the ability of an energy network to modify its generation or demand in response to external signals. In practical terms, flexibility can be improved through various strategies like demand response, energy storage, and flexible generation. Flexibility could be provided by the system’s supply side, network side, demand side, and storage availability [20].

Focussing on the demand side, Demand-side Management (DSM) is a portfolio of measures to improve the energy system at the side of consumption [30], and mentioned as a suitable solution for efficient VRE integration by Kondziella and Brucker [28]. As the energy grid in the Netherlands is increasingly influenced by VRE sources, VFs could contribute to grid stability by adopting DSM measures. This is particularly relevant as the country aims to balance European energy targets with reliable energy supply.

DSM, involves techniques such as load shifting, which combines peak shaving and valley filling, as seen in Figure 2.1. Controllable loads on the consumer side, called Demand Response (DR), can be used to implement load shifting, moving energy usage from peak slots to off-peak slots without changing the overall energy consumption [31]. Price-Based DR stimulates consumers to adjust their energy usage based on real-time electricity prices. When prices are high during peak demand periods, consumers reduce their consumption. Conversely, during off-peak periods when prices are lower, they can increase their usage. In that way, it supports the load management strategies mentioned above: load shifting, peak shaving, and valley filling.

Another advantage is that this approach does not require direct interventions by DSOs or aggregators through physical devices, making it an easy and effective method to enhance grid efficiency and reliability [32]. However, challenges such as the initial cost of implementing these technologies and the need for precise control systems must be addressed. Nevertheless, these advancements provide substantial benefits to various stakeholders both local and higher up in the grid hierarchy [33, 34].

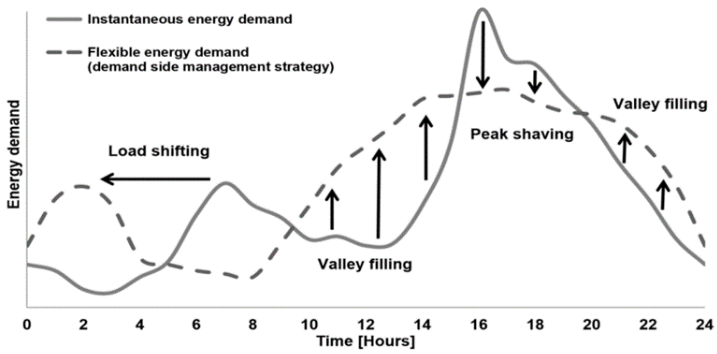

Figure 2.1: Visualization of DSM [31]

Distribution System Operators (DSOs) and Transmission System Operators (TSOs) ensure that electricity flows safely and reliably among users of their grids. Demand-Side Management is valuable from their perspective as it helps maintain continuous network capacity and can reduce the load on energy grids [33, 34]. This flexibility serves as an alternative to short-term grid enhancements or the construction of new electricity grids [20]. There are challenges to using demand-side flexibility, mostly the lack of knowledge and the market that does not match technology capabilities.

Apart from DSOs and TSOs, DSM also has value for Utilities and Consumers. For utilities, it means that more VREs can be integrated as the grid is more stable. For consumers, DSM reduces bills and can even generate revenue. Furthermore, it improves self-consumption of self-owned renewable energy resources [35]. For instance, the Flexible Power Alliance Network (FLEXNET) pilot project in the Netherlands has demonstrated significant reductions in peak load and operational costs through the implementation of demand-side flexibility measures. This project, which involves various stakeholders including DSOs, utilities, and consumers, highlights the practical benefits and potential scalability of such initiatives [36]. To summarize, the objectives of energy flexibility for all stakeholders in the electricity grid can be seen in Figure 2.2.

Utilities	Grid Operator	Commercial Consumer	Residential Consumer
Increased Renewable Energy integration Reduced Dependency on Fossil Fuels Reduced Operational Costs	Supply and demand balancing Improved grid reliability and power quality Avoid costly system upgrades	Reduced energy bill Generation of additional revenue Improved self-consumption (if using RER)	Reduced energy bill Income from selling back to the grid Improved self-consumption (if using RER)

Figure 2.2: Objectives of DSM for key stakeholders in the electric grid [35]

2.2. Energy Management at Vertical Farms

Vertical farming faces significant challenges in energy management due to the high energy demand for artificial lighting and climate control [7, 15]. As plants need a certain total daily light integral (DLI) to grow effectively, this leads to high operational costs and reliance on the grid during peak periods [37, 38]. In an interview with Artechno on April 23, 2024 [39], it was mentioned that dimming lights is a potential strategy for managing energy. As cooling and climate control use about 25% of energy, which could be buffered with a large water tank for storing heat or cold. Lighting uses 70-80% of the energy and drives consumption by bringing heat and causing plant evaporation [39].

Innovations like water-cooled lamps [37] and regaining heat in climate systems [39, 17] are mentioned to significantly reduce energy consumption. Additionally, VFs are researching renewable energy sources such as solar panels [40] and biodigesters [37] to enhance sustainability and energy independence, and some of them have started implementing these solutions. Lastly, some of them are investigating flexible energy use like adjusting lighting times to match solar energy production or battery storage capabilities [39, 38, 40].

VFs can implement load shifting by adjusting their energy usage to off-peak hours, thereby reducing peak demand on the grid [25]. This can be achieved by adapting lighting schedules to match electricity pricing and availability, in that way, VFs can reduce peak energy demands and improve grid stability [25, 8, 17]. DR thus plays a crucial role in managing the high energy demands associated with artificial lighting and climate control. Implementing DR strategies can significantly reduce operational costs and enhance the sustainability of vertical farming [39, 40]. Research by Arabzadeh et al. [25] found that DR can reduce VF electricity costs by 5–30%, depending on the electricity price variability within a day. Additionally, the integration of VFs that use DR into urban energy systems can significantly reduce the amount of power that needs to be exported to external grids, potentially by up to 80%.

A critical component of this strategy are the flexible lighting schedules, this is where the concept of photosynthetic photon flux density (PPFD) becomes relevant. PPFD refers to the amount of light, measured in photons, that plants receive per second per square meter. While it is not necessary to maintain a constant PPFD throughout the day, ensuring that plants receive a consistent total amount of light over a 24-hour period, known as the total daily light integral (DLI), is essential [41, 38]. By adjusting the intensity of LED lights based on real-time energy availability and pricing, VFs can dynamically manage their energy consumption without compromising plant growth [17].

Implementing fluctuating light patterns could generate substantial revenue but also poses risks as there is not much research about plants responding to flexible light schedules [17, 37]. Longer growing times offer for better toleration of alternating light schedules [39], but for microgreens, that only need 12 days, light significantly influences growth time [37]. Fruiting crops need continuous light, though it can sometimes be dimmed, while non-fruiting crops can tolerate more fluctuations [38, 39]. Different light colours impact energy consumption and plant hormones; red light consumes less energy than blue light but each has distinct effects on plants [37, 39].

A decision model based on prices and other energy factors could help determine optimal lighting schedules, especially with minimum constraints like total hours and light intensity [39]. Furthermore, it is crucial to consider whether new light patterns would affect delivery times and the supply chain. While standardized patterns help, fully flexible systems would be ideal as energy prices will continue to vary [22]. Though, integrating these systems with existing energy management infrastructure can be complex and costly. This is also the reason why it is hard to find additional literature on energy management systems at VFs. Furthermore, there is a lack of standardized approaches and best practices for energy management in vertical farming, leading to variability in efficiency and effectiveness.

2.3. Optimization & Modelling for Vertical Farms

Avgoustaki and Xydis [8] proposed an optimization model for energy cost reduction by shifting lighting power demand in the VF facility, and their contribution experimentally showed that savings of up to 25% are possible. Also, Arabzadeh et al. [25] presented a sequential two-stage analysis combining two strategies: the demand side management and the integration of the VF system [16].

A recent study by Pimentel et al. [16] outlined the application of a Mixed-Integer Linear Programming (MILP) to optimize the energy demand of VF systems within an integrated urban energy framework. This model provides an example of a systematic approach to find the most efficient operation plans for VF systems in a single optimization step, setting a foundational model for further research.

Previous models primarily focused on optimizing either the design of VF facilities to seamlessly integrate into urban infrastructures or controlling light power to reduce energy consumption [16]. However, the model by Pimentel et al. [16] brings a new dimension by integrating components such as renewable energy sources, which introduce natural variations to the system. The proposed MILP model addresses these variations and the control of lighting power demand, generating optimal operation plans for diverse system scenarios. It is designed to dynamically respond to fluctuating conditions, achieving sustainable energy management in VF systems.

MILP is a mathematical optimization method where some variables are restricted to integer values. It allows for modeling complex scenarios requiring discrete decisions, like lights on or off for a VF. Its constraints are linear equations or inequalities [42]. MILP is used in various applications of DR [43, 44, 45] making it highly applicable in real-world scenarios like VF energy management.

In conclusion, the MILP model offers a systematic approach to determine the optimal operation plan for VF systems considering renewable energy and local energy dynamics. The model integrates mixed-integer programming to manage fluctuations in raw material availability and prices, variations in photosynthetic photon flux density (PPFD) for lighting control, and the selection of energy sources from urban infrastructure across different operational periods. This aligns closely with the objectives of this research, which also considers energy prices, renewable sources, light demand, and various energy sources.

The insights provided by the model by Pimentel et al. demonstrate that the proposed model for this research should be able to handle binary decisions and manage the variability in energy sources, thereby generating the best possible operation plans for VF systems. The integration of MILP into VF energy management provides a base that can adaptively manage energy resources to optimize operational costs, enhance sustainability, and maintain crop productivity under variable environmental and market conditions. This approach not only reduces reliance on grid energy but also promotes the sustainability and economic viability of vertical farming operations [25, 16].

3
Methodology

First, the case study will be discussed, then chapter 3.2 discusses data handling and exploration, chapter 3.3 the model formulation, and chapter 3.4 the assessment of the results.

3.1. Case Study Location

The selected case study focuses on Own Greens, a VF in Zeeland, which is a province in the South-West of the Netherlands. The VF is located in the Noordring area which is affected by significant grid congestion issues. The reason for that is that the Noordring electricity network was originally constructed for the (one-way) transmission of electricity from large power plants to various core areas of electrical energy consumption [27]. For the municipality of Schouwen-Duiveland, these are the 50/10 kV stations in Zierikzee and Oosterland [26]. Currently, this area experiences congestion for both feeding energy into and drawing energy from the grid, as shown in Figure 3.1.

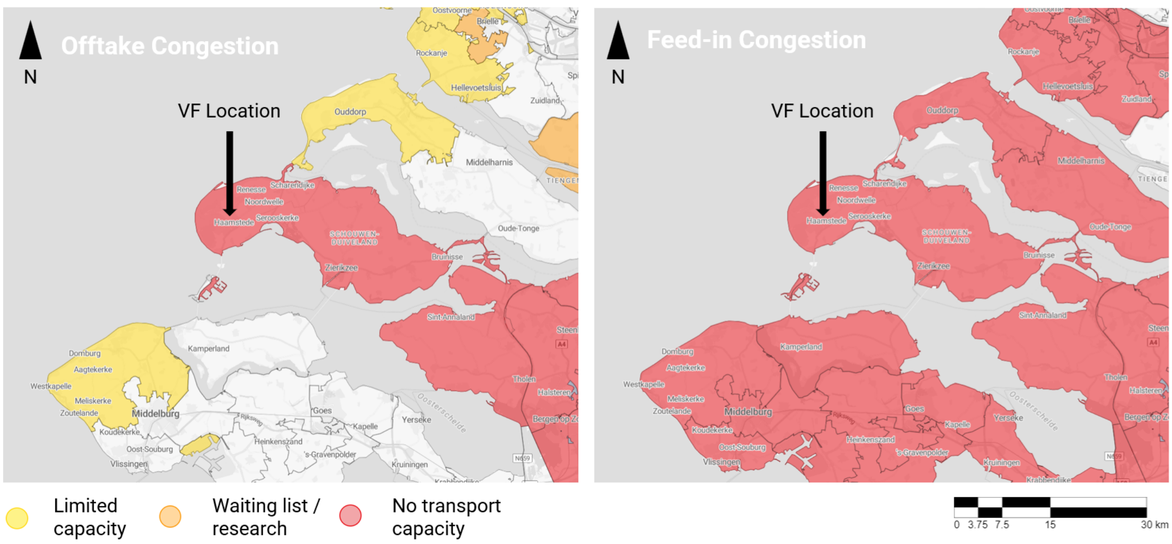

Figure 3.1: Congestion Maps for the VF Location [24]

The congestion primarily results from the large solar and wind parks in the region which generate substantial amounts of energy at varying times (A.1). Additionally, many residents already have PV panels, and it is anticipated that even more will be installed in the next two years [27]. This increasing local energy production influences energy prices significantly. When energy prices are negative, it indicates an excess supply making it beneficial to consume energy locally to balance the grid [46]. Conversely, in regions with less energy production, such as the east of the country, negative prices are less reflective of local conditions and could potentially cause congestion as the surplus energy travels across the country [46].

Figure 3.2 provides a forecast of the required transport capacity on the 50 kV North Ring in 2027. This is the transport capacity required to meet the current demand of consumers excluding the requested transport capacity [26]. Negative values represent feed-in to the grid.

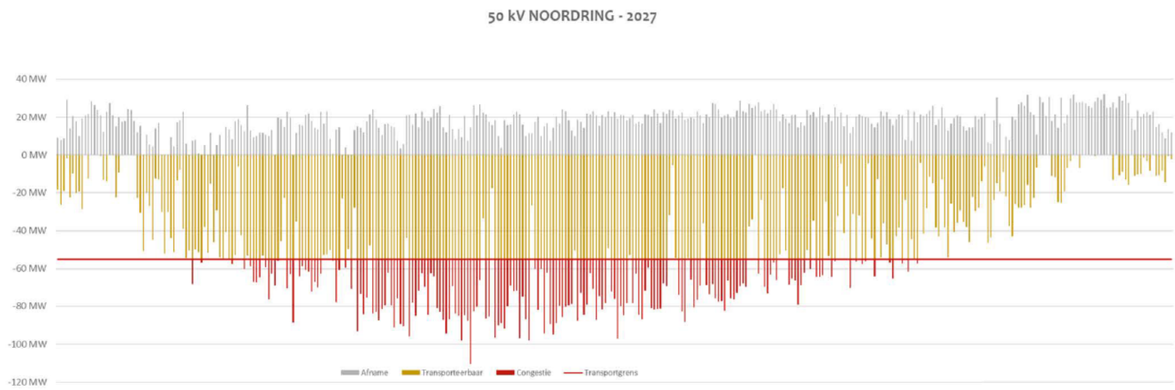

Figure 3.2: Expected loads for Noordring 2027 [26]

The forecast indicates that in 2027 Stedin will be unable to meet the transport needs of the current connections for approximately 751 hours. The expected transport demand including peak capacities is highly dependent on external conditions such as the weather situation. As a result, the annual profile has an irregular shape. This is related to the large amount of installed wind and solar power in the congestion area. The highest feed-in occurs during times of abundant sunshine. It is not possible to make an exact prediction of the precise moments of physical congestion [26]. The local context of high renewable energy generation and the associated grid congestion challenges underline the importance of this case study [46]. Understanding and managing these dynamics is crucial for optimizing energy usage and mitigating congestion in the Zeeland area.

Congestion management involves different phases where the measures become more stringent as the grid capacity limit is approached. During the voluntary participation phase, technical possibilities within the electricity grid were explored, companies and organizations were asked to offer flexible power and some voluntarily provided flexible power leading to contracts with Stedin. However, this phase did not yield enough flexible power to sufficiently alleviate congestion. Consequently, on February 1, 2024, Stedin announced a mandatory phase targeting large consumers with a return capacity of over 8 MW. These customers must offer their flexible power and can negotiate compensation for these services. Market-based contracts are used to reduce growing congestion. For those who do not reach agreements in the mandatory phase, non-market-based congestion management is applied where customers receive statutory compensation for their flexible power [46].

3.2. Own Greens

Own Greens, also known as Vitroplus, is the selected VF in Burgh-Haamstede that produces ferns with a cultivation time of 15 weeks. The farm focuses on young fern plants, hundreds of species. Other young plants could also be put in the 15-ply trolleys. Additionally, herbs and lettuce are grown in 7-layer trolleys. The farm has a total area of approximately 10000 m² and a cultivation area of 4800 m² of which they currently only use 2400 m².

Because the farm is in a critical congestion area, it cannot get a bigger energy contract while they would prefer to grow. Since the end of 2023, increasing contracted capacity has not been possible. Currently, the farm uses alternating light schedules for summer and winter to save on energy costs. The ferns require a light intensity of 60 µmol/m²/s for 12 hours each day. Currently, they are grown under a 12/12 light schedule with lights on for 12 hours and off for the remaining 12 hours. From the 15th of April till the 15th of October, the 12 hours of light are from 9:00 till 21:00 in the evening. From the 15th of October till the 15th of April, the 12 hours of light are from 21:00 till 9:00 in the morning [40].

Furthermore, Own Greens started researching alternative light periods for the plants. They are currently testing a 6/6/6/6 schedule which means 6 hours light, 6 hours dark, 6 hours light, and again 6 hours dark with good results. Furthermore, they are also testing a 9/6/3/6 light scenario with the price they received for a Boost the Grid challenge [40].

Additionally, solar panels were installed at September 20th in 2023, these are estimated to generate 209 MW per year. The maximum generation capacity of the solar panels is 157 kWh. The VF has a lithium phosphate battery with a charging capacity of 225 kW, the charging and discharging rate is 125 kWh with a charging efficiency of 0.9. The HVAC (heating, ventilation, and air conditioning), lights, and operation machines consume energy. With the lights on, the cultivation area of 2400 m² consumes 90 kWh, with the lights off the cultivation area consumes 40 kWh [40]. The 50 kWh difference is a lot of flexibility that could be used for DR of the VF to contribute to stabilizing the local energy grid.

3.3. Data Handling and Exploration

The data handling process involves preparing and analysing various datasets to model and optimize energy usage for the VF. The key datasets are:

- **Energy Prices:** Hourly energy price data from 2013 to 2024 sourced from Jeroen.nl [47]. This dataset captures fluctuations and trends in energy prices over the years.
- **PV Generation Data:** Hourly PV generation data for Zeeland sourced from Nationaal Energie Dashboard [48] and Own Greens private data.

The energy price dataset from 2013 till 2024, retrieved from Jeroen.nl [47], has an hourly granularity. As shown in A.2, it starts fluctuating more and more over the years but also over the hours A.4, this volatility, caused by the growing influence of solar and wind energy A.3, highlights the importance of flexibility in energy use. With the energy prices, the first estimation was made of the best hours to use energy for VFs in the Netherlands A.5. The results show seasonality, and again the influence of solar energy is clearly visible.

Now focusing on the data used for the model between the date 16-05-2023 and 16-05-2024, the end date was determined by the thesis planning and it should be at least one year to see the effects of the seasons. The energy prices for this year are visualized in A.6, which show seasonality. Own Greens has PV panels from September 2023, for the other hours, a dataset of the National Energy Platform [48] was used to calculate the PV generation A.7.

For the VF, the average baseline energy profile (with a Battery) can be seen in figure 3.3 below. One shows the summer light scenario (on from 9:00 till 21:00), the other shows the winter light scenario (21:00 till 9:00). The other lines are averaged over the year (16-05-2023 till 16-05-2024).

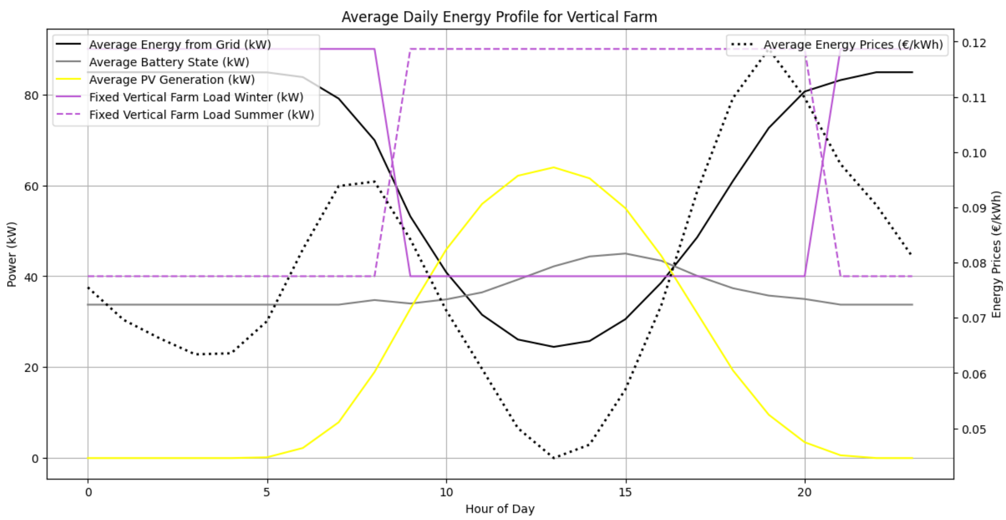

Figure 3.3: Average Daily Energy Profile for the Vertical Farm (Baseline with Battery)

For this baseline profile, the annual profile of PV generation, grid energy consumption, energy returned to the grid, and energy prices can be plotted, as shown in figure 3.4. PV generation peaks in summer, reducing grid energy demand, which is highest in winter. Excess PV generation is fed back to the grid, which is a problem in the congested area [26] that needs to be handled by the model. Energy prices also fluctuate monthly, with the lowest peak in June, likely due to generation of VRE sources.

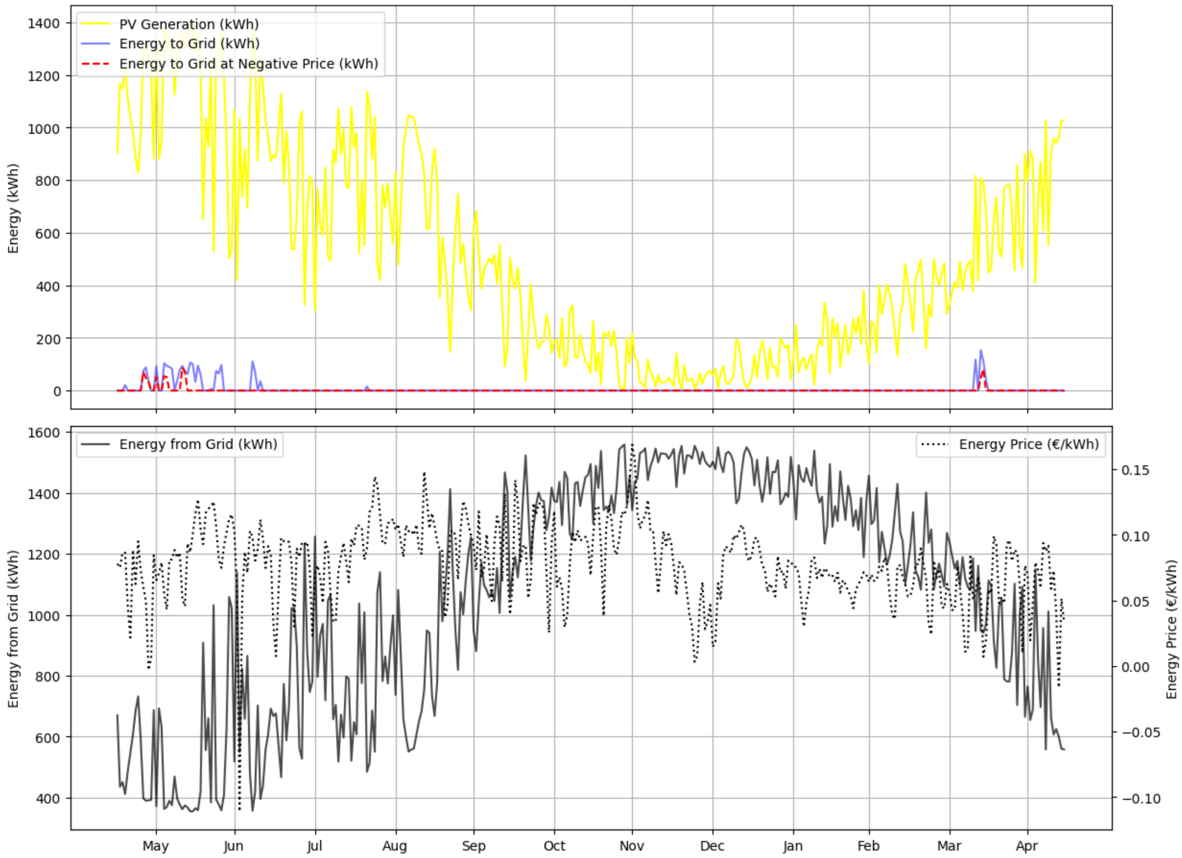

Figure 3.4: Annual Energy Profile of the Vertical Farm (Baseline with Battery)

Instead of the yearly energy profile, figure A.8 shows the energy profile of the VF for the first week of June. This would be the scenario where the VF has no battery to create the absolute baseline. It shows the first week of June which is interesting as June has the highest PV generation A.7. It shows that not all PV generation can be used which means that it must go back to the grid, this could cause congestion which would mean that the PV panels get turned off by the grid operator [40]. Especially when the prices are negative, there is no place for the energy to go to and a high chance of congestion [26]. Figure 3.5 shows the energy profile with Battery, so as it is currently, there is still not enough capacity to store all the generated energy of the PV panels. This highlights the importance of energy management.

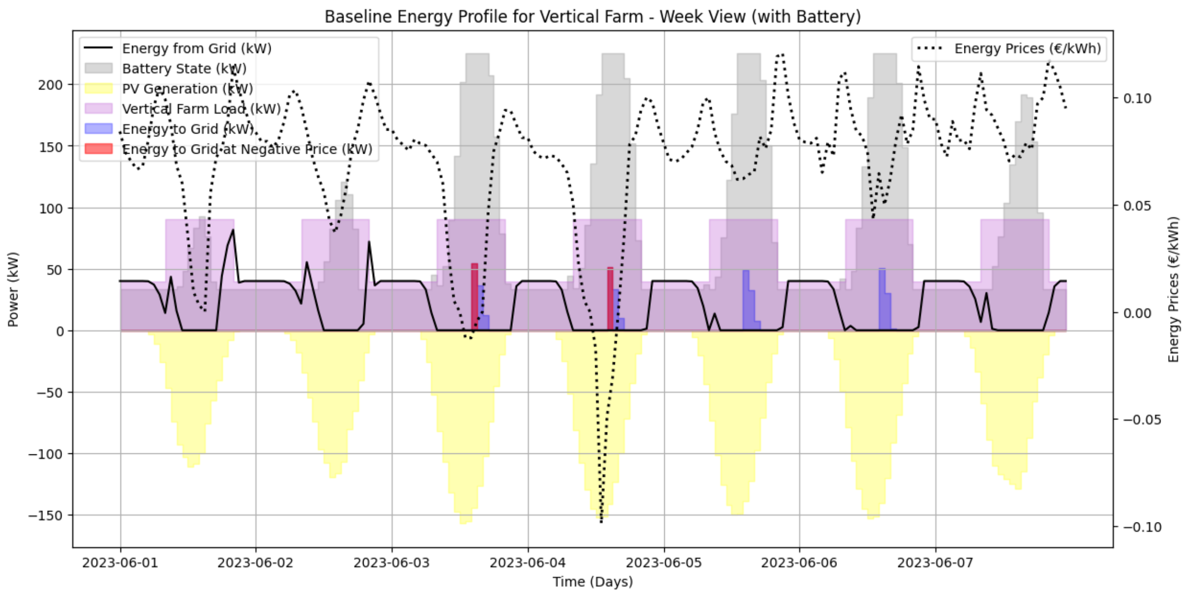

Figure 3.5: Baseline Energy Profile for Vertical Farm (with Battery)

3.4. Model Formulation

From analyzing the initial data, it became clear that the model should incorporate hourly data of PV generation and energy prices. The output variables, including battery charge levels and light schedules, should be able to change per hour. The model must determine optimal times for charging and discharging the battery, turning lights on and off, and drawing energy from or feeding energy back to the grid. These decisions should be driven by the following objectives:

- **Minimizing Energy from and to the Grid:** Given the congestion issues in the area, another crucial objective is to minimize the amount of energy drawn from the grid and to limit the energy fed back into the grid. .
- **Minimizing Costs:** This objective focuses on reducing the operational costs associated with vertical farming, thereby enhancing its feasibility.

Ideally, the model would balance these two objectives, striving for a solution that minimizes costs while also reducing grid dependency and feedback. However, the feasibility of achieving both objectives simultaneously needs to be evaluated.

The following diagram 3.6 illustrates the model's inputs, decision-making processes, and outputs in a simplified manner with the model decisions in the middle.

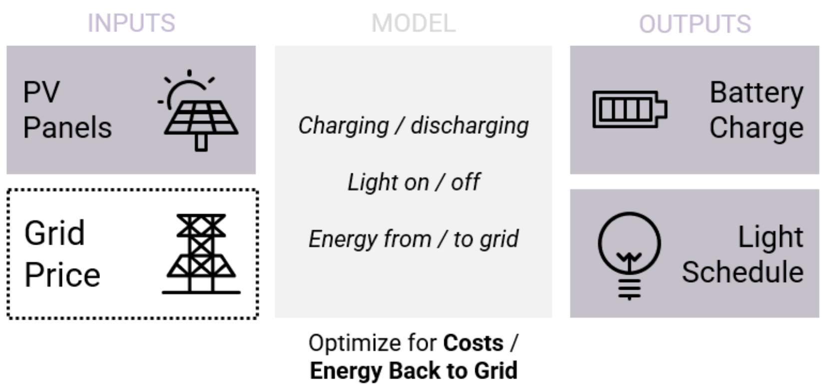

Figure 3.6: Model Visualization

The energy flows included in the model are depicted in simplified diagram 3.7. It shows the different parts with arrows indicating the possible energy flow directions. By optimizing these energy flows, the model aims to minimize costs and reduce the impact on the grid, thereby enhancing the feasibility and sustainability of the VF in a congestion area.

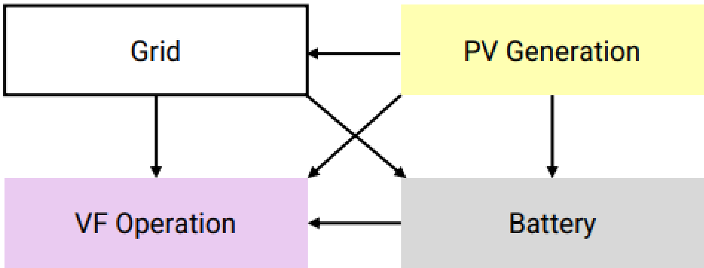

Figure 3.7: Simplified Energy Flows

As can be seen in diagram 3.7, the battery does not discharge energy back to the grid. The other primary flows of energy that the model needs to make decisions about are as follows:

- **PV Generation:**
  - Can be used directly to power the Vertical Farm (VF) operation.
  - Can charge the battery.
  - Surplus PV generation after charging the battery and supplying the VF can be fed back to the grid. Although feeding back to the grid is not preferred due to congestion, it is necessary to include this option to prevent a model that is not solvable.
- **Battery:**
  - Can supply energy to the VF operation.
  - Can be charged from the PV generation.
  - Can also charge from the grid when energy prices are negative, helping to stabilize the grid.
- **Grid:**
  - Can directly power the VF operation depending on energy prices.
  - Can charge the battery particularly during periods of negative energy prices.
- **VF Operation:**
  - Turning lights on (90 kWh) or off (40 kWh) while there remains a total of 12 hours per 24 hours based on the other flows.

3.4.1. Model Variables and Constraints

Variables in an optimization problem represent quantities that can be adjusted to find the optimal solution. They are the unknowns that the optimization algorithm will solve for. In this model, these are the variables.

BatteryCharge_t : Continuous variable for battery charging at hour t
$\text{BatteryDischarge}_t$: Continuous variable for battery discharging at hour t
BatteryState_t : State of charge of the battery at hour t
GridEnergy_t : Continuous variable for energy drawn from the grid at hour t
EnergyToGrid_t : Continuous variable for surplus energy sent to the grid at hour t
LightOn_t : Binary variable indicating whether the light is on at hour t
PVUsedForLoad_t : Continuous variable for solar PV energy used to meet the load at hour t
SurplusPV_t : Continuous variable for surplus solar PV energy at hour t
Demand_t : Continuous variable for total energy demand at hour t
$\text{NegativePriceEnergyToGrid}_t$: Continuous variable for energy sent to the grid when prices are negative at hour t

Constraints are conditions that the solution must satisfy. They define the relationships between the variables and set limits on their values to ensure feasibility. In the model, the following constraints are included.

After that the initial battery state is set to zero as it starts empty and then charges when there is energy to charge it.

$$\text{BatteryState}_0 = \text{InitialBatteryState} \tag{3.1}$$

Then there are various constraints starting with the minimum of hours that the light should be on, this is set to 12 out per 24 hours as the crop requires 12 hours of light per day in total.

$$\sum_{t=1}^{24} \text{LightOn}_t = 12 \tag{3.2}$$

The next constraint is there to assure that the battery state can never be lower than zero and never higher than the capacity of the battery, which is 225 kW [40].

$$0 \leq \text{BatteryState}_t \leq \text{BatteryCapacity} \tag{3.3}$$

The demand is determined by the base load, which is 40 kWh [40] when the lights are off, when the lights are on, the binary value is 1 instead of 0, adding an additional 50 kWh per hour to the demand as the energy use with the lights on is in total 90 kWh [40].

$$\text{Demand}_t = \text{BaseLoadFixed} + \text{LightOn}_t \times 50 \tag{3.4}$$

This constraint specifies the amount of solar photovoltaic (PV) energy used to meet the load (demand) at a given hour t, it ensures that the PV energy used is the lesser of the PV energy generated and the total energy demand.

$$\text{PVUsedForLoad}_t = \min(\text{PVGeneration}_t, \text{Demand}_t) \tag{3.5}$$

Surplus PV refers to the amount of solar energy generated that exceeds the energy demand. After meeting the load (demand) using the available PV generation, any excess energy is considered surplus.

$$\text{SurplusPV}_t = \text{PVGeneration}_t - \text{PVUsedForLoad}_t \tag{3.6}$$

The surplus PV can either go to the battery or back to the grid when there is no other option as the demand is already fulfilled.

$$\text{SurplusPV}_t = \text{BatteryCharge}_t + \text{EnergyToGrid}_t \tag{3.7}$$

As the battery can either charge or discharge, the battery state is the charging efficiency times the charge or discharge. During the charging process from AC to DC, efficiency losses occur. These losses are primarily caused by the conversion inefficiencies inherent in the charging systems. The efficiency of charging is generally set to 0.9, indicating that only 90% of the energy is effectively utilized, while the remaining 10% is lost during the conversion process [49].

$$\text{BatteryState}_{t+1} = \text{BatteryState}_t + \eta_{\text{Charge}} * \text{BatteryCharge}_t - \eta_{\text{Charge}} * \text{BatteryDischarge}_t \tag{3.8}$$

The battery charge should never be more than the charge power of the battery, which is defined as 125 kWh [40].

$$\text{BatteryCharge}_t \leq \text{ChargePower} \tag{3.9}$$

The same accounts for battery discharge, which should never be more than the discharge power, which is also 125 kWh [40].

$$\text{BatteryDischarge}_t \leq \text{DischargePower} \tag{3.10}$$

Additionally, the battery can never discharge more than the total energy in the battery, defined by the battery state.

$$\text{BatteryDischarge}_t \leq \text{BatteryState}_t \tag{3.11}$$

The energy from the grid, battery discharge and PV used should always fulfill the demand together as there are no other energy flows possible.

$$\text{GridEnergy}_t + \eta_{\text{Charge}} * \text{BatteryDischarge}_t + \text{PVUsedForLoad}_t = \text{Demand}_t \tag{3.12}$$

The battery state should always remain at 15% of its total capacity for the lifetime of the battery [40].

$$\text{BatteryState}_{t+1} \geq 0.15 \times \text{BatteryCapacity} \tag{3.13}$$

It should not be possible to send 'negative' energy to the grid, this is made sure by the constraint below.

$$\text{EnergyToGrid}_t \geq 0 \tag{3.14}$$

To be able to measure the amount of energy sent to the grid when energy prices are negative the following needs to be implemented.

$$\text{NegativePriceEnergyToGrid}_t = \text{EnergyToGrid}_t \times (\text{EnergyPrices}_t < 0) \tag{3.15}$$

3.4.2. Objective Functions

The first objective is minimizing costs associated with energy usage from the grid. This involves smart utilization of the grid, solar panels, and battery storage to exploit variations in energy prices throughout the day. By dynamically adjusting energy sources, the model can capitalize on lower energy prices during off-peak hours. The cost function incorporates energy prices as a variable component reflecting real-time market conditions, and it also incorporates that when the energy prices are negative, feeding energy to the grid will cost money, so it minimizes for that.

Formally, the objective is defined as follows:

$$\text{Minimize} \quad \sum_{i=0}^{23} (\text{EnergyPrices}_t \cdot \text{GridEnergy}_t - \text{EnergyPrices}_t \cdot \text{EnergyToGrid}_t)$$

The objective is to minimize the total energy costs over a 24-hour period. This is achieved by summing up the costs of energy drawn from the grid and subtracting the revenue from energy sent back to the grid, taking into account the varying energy prices at each hour.

The second objective is minimization of energy fed back to the grid. This could happen when there is a lot of PV generation and it cannot be used for the demand nor stored in the battery. By minimizing the energy fed back to the grid to model would contribute to reducing grid congestion, which occurs mostly during periods of high solar generation [46]. The objective is formulated as follows:

$$\text{Minimize} \quad \sum_{t=0}^{23} \text{EnergyToGrid}_t \tag{3.16}$$

This objective ensures that the model seeks to reduce the amount of surplus energy fed back to the grid, encouraging more efficient use of the available PV generation and battery storage, while also mitigating potential grid congestion.

Due to the congestion area, it is extremely important that energy to the grid is minimized, therefore this is the primary objective of the combined optimization. However, it should also be feasible for the VF, therefore, the second objective is to minimize costs. In that way, both objectives are combined. Furthermore, the objective takes into account that when it feeds back to the grid, the price is taken into account, making it more profitable to feed back to the grid when the prices are high and unprofitable to feed back to the grid when the prices are negative. In that way, it could contribute to stabilizing the grid.

$$\begin{aligned} &\text{PrimaryObjective} : \text{Minimize} \quad \sum_{t=0}^{23} \text{EnergyToGrid}_t \\ &\text{SecondaryObjective} : \text{Minimize} \quad \sum_{t=0}^{23} (\text{EnergyPrices}_t \cdot \text{GridEnergy}_t - \text{EnergyPrices}_t \cdot \text{EnergyToGrid}_t) \end{aligned} \tag{3.17}$$

3.4.3. Mixed-Integer Linear Programming and Gurobi

As mentioned in chapter 2, Mixed-Integer Linear Programming (MILP) is a suitable approach to formulate the optimization problem of the VF. The formulation considers fluctuations in energy prices, the ability to switch lights on and off to control lighting power demand, solar energy generation from the PV panels, and the battery's charging and discharging capabilities. The need to use MILP to solve the model comes from the inclusion of binary decisions, in this case the lights on and off.

The model is solved using Gurobi with Python in Google Colab, Gurobi is an optimization solving algorithm designed to handle binary decisions effectively, generating the best energy management scenario for all variations. Gurobi is well known for solving large-scale linear programming (LP), mixed-integer linear programming (MILP), and other complex optimization problems efficiently and offers a free academic license. The model is widely used in energy management [50, 51] and can determine which energy sources should be used and at what times while also generating the ideal light schedule. Consequently, the best hourly operation plan of the VF with all its energy systems can be determined based on real data, promoting the system's sustainability and energy efficiency, and contributing to grid stabilization.

3.5. Assessment of Results

To assess the results, the different objective functions are compared based on costs, energy to grid, energy to grid at negative price moments, and energy used from the grid. With that, the best objective function will be chosen to define the ideal hours at which the VF should put the lights on. The optimal light hours are identified by selecting hours with the highest probabilities based on the best objective selected before. These fixed hours are then standardized for implementation across different seasons. After that the fixed light schedules derived from the probabilistic analysis are compared to the flexible optimization scenario. This is done by simulating the fixed light schedules over a year. Afterwards, the performance of these fixed schedules is again evaluated in terms of costs, energy to grid, energy to grid at negative price moments, and energy used from the grid

4 Results

For the results, chapter 4.1 discusses the best objective for the optimization. Based on that the ideal light scenario can be made, discussed in chapter 4.2 which will then be compared to all scenarios 4.3.

4.1. Comparing Objectives for Optimization

The baseline scenario is a scenario with no optimization: one is with a battery and the other is without a battery. It uses solar energy when available and stores excess solar energy in the battery or feeds it to the grid when no other option is available. The lights are fixed and on for 12 hours from 9:00 in the morning till 21:00 in the evening in summer. In winter, it is turned around; the lights are on from 21:00 till 9:00 in the morning as mentioned in section 3.2 of chapter 3.

The scenario where the objectives are tested is a flex scenario meaning that the lights can be switched on and off but must remain on for a total of 12 hours within 24 hours. The optimization model decides when to put the lights on based on the constraints and for 3 different objectives mentioned in paragraph 3.4 of chapter 3. One of them focusing on minimizing costs, another on minimizing energy sent to the grid, and the third on both.

The three objectives are assessed on costs, energy from grid, energy to grid and energy to grid at negative price hours. Overall, the combined grid & costs objective consistently performs the best across all categories, this is further explained in Appendix A.2. The objective effectively reduces operational costs, minimizes grid energy usage, and limits energy feedback to the grid, especially during negative price periods. This makes it the most suitable model for determining the ideal light schedule for the VF.

Given these results, the optimization model, focusing on both grid management and cost savings, will be used to determine the ideal light schedule for the VF. While the results show the optimization for flexible hourly light operations, it is also crucial to identify standardized patterns that the VF can implement, especially for the testing scenarios of 6/6/6/6 and 9/6/3/6 used by the VF which was mentioned in section 3.2 of chapter 3. This approach ensures that the VF operates efficiently while mitigating congestion and maximizing cost savings.

4.2. Determining Ideal Light Schedule

Looking at the probabilities for each hour across all months in Figure 4.1, distinct patterns emerge. During the winter months (November to February), there is a higher probability of the lights being on during the night. This pattern aligns with the lower availability of PV generation during the day (A.7) and the need to utilize grid energy during off-peak hours to minimize costs. Conversely, in the summer months (May to August), the probability of the lights being on is higher during the day. This corresponds to the peak of solar PV generation (A.7), making it cost-effective to use self-generated solar energy and reduce reliance on the grid. In the transition months (March, April, September, October), there is a mix of daytime and nighttime light schedules. The probability distribution during these months reflects the variability in solar PV availability and grid energy costs, necessitating a flexible approach to light scheduling.

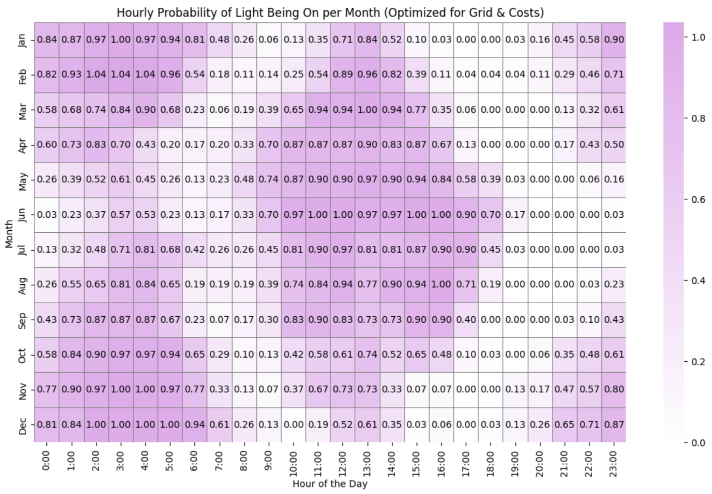

Figure 4.1: Probabilities of Light Being On for When Lights Can Go On and Off Each Hour (Flexible)

The patterns in figure 4.1 indicate that standardized light schedules can be implemented based on seasonal variations. For instance, a night-focused schedule during winter and a day-focused schedule during summer can optimize energy use and cost savings. The highest probability of lights being on occurs during periods of lowest energy costs or highest solar PV generation, effectively balancing cost savings with grid management.

By analyzing these hourly probabilities, it is possible to develop light schedules that align with the optimization model. These schedules can be adjusted seasonally to ensure efficient operation, minimize energy costs, and reduce grid congestion. The patterns observed also support the testing scenarios of 6/6/6/6 and 9/6/3/6, providing a foundation for further refinement and implementation of optimal light schedules in the VF.

From the hourly probability data, we can determine the optimal start hour for various light schedules, further explained in Appendix A.2.2 including 12/12 (A.21), 6/6/6/6 (A.22), and 9/6/3/6 (A.23). This is determined by adding up the probabilities of the hours when the light is on. The total probability of each start hour is calculated and the highest one is selected per month. The visualisation involves creating a mask over probabilities of the optimization model to visualize the ideal hours of the light being on for each month.

By calculating the total probability for each light schedule with its ideal start hour, it can be determined what the best schedule for each month would be based on the highest probability across the 3 light schedules. Table 4.1 summarizes the ideal start hour and the corresponding light schedule for each month:

Month	Ideal Start Hour	Schedule
1	21	9/6/3/6
2	21	9/6/3/6
3	11	6/6/6/6
4	10	6/6/6/6
5	9	9/6/3/6
6	8	12/12
7	10	9/6/3/6
8	10	9/6/3/6
9	11	6/6/6/6
10	22	9/6/3/6
11	21	9/6/3/6
12	20	12/12

Table 4.1: Ideal Scenario per Month

Figure 4.2 visualises the optimal light schedule for each month, with purple being light on, highlighting the best hours for lights to be on based on the highest probability of low energy costs or high solar PV generation. While also minimizing energy fed back to the grid.

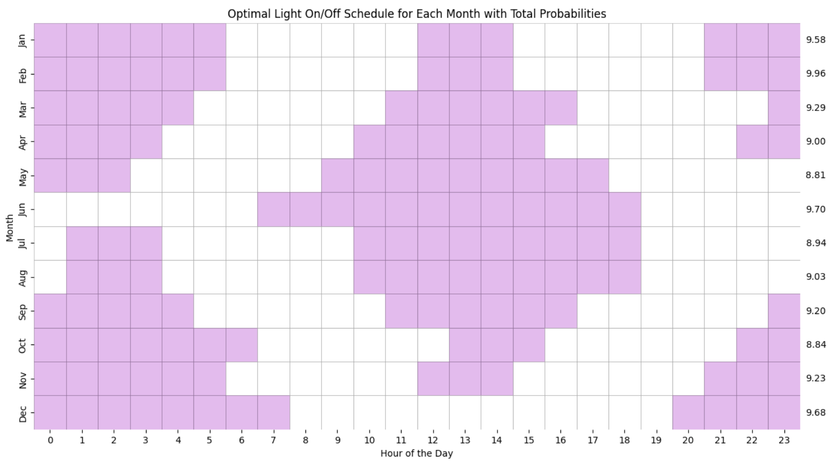

Figure 4.2: Ideal Light Scenario per Month

The similarity between the optimal schedule (figure 4.2) and the original probabilities plot (figure 4.1) suggests that fixed light scenarios can still effectively align the VF's energy use with energy availability. This means that by following these optimized schedules, the VF can operate more efficiently, making the most of periods with high solar PV generation and low energy costs. Implementing these optimized light schedules can lead to significant improvements in energy efficiency, reduce operational costs, and enhance grid stability.

4.3. Results when Implementing Ideal Hours per Month

In this section it is discussed what the impact would be if the standardized light schedules for each month are implemented. All the different scenarios are evaluated to determine the effectiveness of implementing ideal light schedules based on the highest probability hours. Energy management means whether the optimization model is still active but the hours are fixed. As the model can still decide to charge or discharge the battery to make space for the upcoming solar peak. To summarize the results of all the scenarios, the costs, energy from grid, energy to grid, and energy to grid at negative prices are compared in figures.

In the baseline scenarios, both with and without a battery, energy usage from the grid and energy fed back to the grid are plotted in Appendix A paragraph A.1.3, figure A.9 for baseline without battery and figure A.10 with battery. These scenarios highlight the reliance on grid energy, particularly during peak hours when prices are higher. The addition of a battery reduces grid dependency and fed back by storing excess solar energy, but it does not eliminate the issue of energy being fed back to the grid, especially during negative price periods.

The flexible optimization scenario with combined objectives for grid and costs allows the model to dynamically adjust the light schedules each hour based on energy costs and availability. These results can be seen in Appendix paragraph A.2.1, figure A.16. This approach shows significant improvements compared to the baseline scenarios figures A.9 and A.10. The flexibility in scheduling leads to better alignment with periods of low energy costs and high solar PV generation, reducing costs and the amount of energy fed back to the grid .

The scenario that combines the ideal light schedules (without energy management) implements fixed light schedules based on the highest probability hours without active energy management. As seen in Appendix A, paragraph A.2.3, figure A.25 there are improvements in cost efficiency and grid usage compared to the baseline (figure A.10, the lack of dynamic adjustments means some opportunities for optimization are missed. The energy fed back to the grid during negative price periods is also higher compared to the flexible optimization scenario.

In the scenario that combines the ideal light schedules (with energy management), paragraph A.2.3 of Appendix A, the model actively manages energy by adjusting battery usage and light schedules even with fixed hours. In figure A.27, this approach shows the best performance, closely matching the flexible optimization scenario in terms of cost efficiency and minimizing grid dependency. The active energy management ensures that the battery is optimally charged and discharged, further reducing the amount of energy fed back to the grid during negative price periods.

4.3.1. Costs Results

Comparing the five scenarios mentioned above, the grid and costs optimization scenario scores the best in terms of cost savings (see Figure 4.3). This result is expected as this model dynamically adjusts the light schedules each hour based on current energy prices, ensuring optimal use of low-cost energy periods and reducing overall costs.

The combined schedules, both with and without energy management, show similar costs. This indicates that even with fixed light schedules, the implementation of active energy management (such as optimizing battery usage) can significantly reduce costs. The ability to load and unload the battery to make room for solar peaks further helps in managing energy costs effectively.

Comparing these scenarios highlights the cost advantages of flexible optimization models. While the baseline scenarios demonstrate higher costs due to their fixed schedules and lack of optimization, the combined schedules with energy management closely approach the cost efficiency of the grid and costs optimization scenario.

Overall, implementing dynamic light schedules and active energy management strategies can lead to substantial cost savings. The results emphasize the importance of flexibility and real-time energy management in reducing operational costs and enhancing the economic viability of the VF.

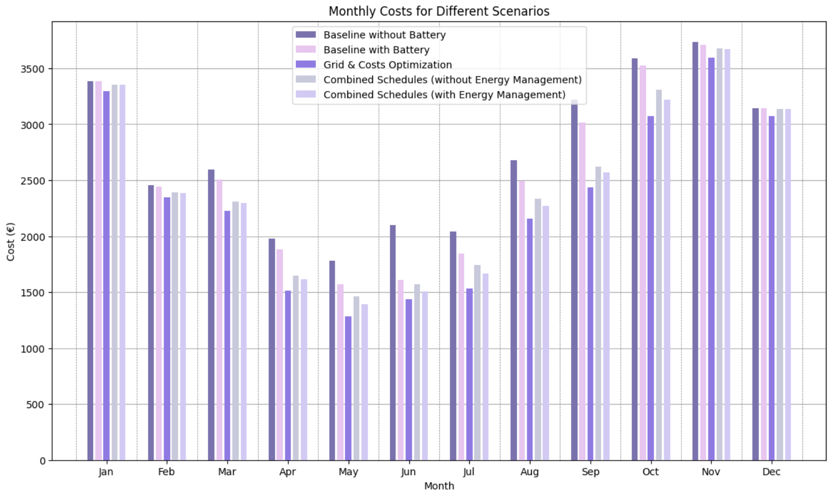

Figure 4.3: Monthly Costs

4.3.2. Energy from Grid Results

Figure 4.4 shows the monthly energy usage from the grid for the five scenarios. During the winter months, energy usage from the grid is similar across all scenarios, which makes sense since there's no solar energy available. In the summer months, energy usage patterns diverge slightly. The baseline without a battery shows higher grid energy usage because there's no way to store excess solar energy.

The baseline with a battery and the combined schedule without energy management perform the best in terms of reducing grid energy usage. The battery helps store solar energy for use during non-sunny periods, lowering the reliance on grid energy. Combined schedules with energy management also perform well, making effective use of both solar energy and stored energy in the battery.

Overall, the scenarios with a battery, whether optimized or not, show a clear advantage in reducing grid energy usage, especially during the summer when solar generation is high. This demonstrates the importance of having a battery system to store solar energy and reduce dependence on the grid.

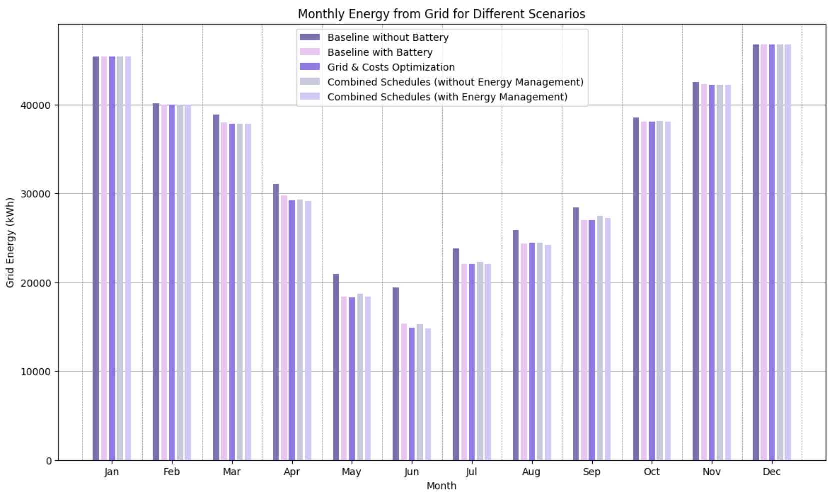

Figure 4.4: Monthly Energy from Grid

4.3.3. Energy to Grid Results

Figure 4.5 illustrates the monthly energy fed back to the grid for all the scenarios. There are clear differences in the amount of energy sent back to the grid among the scenarios. The scenario without a battery performs the worst because it must deliver all excess solar PV energy directly to the grid, especially during high-generation months like June A.7. This leads to significant spikes in energy fed to the grid. In contrast, the baseline with a battery scenario shows reduced energy feedback; the battery allows for storage of excess solar energy which can be used later rather than being sent back to the grid immediately.

The baseline scenario has a more basic approach, resulting in less interaction with the grid but higher overall costs. The optimized scenario and the combined schedules with energy management demonstrate slightly higher energy feedback to the grid. This is due to the combined objective of not only minimizing energy fed to the grid but also minimizing costs. This causes the model to use energy pricing and the battery in order to minimize overall energy costs by selling energy to the grid when prices are high. Although this results in increased energy sent to the grid, it balances cost savings with effective energy management, considering solar surplus and grid pricing dynamics. Feeding back to the grid can stabilize when there is sufficient demand, but it could also cause congestion if too much energy is fed back into the grid in the region. The exact impact on the grid remains unknown due to the unpredictability of congestion times.

The combined schedules with and without energy management send a noticeable amount of energy to the grid in September. While in April, the baseline with battery delivers energy back to the grid. This can be explained by the average price of energy being higher in September than in April (Appendix A, figure A.6), making it more profitable to send energy back to the grid in September.

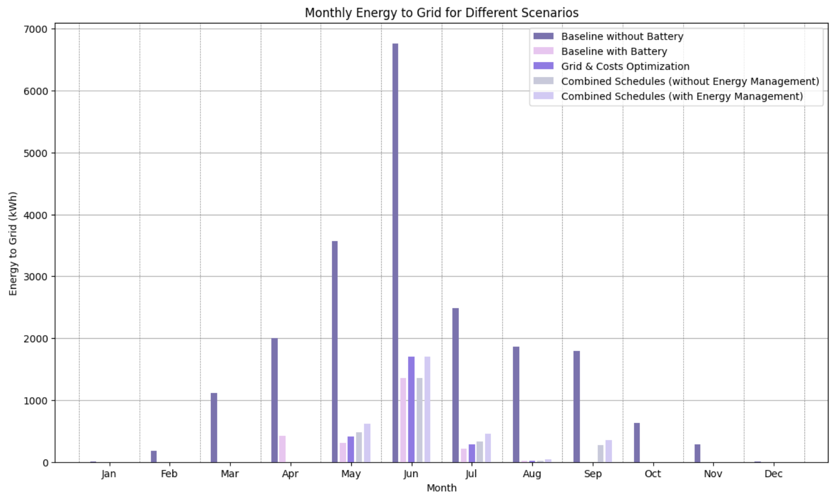

Figure 4.5: Monthly Energy to Grid

4.3.4. Energy to Grid at Negative Prices Results

Figure 4.6 shows the monthly energy fed back to the grid at negative prices for the different scenarios. Negative energy prices occur when there is an oversupply of energy, making it crucial to minimize energy fed back to the grid as there is congestion at 90-95% of the times when there are negative prices [46] in the Noording region. Furthermore, feeding back to the grid would cost money which the model minimizes for. The data reveals significant differences among the scenarios.

The baseline without a battery scenario performs the worst, as expected, showing substantial energy feedback to the grid during months with high solar generation, particularly in May and June. This is because there is no way to store the excess solar energy, leading to higher energy exports during negative price periods.

The baseline with a battery scenario performs better as the battery stores some of the excess energy, reducing the amount sent back to the grid at negative prices. However, there are still notable amounts of energy being fed back during negative prices. This is the same for the combined schedules without energy management as this model does not integrate a smart use of the battery to prepare for the upcoming peak in solar generation.

In contrast, the combined schedules with energy management and the grid & costs optimization scenario perform significantly better. These systems can manage energy more effectively by discharging the battery before expected solar generation peaks, creating space to store excess energy. Additionally, they can deliver stored energy back to the grid during hours when prices are not negative, thus avoiding feeding energy back during negative price periods.

In conclusion, incorporating a battery and active energy management reduces the amount of energy fed back to the grid during negative price periods. The combined schedules with energy management and the grid & costs optimization scenario demonstrate the most effective strategies for minimizing costs and improving energy efficiency, highlighting the importance of flexible scheduling and real-time energy management.

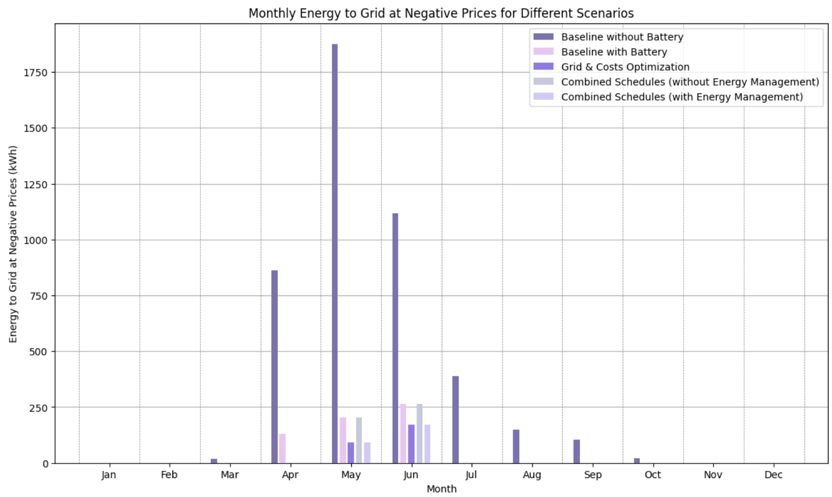

Figure 4.6: Monthly Energy to Grid at Negative Prices

4.3.5. Summarized Results Yearly

In table A.1 in Appendix paragraph A.2.4 the results can be seen in numbers for the year. To make the results easier to compare in table 4.2, they are expressed in percentage compared to the baseline with a battery as this is the current situation at Own Greens. In the table, increasing percentages are highlighted in red to indicate a negative outcome for minimization objectives, while decreasing percentages are highlighted in green to indicate a positive change.

The grid and costs optimization scenario performs the best overall. This scenario has the lowest costs and minimal energy sent to the grid during negative price periods, making it the most efficient. The combined schedules scenarios also perform well, particularly in reducing energy to grid at negative prices but also in reducing costs. However, combined schedules with energy management feeds a lot of energy back to the grid due to the objective of minimizing costs, this could either stabilize the grid or cause congestion, as discussed in paragraph 4.3.3. For the other scenarios there is also an increase in energy fed back to the grid, which can also be explained by the optimization objectives mentioned above. Further details on each individual assessment criterion, such as costs, are provided in the respective paragraphs above.

Scenario	Energy to Grid (%)	Energy to Grid Negative Prices (%)	Costs (%)	Energy from Grid (%)
Baseline without Battery	+891.33%	+761.85%	+5.09%	+3.70%
Baseline with Battery	0%	0%	0%	0%
Combined Schedules (no Energy Management)	+5.52%	-21.80%	-5.07%	+0.09%
Combined Schedules (Energy Management)	+36.98%	-55.89%	-6.70%	-0.34%
Grid & Costs Optimization	+4.27%	-55.89%	-10.25%	-0.33%

Table 4.2: Comparison of Baseline with Battery to All Scenarios

To conclude, the grid & costs optimization scenario is the most effective strategy, providing the best balance of cost efficiency and minimal negative price impacts. However, the combined schedules with energy management also offer substantial benefits and can be considered a viable alternative, especially in scenarios where dynamic optimization is not feasible. But while the 6/6/6/6 and 9/6/3/6 light scenarios are being tested, others should be tested too. Especially a scenario where the lights go on and off each hour as this would be beneficial for the flexibility of the VF. Furthermore, the light schedule is only researched for ferns, so the broader application of it remains to be researched. It could be valuable to grow and test other crops to investigate the economic benefits.

Having a crop that is able to resist fluctuating light is especially important given the congestion issues in the area (chapter 3, section 3.1). Because of that it is crucial to avoid sending energy to the grid at negative prices. In practice, solar panels may need to be shut off during peak generation periods to prevent this. The data indicates that June is a particularly challenging month due to high PV generation (figure A.7). Therefore, additional solutions such as improved energy storage and dynamic energy management are essential to optimize the VF's energy use and reduce its impact on the grid, these will further be discussed in chapter 5.

5 Discussion

The discussion chapter starts with section 5.1, in which the model formulation and the results are discussed. Then placing them into a broader context of other strategies that contribute to grid stability in section 5.2.

5.1. Model Formulation and Results

The practical application of this model is very significant for Own Greens (Vitroplus) in Burgh-Haamstede in Zeeland, the Netherlands. By effectively managing energy usage, the vertical farm can operate more sustainably and economically even within the constrained grid environment of the Noordring area. The use of MILP combined with the computational capabilities of Gurobi enables the model to handle real-world energy management scenarios. The model could determine the optimal times for charging and discharging the battery, turning lights on and off, and drawing energy from or feeding energy back to the grid. While now only data for Own Greens was implemented, other vertical farms could also implement their data in the model as the PV generation, total energy use with lights on and off, and battery constraints can easily be implemented. In that way, other light intensity needs for other crops can also be integrated into the model as the model only needs energy consumption with lights on and off as input.

The assessment of the model's performance involved comparing different objective functions based on costs, energy feedback to the grid (at negative hours), and energy usage from the grid. The results indicated that the cost minimization objective effectively reduced operational costs by leveraging periods of low and negative energy prices for charging the battery and operating the vertical farm. Additionally, the grid minimization objective successfully reduced the energy fed back into the grid; however, it does not consider negative price hours, which does not help with the congestion in the area. This meant that the objectives need to be combined to achieve the best performance. Because of the congested area, the grid minimization was the primary objective and minimizing costs the secondary. By balancing these objectives, the model provided an optimal solution for the vertical farm's energy management, ensuring both economic and operational efficiency. The ability to dynamically adjust to PV generation and energy prices underscores the model's practical utility.

Several considerations and limitations were identified during the application of the model. Firstly, the battery currently only charges from the grid when prices are below zero. This approach could be expanded to include charging when prices are, for example, in the lowest 10% to optimize battery usage further, especially in winter when the battery is not as much used as there is not much PV generation [52]. However, this adjustment could lead to local congestion if many entities in the area adopt the same strategy, potentially exacerbating the grid's constraints. Secondly, the model's objective to minimize energy feedback to the grid occasionally conflicts with its cost minimization objective. While the primary goal is to reduce grid congestion by minimizing energy fed back to the grid, the model sometimes opts to sell energy to the grid when the return prices are high. This discrepancy highlights a need for further research as it could be beneficial for the local grid if there is energy available when the prices are high, indicating that there could be an energy shortage.

Another significant consideration is the treatment of PV generation curtailment. In reality, PV generation is often curtailed to manage grid constraints [26]. However, this was not modelled to explore potential alternative uses for excess energy. This decision leads to non-realistic cost scenarios as the model sometimes generates revenue from feeding energy back to the grid (when the price is profitable). In practice, this revenue might not be realized due to the need for curtailment during periods of local congestion, which the model does not currently account for. However, this could be solved by implementing additional energy management strategies, which will be discussed further in the discussion chapter.

Additionally, there is a limitation regarding the potential for local congestion even when prices are positive as the region has a lot of energy production. This scenario could lead to PV generation being curtailed and no revenue being generated from energy feedback to the grid. The current model assumes profitability whenever prices are positive, which does not reflect the real-world complexities of grid management and local congestion issues. However, properly timed energy feedback can be advantageous, and the model currently optimizes this by selling energy back at the highest price.

Lastly, a limitation is that the PV panels have only been installed for one year, meaning that the data only spans for a short period of time. This means that the ideal light schedules are based on one year, which could cause the pattern to be different for the next year. This highlights the need for an energy management system that uses real-time data. However, because of the variability in energy price, it could also be an advantage that the data only spans for one year as every year the prices are more volatile.

The exact impact on grid stability of the results is hard to measure due to a lack of data. Data about which hours there was congestion in the area is private, so it cannot be used to test the model. However, it is mentioned by Stedin that minimizing energy back to the grid at negative prices would help the congestion for 90-95% of the congestion moments in the Noordring area. This is because of the high amount of renewable energy production in the area. However, for other vertical farms situated in different parts of the country or world, this could not be true; it could cause extra congestion if prices are negative but there is no production of energy in that area. Because of the congestion being linked to the prices for Zeeland, it is assumed in the model that when energy is going back to the grid at negative price hours, there would be congestion, which means that the solar panels get turned off.

By addressing these considerations and limitations, the model can be refined to provide more accurate solutions for energy management in vertical farming and other energy-intensive operations within constrained grid environments. It would be highly beneficial to receive real hourly data about the congestion hours to compare the model to.

5.2. Other Strategies to Solve Energy Fed Back to the Grid

As demand response does not solve all the energy going back to the grid for the vertical farm, other additional strategies should be considered too. First, it is important to consider energy storage systems. It would be possible to extend the existing battery with another battery of 225 kW. However, the costs are high, and it would only be beneficial in the summer, especially in June and July, as these months have the most surplus PV. Therefore, it is interesting to look at other storage solutions. As there is a fridge for cooling the plants, the fridge could buffer some energy by cooling additional degrees when the prices are low or when there is excess PV energy; the fridge does not have to cool at peak hours. Another way of storing energy is thermal energy storage (TES), an effective method for load shifting and demand response in buildings [52]. One way of doing that is with a large water tank, which can be cooled during off-peak hours and then be used to cool down LED lights inside the vertical farm. Furthermore, it could also be used to cool down the vertical farm growing chambers. Another way of TES is using ice-based energy storage systems. A typical ice-based TES system charges the ice storage during off-peak hours. The ice storage tank functions as a thermal battery to shift loads. Additionally, excess heat generated by the LED lights could be used for local residential buildings or offices [17], even the office of Own Greens itself.

Another way of looking at it could be working together with the grid, functioning as a decentralized energy grid where energy can be shared with other industries, residents, and offices in the neighbourhood [53]. This is because decentralized flexibility options connected to the distribution grid can also be used for congestion management in the transmission grid. In the decentralized grid, the following load management strategies are considered: smart charging of electric vehicles and smart operation of heat pumps [53]. At the location of the vertical farm, an EV charging pole could be implemented; there is an auto garage nearby which the vertical farm could share the charging point with. Furthermore, it can be used by the employees of the vertical farm for their personal cars, but also for a delivery van. It would be extra beneficial to have a smart charging pole that only loads energy to the vehicles when there is excess or when the prices are low. On top of that, having an electrical vehicle that could charge bidirectionally would add extra value as it can supply back at peak hours [54]. Additionally, peer-to-peer energy trading systems could provide an outlet for excess energy, allowing the vertical farm to sell surplus energy directly to other users in the area [55].

6 Conclusion

This study explored the integration of vertical farming (VF) with local energy grid management to address agricultural and energy challenges. By analyzing and optimizing energy management strategies, the research demonstrated how VFs can contribute to grid stabilization while reducing operational costs. The case study of a vertical farm in Zeeland, Netherlands, highlighted the potential benefits and challenges of implementing such systems in regions with renewable energy production and grid congestion issues.

Vertical farming presents a viable alternative to traditional agriculture, offering advantages such as efficient land use, higher yields, reduced water and nutrient consumption, and minimal pesticide use. This is particularly relevant in the Netherlands, where the nitrogen crisis significantly impacts agriculture. However, one of the primary challenges of vertical farming is its high energy demand, especially for artificial lighting and climate control, posing economic and sustainability concerns in regions with high electricity costs, like the Netherlands.

To address these challenges, the research developed an energy management model using Mixed-Integer Linear Programming (MILP) to optimize VF energy consumption. The model dynamically adjusted energy usage based on real-time data from photovoltaic (PV) panels, battery storage, and grid prices. Optimizing light schedules and battery usage allowed VFs to significantly reduce operational costs and minimize their impact on the local grid, especially during negative price periods caused by excess generation and grid congestion. The combined objective of minimizing costs and grid energy feedback proved most effective.

The case study of Own Greens (Vitroplus) in Zeeland illustrated the practical application of this model. Located in a region with high renewable energy generation and grid congestion, the farm faced challenges in extending its energy contract. The model demonstrated that flexible light schedules and active energy management could enhance the farm's energy operation. Optimal light schedules varied seasonally, with winter schedules favoring nighttime operation and summer schedules aligning with peak solar PV generation.

Vertical farms, through optimized energy management, can contribute to grid stability by adjusting their energy consumption to match renewable energy production profiles, reducing the impact on the grid during peak periods, and mitigating congestion issues. The study emphasized the importance of minimizing energy feedback to the grid during negative price periods to avoid exacerbating local congestion. By strategically managing battery storage and consumption patterns, VFs can help balance supply and demand more effectively.

Besides demand response with flexible light schedules, the study suggested other strategies to manage excess energy, such as extending battery capacity, utilizing thermal energy storage (TES), and implementing decentralized energy grids. Integrating VFs with local energy infrastructure, such as electric vehicle (EV) charging stations and peer-to-peer energy trading systems, can further enhance energy flexibility and sustainability.

6.1. Addressing the Research Gap

This research addresses a critical gap by developing an energy management strategy that optimizes energy usage in vertical farms within the context of the Dutch energy landscape, characterized by high urban density and significant renewable energy production. Focusing on a specific geographic area with distinct energy challenges provides a better understanding of how vertical farming can contribute to local grid stabilization. The detailed case study of Own Greens in Burgh-Haamstede provides empirical evidence supporting the feasibility and benefits of optimized energy management.

By concentrating on real-life data from PV panels, battery storage, and grid prices, this research bridges the gap between theoretical benefits and practical applications of vertical farming, particularly in energy management. It offers a model for vertical farms to operate within existing energy infrastructure, contributing to both local environmental goals and broader EU climate neutrality targets by 2050. The insights gained, especially regarding flexible lighting schedules and energy management strategies, offer valuable contributions to the field, highlighting the importance of real-time energy management in reducing operational costs and enhancing grid stability.

6.2. Future Research

Future research should refine the MILP model to include data on local congestion hours and additional energy storage and management solutions. Investigating the impact of flexible light schedules on different crops would provide a broader understanding of the model's applicability. Additionally, analyzing multiple years of real PV data would enhance the robustness of the optimization model and the ideal light schedules it generates. The scalability of the proposed energy management strategies to other vertical farming operations and geographic contexts should also be explored. Adding to that, including various crops to validate its generalisability and practical utility is needed. Lastly, the model should be adapted to function in real-time, using day-ahead energy prices and expected solar generation based on weather forecasts. While light schedules may remain similar, real-time adjustments in the energy management system are crucial for optimal battery charging and discharging decisions.

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A
Appendix

A.1. Methodology

A.1.1. Case Study

Figure A.1 shows the current energy situation of Schouwen-Duiveland, the part of Zeeland where the VF is located. There are many different energy producers and users. On the left is Burgh-Haamstede, where the VF is located. It can be seen that wind energy is generated and that there are solar panels and electric vehicles.

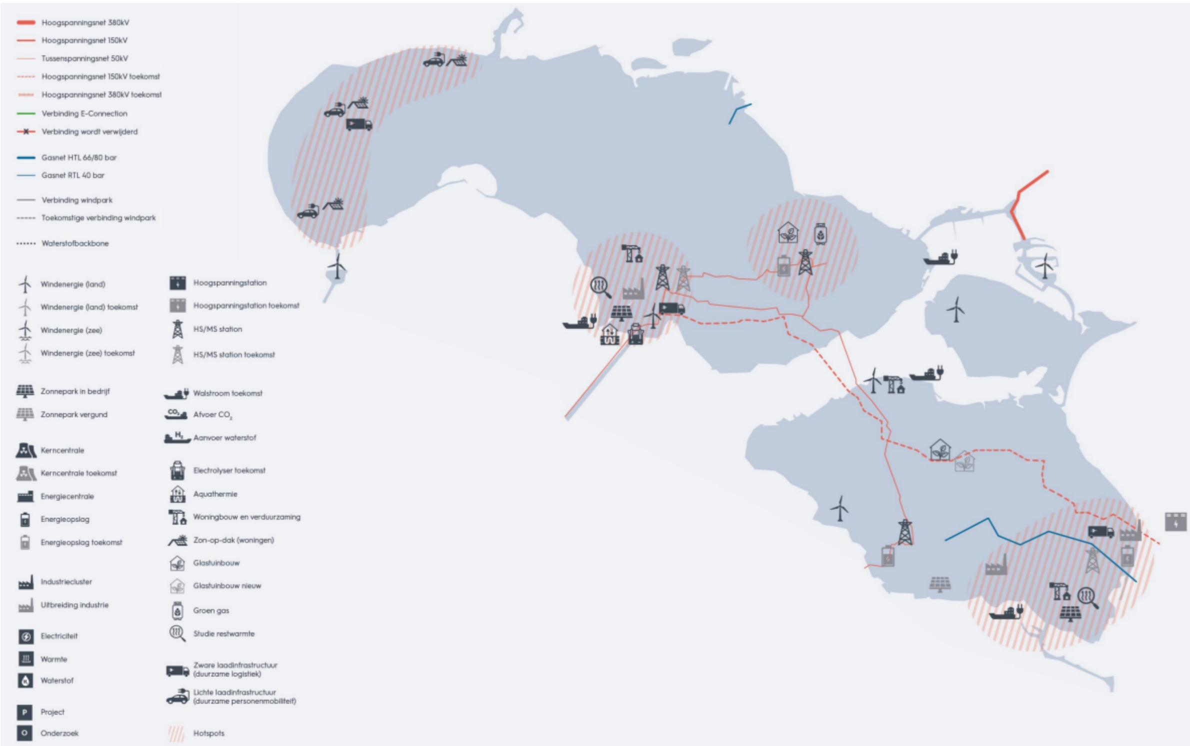

Figure A.1: Congestion Maps for the VF Location [27]

A.1.2. Data Handling

Figure A.2 illustrates the increase in fluctuation of prices over the years.

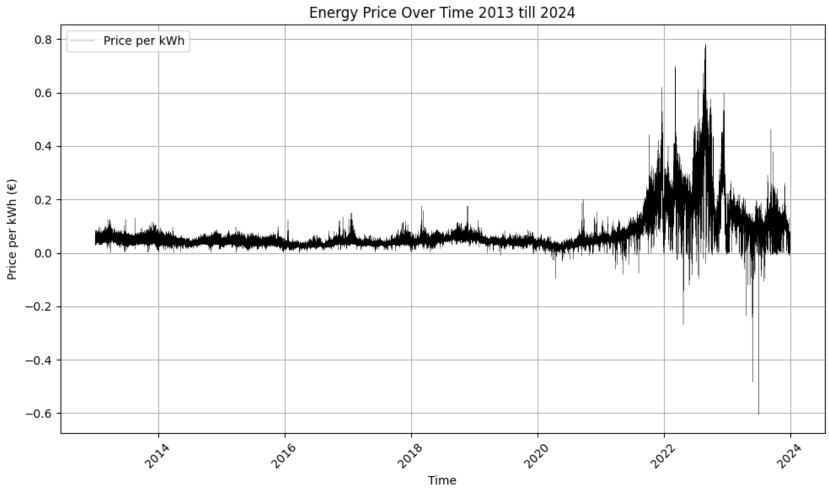

Figure A.2: Energy Prices from 2013 till 2024, data from:[47]

The volatility of the prices is influenced by the increasing influence of solar and wind generation in Europe seen in figure A.3

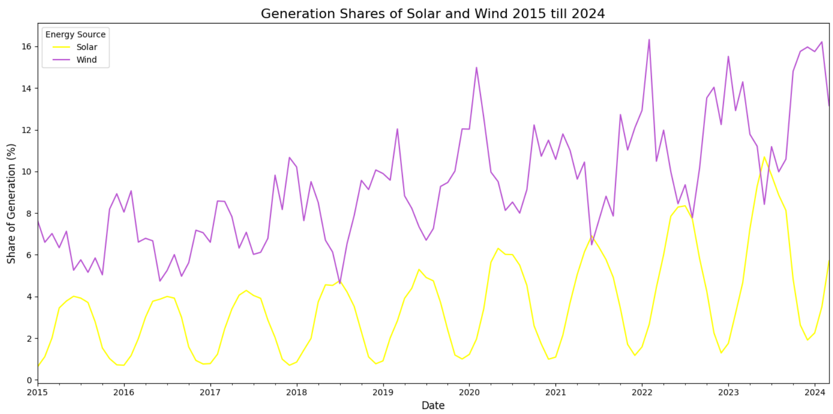

Figure A.3: Solar and Wind Generation Share of Total Energy Generation in Europe, data from:[56]

Furthermore, the difference in energy price over the hours of the day is higher which can be seen in figure A.4, where the price of that hour is compared to the average daily price in percentage to make the years comparable.

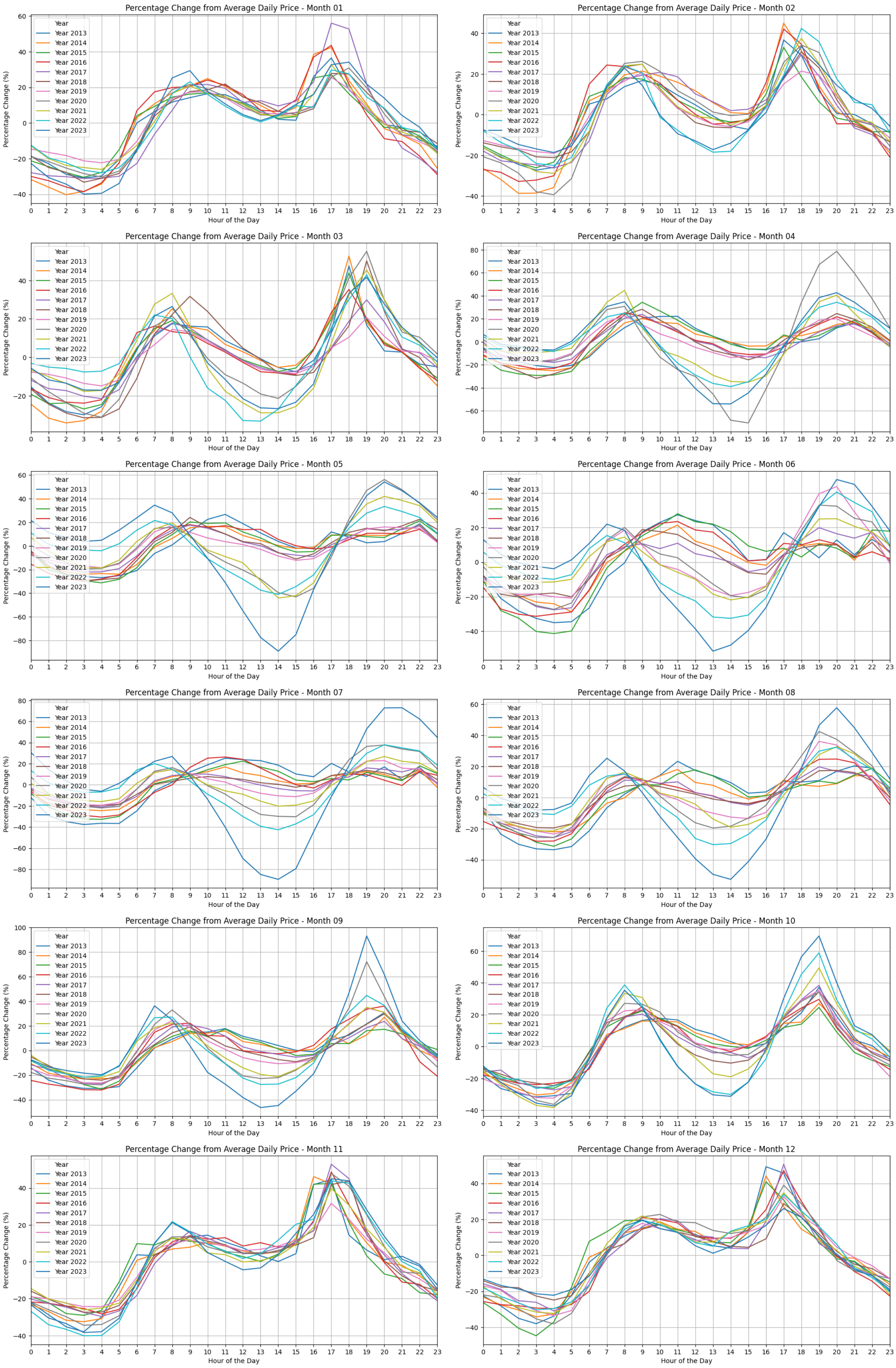

Figure A.4: Percentage Price Change Compared to Average Daily Price, data from:[47]

By counting the hours in which the energy was most often in the cheapest price range figure A.5 could be formed. This gives a first impression about hourly patterns at which VFs could operate. Scenerios that are being tested, lilke 6/6/6/6 and 9/6/3/6 can be seen for some months, highlighting the potential of testing these scenarios.

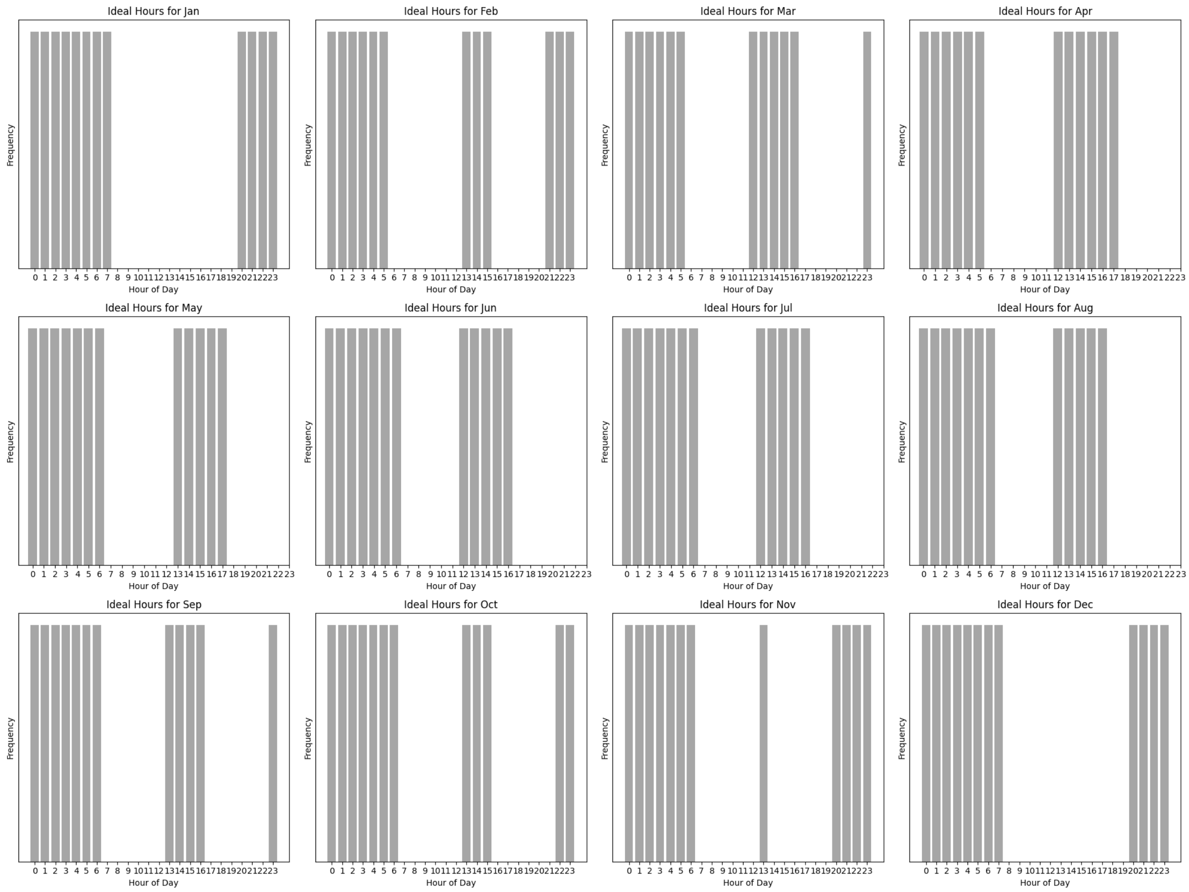

Figure A.5: Cheapest 12 hours per Month 2013 till 2024

Zooming into the year of the analysis, the prices from 15-05-2023 till 15-06-2023 are shown in the boxplot below A.6 and show the volatility of the price again, especially visible in the many outliers, more extreme and more visible in summer months.

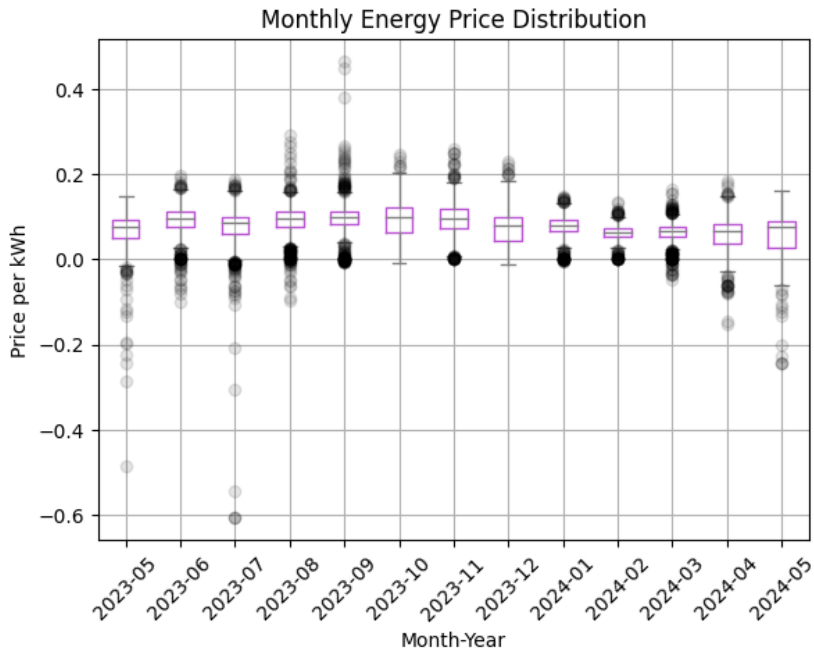

Figure A.6: Boxplot of Energy Prices from 15-05-2023 till 15-05-2024, data from:[47]

This volatility in summer months can be explained by the generation of the PV panels, figure A.7 shows the PV generation of Own Greens for 15-05-2023 till 15-05-2024. Partly this is real data and partly calculated with data from the National Energy Platform [48] for Zeeland. The way it is calculated is with the % of total generation for each hour in the dataset of National Energy Platform [48] and multiplying that by the yearly generation of Own Greens for the months May, June, July, August 2023, as the PV panels were installed in September 2023. In that way, generating an hourly dataset of the PV production of Own Greens.

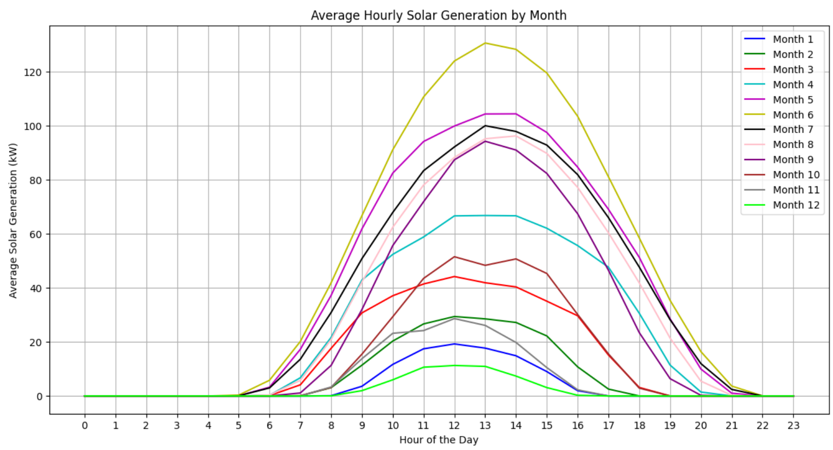

Figure A.7: PV Generation Own Greens 2023-2024

A.1.3. Results Baseline with and without Battery

Figure A.8 shows the absolute baseline scenario without battery for the first week of July.

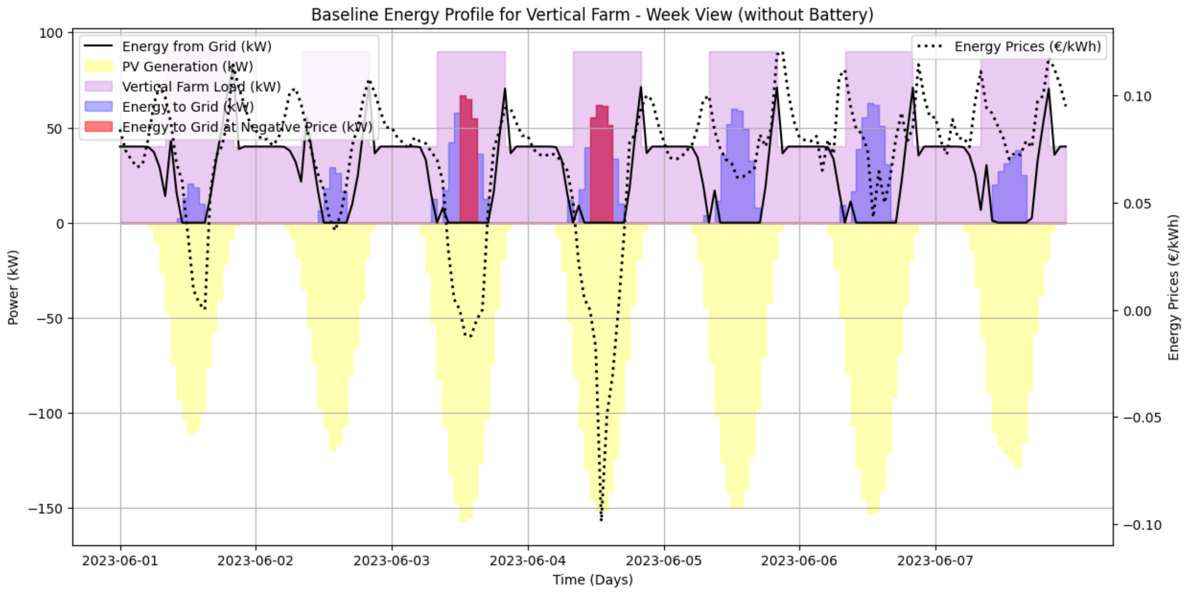

Figure A.8: Baseline Energy Profile for Vertical Farm (without Battery)

Per month the baseline scenario with no battery is visualised in figure A.9, showing the hourly energy profile for each month. Especially in summer months there is a lot of energy fed back to the grid (in blue), furthermore quite a lot of energy is fed back to the grid at negative price hours (red) which could lead to significant congestion issues.

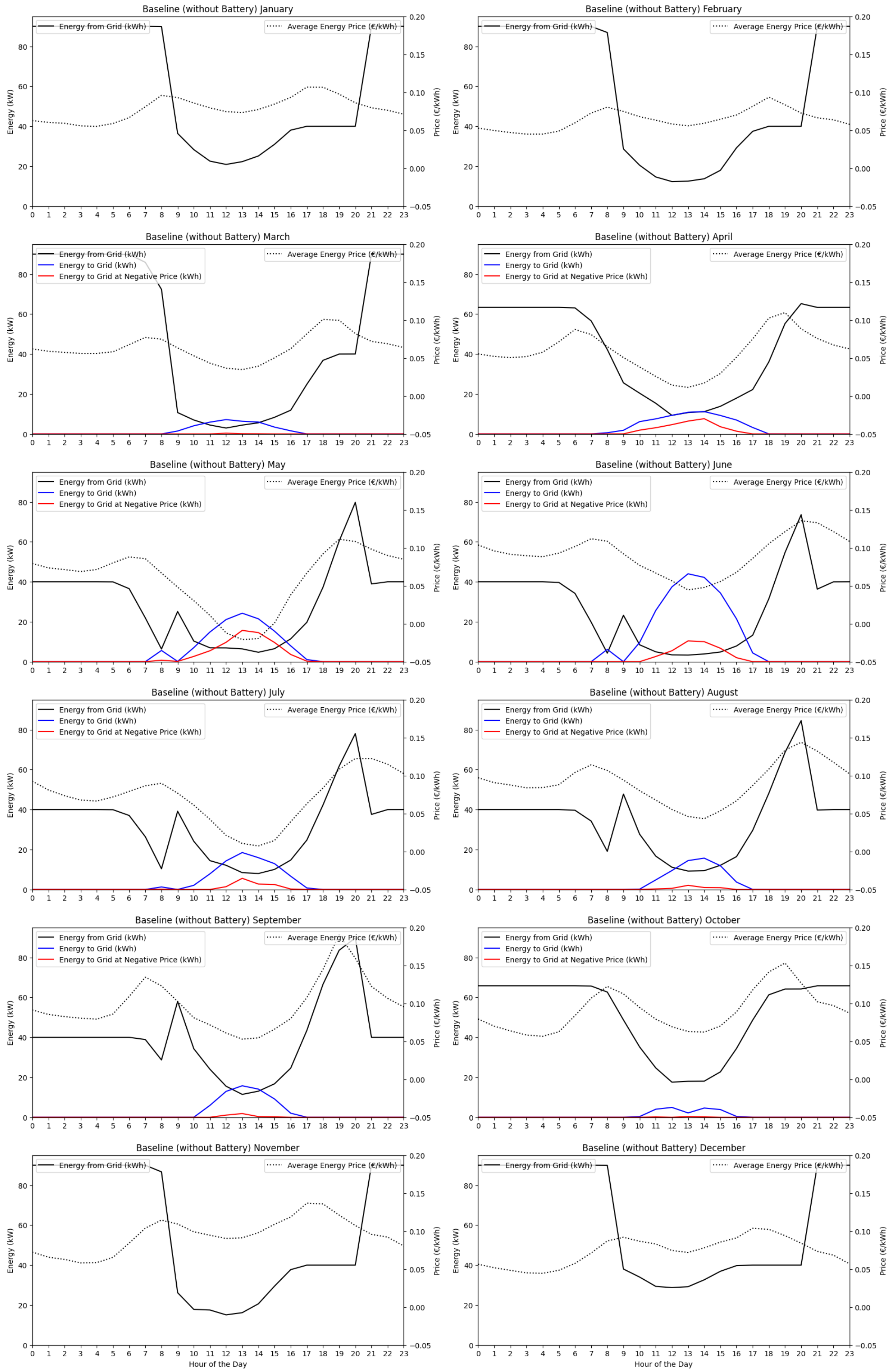

Figure A.9: Hourly Energy Profile per Month for Baseline without Battery

For the baseline scenario with a battery, figure A.10 represents the hourly energy profile per month. A battery significantly improves energy fed back to the grid, and thus also energy fed back to the grid at negative prices.

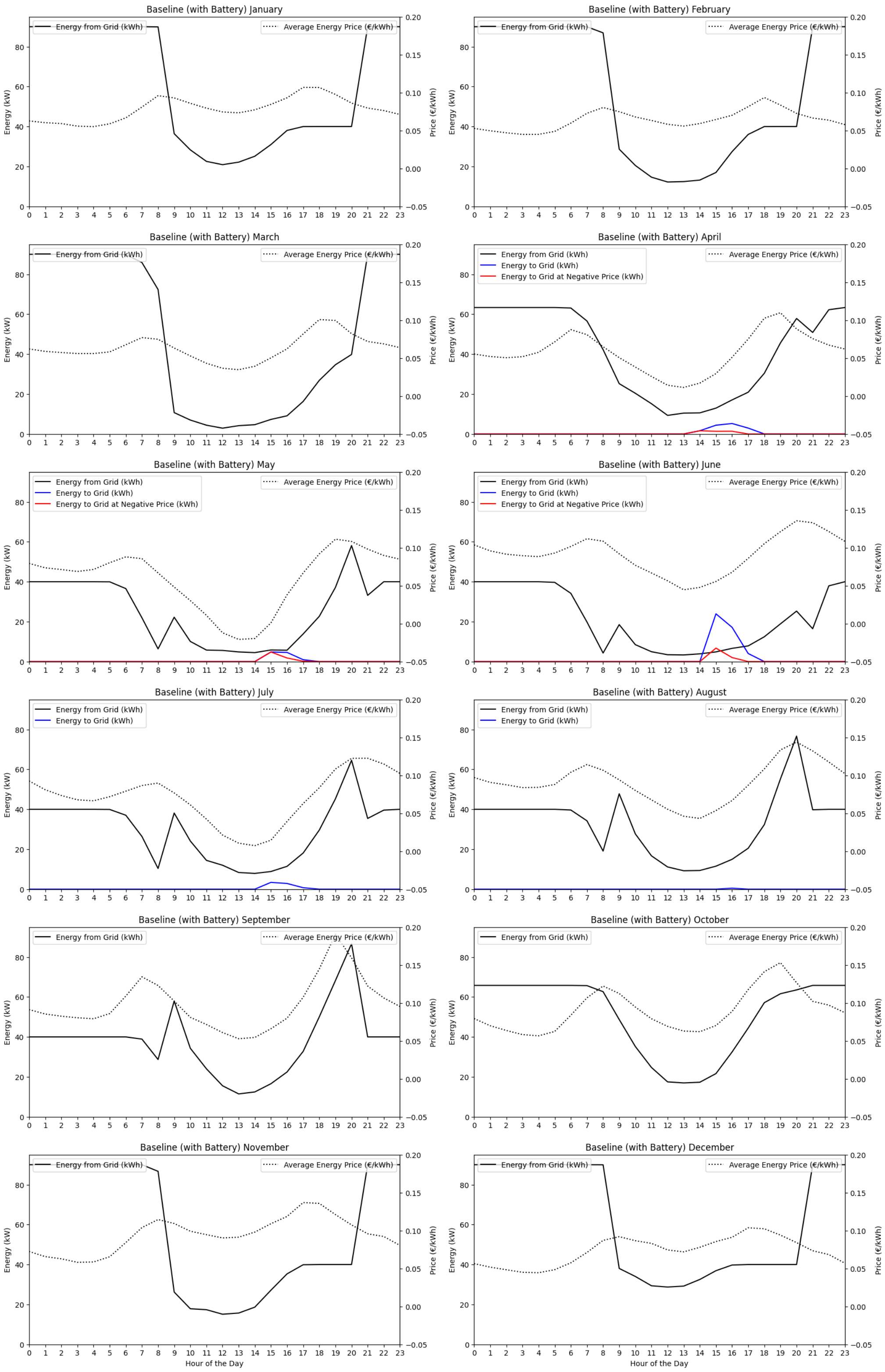

Figure A.10: Hourly Energy Profile per Month for Baseline with Battery

A.2. Results

A.2.1. Comparing Objectives

To compare the monthly energy profiles of the baseline scenarios (A.9, A.10) to the different optimization objectives, the objective results are plotted below to see the effect of each objective on the hourly energy profile per month.

First the energy profile of the first week of June is visualized in figure A.11 , then the monthly profiles for the objective cost minimization in figure A.12.

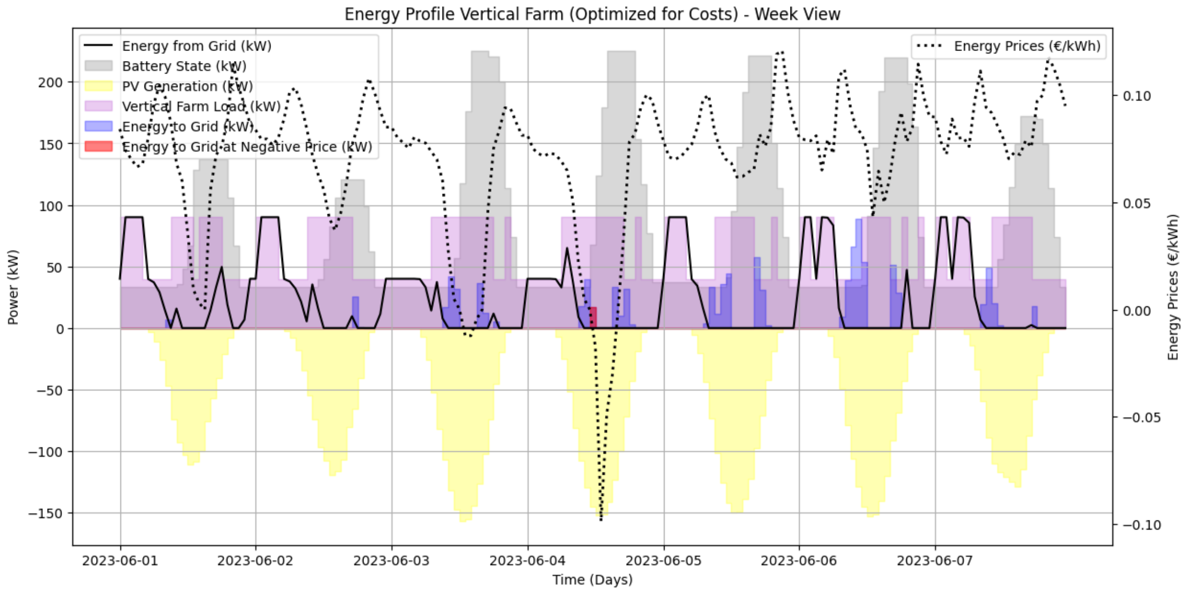

Figure A.11: Hourly Energy Profile per Month for Costs Objective

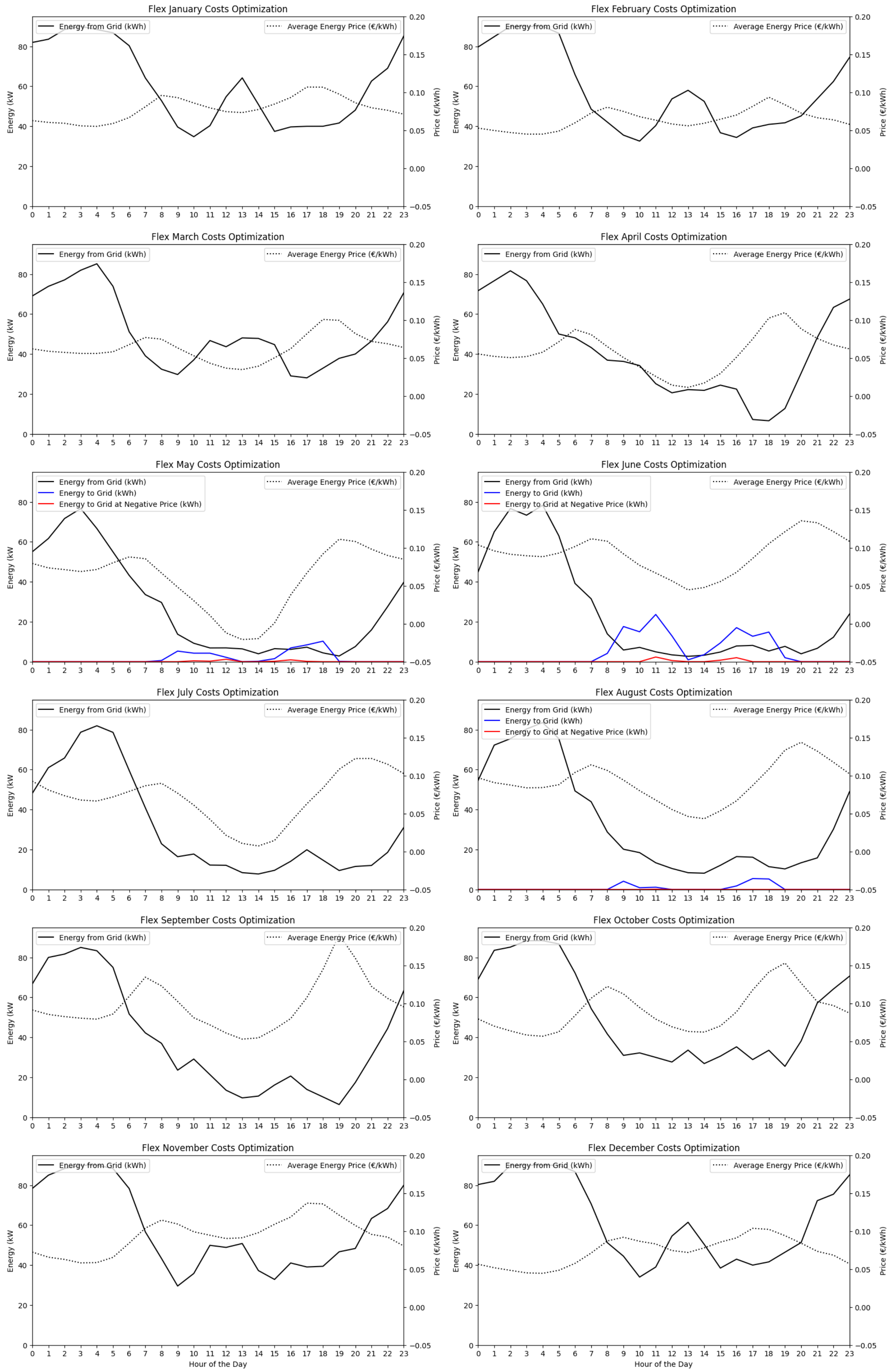

Figure A.12: Hourly Energy Profile per Month for Costs Objective

Then the profiles for the objective grid minimization for one week in figure A.13 and for each month in figure A.14.

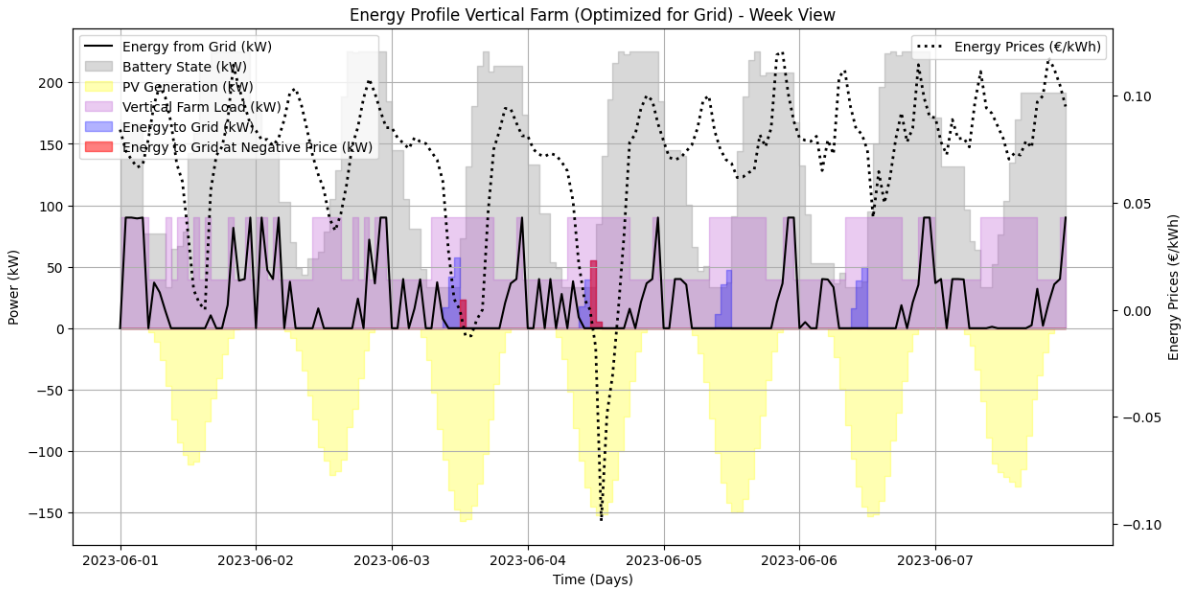

Figure A.13: Hourly Energy Profile per Month for Costs Objective

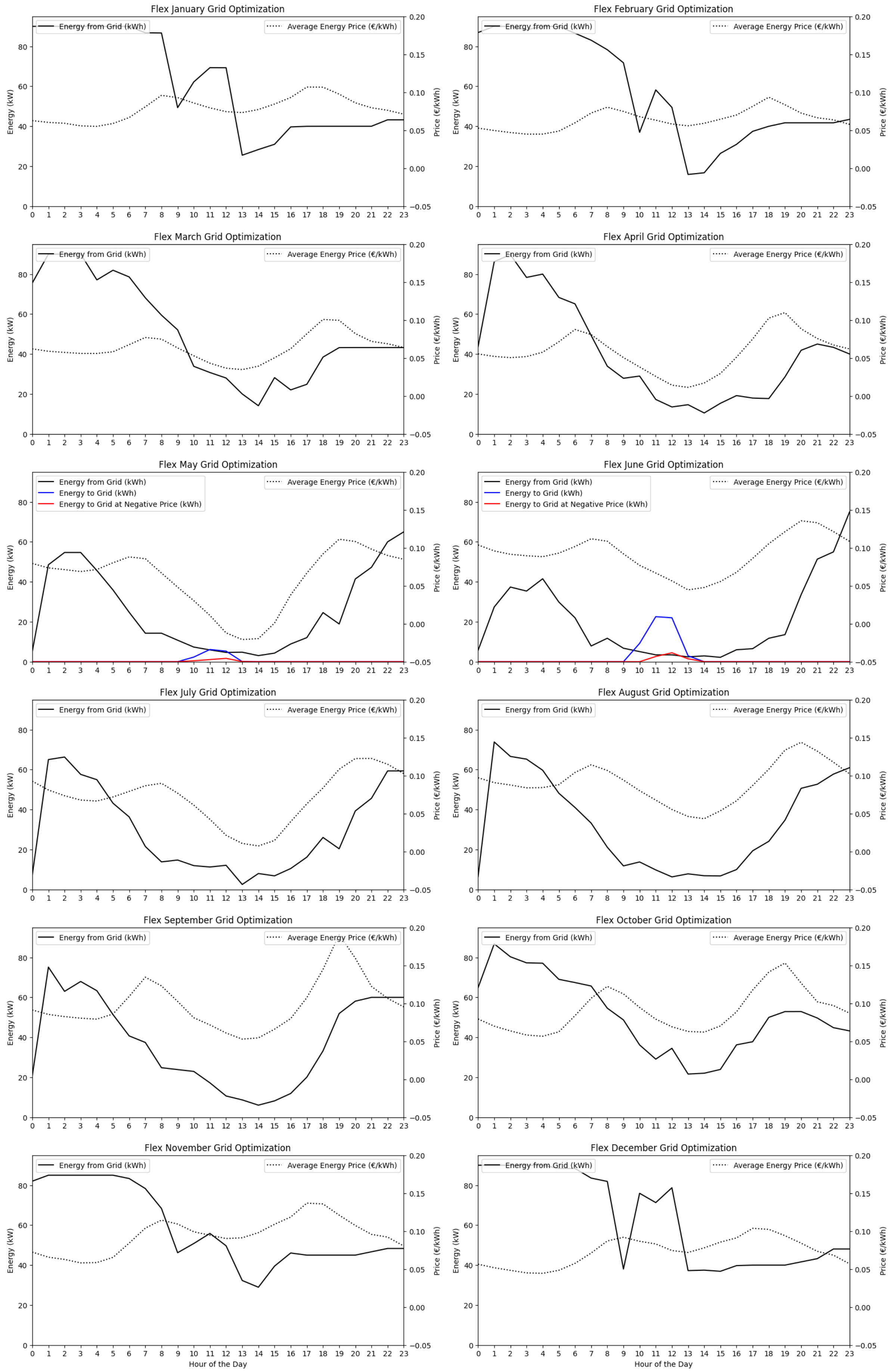

Figure A.14: Hourly Energy Profile per Month for Grid Objective

Lastly, the profiles for the objective grid and costs minimization for one week in figure A.15 and for all months in figure A.16.

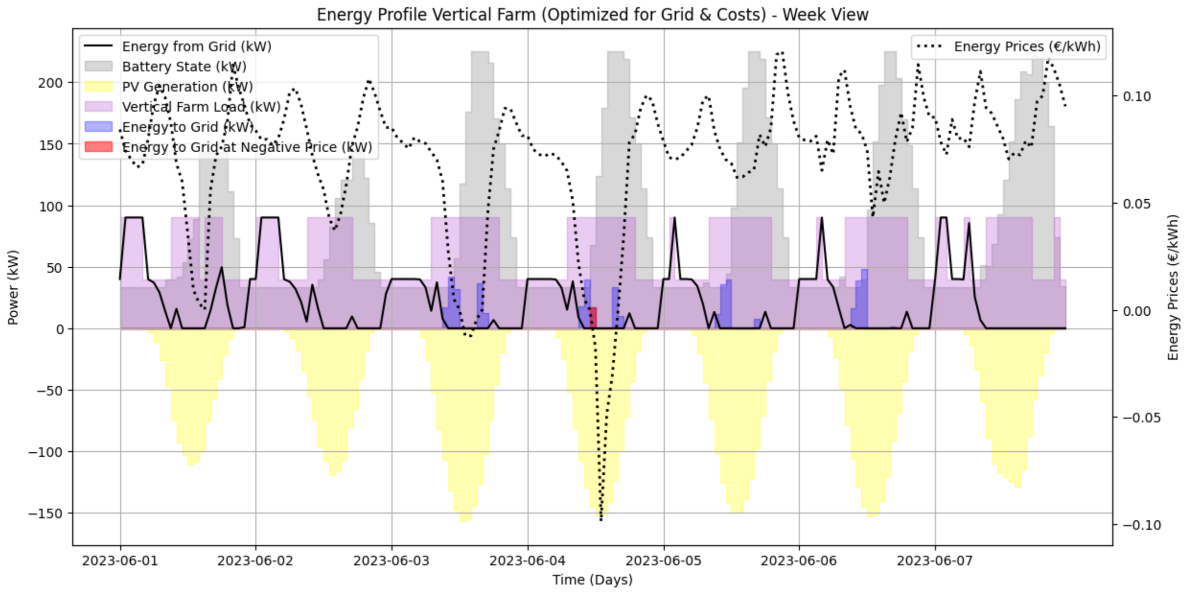

Figure A.15: Hourly Energy Profile per Month for Costs Objective

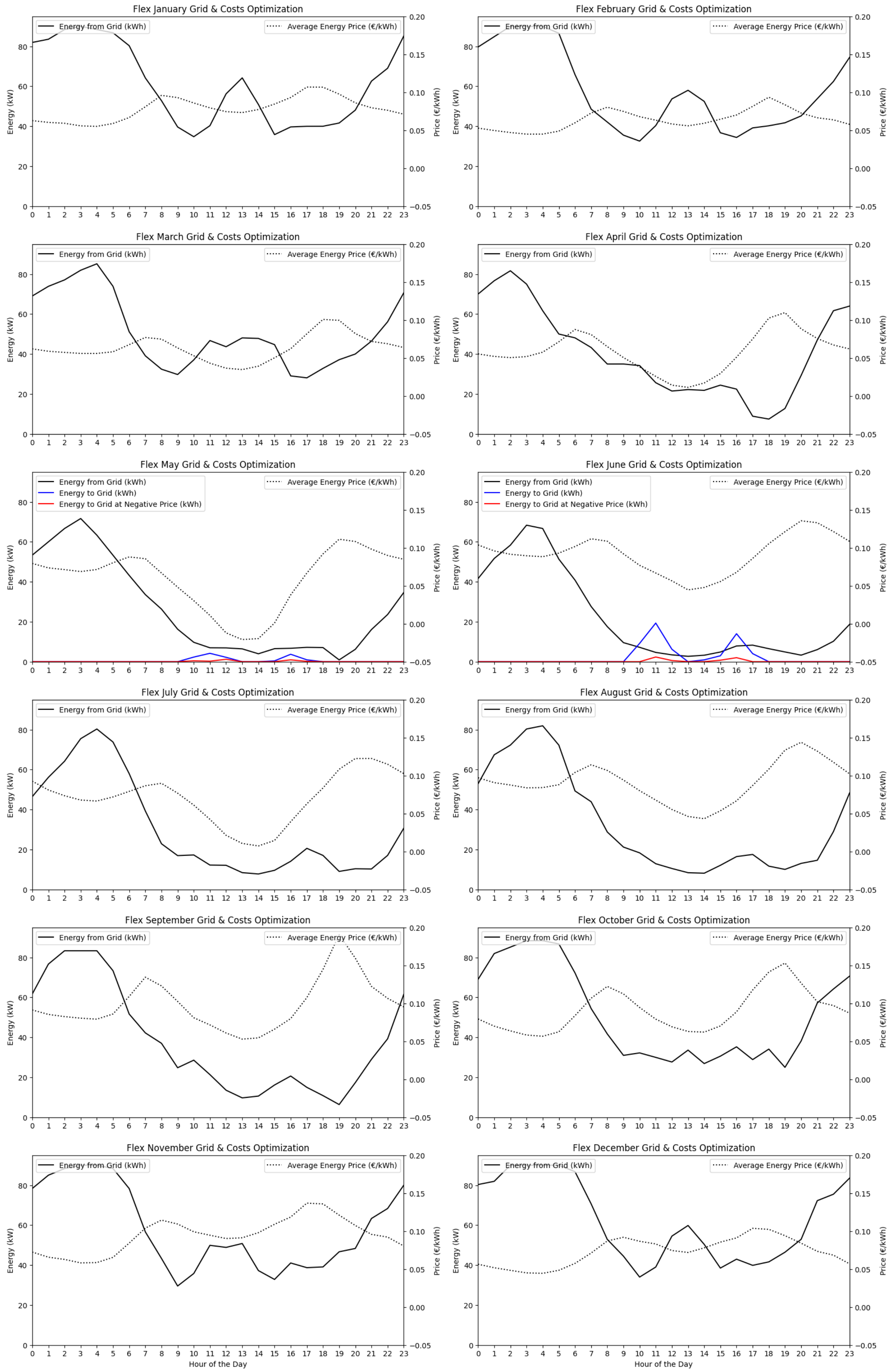

Figure A.16: Hourly Energy Profile per Month for Grid & Costs Objective

After looking at the profiles some things are visible in the graphs, the objective for costs (A.12 sells energy to the grid when prices are positive so exports quite a lot of energy (blue), looking at the energy to grid at negative energy prices (red) it is less than for baseline without battery (A.9) and baseline with battery (A.10) which is a good result.

When minimizing for the grid objective less energy to the grid (blue) is seen in figure A.14 but there is more energy back to the grid at negative hours (red) compared to optimizing for costs A.12, because there is no financial consequence when energy is fed back to the grid at negative hours.

Monthly Costs for Different Optimization Scenarios
Further looking into the costs of each scenario, the optimization for the grid has the highest costs (see Figure A.17). Surprisingly, this is followed by the optimization for costs, while you would expect that this one would have the lowest costs based on the objective of minimizing the costs. The optimization for both grid and costs scores the best. A reason for this could be the costs for sending energy to the grid at negative moments. When this is also minimized, it reduces costs.

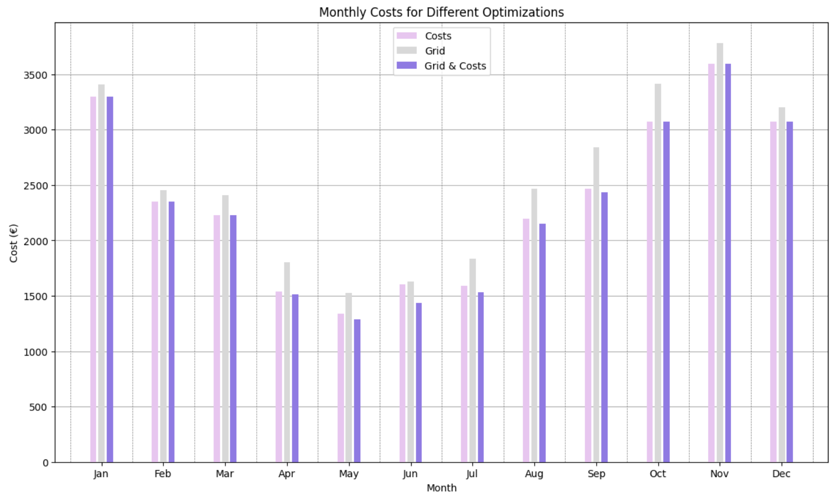

Figure A.17: Monthly Costs for Different Optimizations

Monthly Energy from the Grid for Different Optimization Scenarios
Then the energy used from the grid is assessed, figure A.18 illustrates the monthly energy usage from the grid for different optimization scenarios: costs optimization, grid optimization, and combined grid & costs optimization (see Figure A.18). During the winter months (from November till February), all scenarios show high grid energy usage due to the reduced solar PV generation. The combined grid & costs optimization scenario demonstrates the most balanced usage, indicating efficient management of grid energy.

In the summer months (from June till August), the costs optimization scenario shows higher grid energy usage compared to the other scenarios, suggesting an increased reliance on grid energy. Conversely, the grid optimization and combined optimization scenarios better utilize solar PV generation, thereby reducing grid dependency.

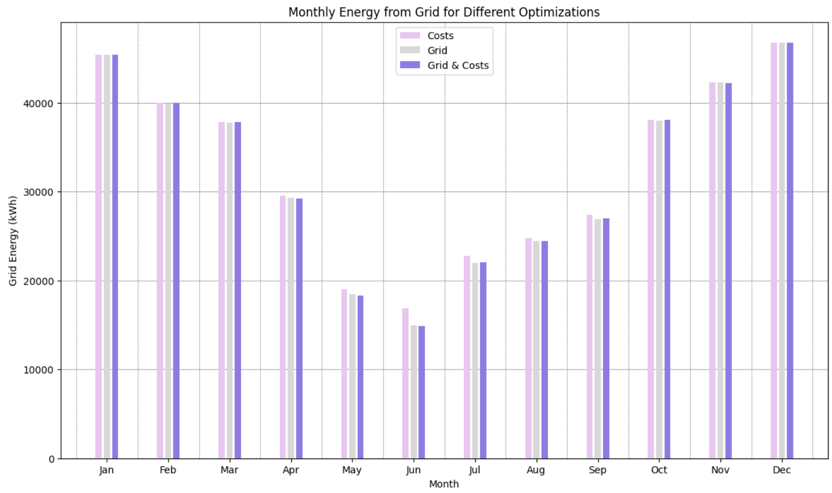

Figure A.18: Monthly Energy from Grid for Different Optimizations

Monthly Energy to the Grid for Different Optimization Scenarios
In the next plot, energy to the grid is compared for the optimizations (see Figure A.19). It shows that costs optimization is way higher than grid and grid & costs. This is expected as the costs optimization strategy focuses on minimizing operational costs, which can involve selling excess energy to the grid when prices are favorable. The primary goal here is financial gain, which results in a higher grid feedback, particularly noticeable in the peak months.

In contrast, the grid optimization scenario shows much lower levels of energy fed back to the grid. This scenario prioritizes minimizing the amount of energy sent back to the grid, ensuring better utilization of own PV energy and reducing the impact on the grid.

The combined grid & costs optimization scenario also demonstrates low levels of energy fed back to the grid, similar to the grid optimization approach. This indicates an effective balance between reducing energy feedback and minimizing costs.

During the summer months, particularly in June, the costs optimization scenario exhibits a significant spike in energy fed back to the grid. This aligns with the period of highest solar energy generation where excess energy is sold back to the grid. The grid and combined optimization scenarios manage this excess more effectively with lower grid feedback.

Overall, the costs optimization scenario, while financially beneficial, leads to higher energy feedback to the grid, potentially exacerbating congestion issues. However, it does select the hours at which it is the most profitable to sell back to the grid, taking into account negative hours and selling when the demand is higher, so the price is higher too.

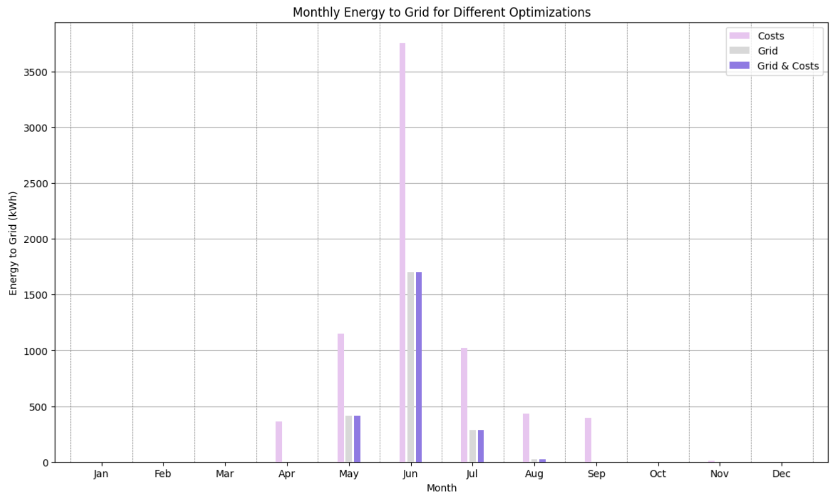

Figure A.19: Monthly Energy to Grid for Different Optimizations

Monthly Energy to the Grid at Negative Prices for Different Optimization Scenarios
The figure illustrates the monthly energy fed back to the grid at negative prices for the different optimization scenarios: costs optimization, grid optimization, and combined grid & costs optimization (see Figure A.20).

Energy feedback to the grid at negative prices is critical due to the congestion issues in the area. The grid optimization scenario scores poorly in this regard as it does not adequately account for negative energy prices, leading to higher amounts of energy being fed back to the grid when prices are negative. This is particularly evident in the peak month of June.

The costs optimization scenario performs slightly better than grid optimization but still shows significant energy feedback at negative prices. This is because the primary focus is on cost savings, which could lead to loading the battery full when the price is low, resulting in not enough space left for the PV generation.

The combined grid & costs optimization scenario performs the best with the lowest levels of energy fed back to the grid at negative prices. This approach effectively balances minimizing costs while managing grid feedback, reducing the impact on the congested grid.

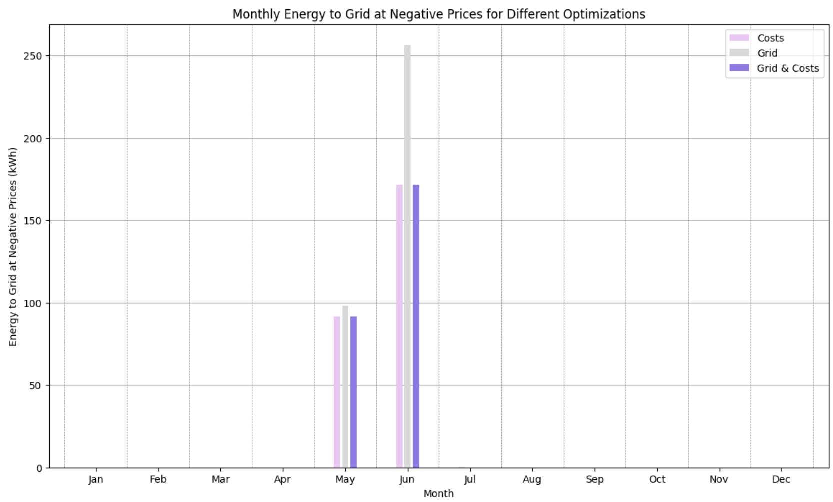

Figure A.20: Monthly Energy to Grid at Negative Price Hours for Different Scenarios

A.2.2. Light Schedules

The 12/12 Light Schedule

As seen in figure A.21, for the 12/12 schedule, there is a clear difference between the calculated start hours and those currently used in the real-life operation of the VF. By aligning the light schedules with periods of high solar PV availability and low energy costs, the VF can reduce its reliance on grid energy, mitigate congestion issues, and optimize operational costs.

In the winter months, the optimal 12-hour light periods are primarily during nighttime, aligning with lower grid energy costs and reduced solar PV availability. Conversely, in the summer months, the light periods shift to daytime hours to take full advantage of solar PV generation.

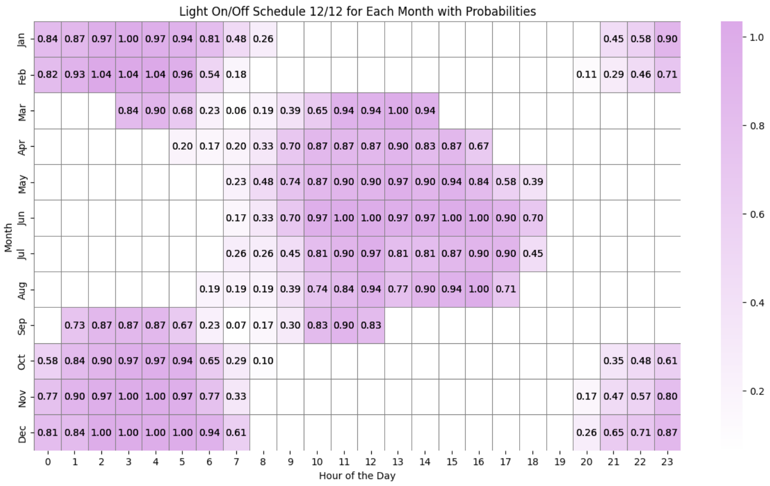

Figure A.21: Ideal Hours for 12/12 Based on Probabilities

The 6/6/6/6 Light Schedule

Figure A.22 below shows the 6/6/6/6 light schedule, alternating six-hour periods of light and darkness. Start hours are determined by the total added up probabilities and visualized by creating a mask over the original probabilities plot.

This schedule is more consistent across months compared to the 12/12 schedule (A.21). During winter, lights are on mainly at night and early morning, aligning with lower grid energy costs and reduced solar PV availability. In summer, lights are scheduled during the day to maximize solar PV generation, reducing reliance on grid energy and mitigating grid congestion. From the eye, it looks like this scenario cuts off ideal hours in some months. It is probably not the most favorable scenario for all months.

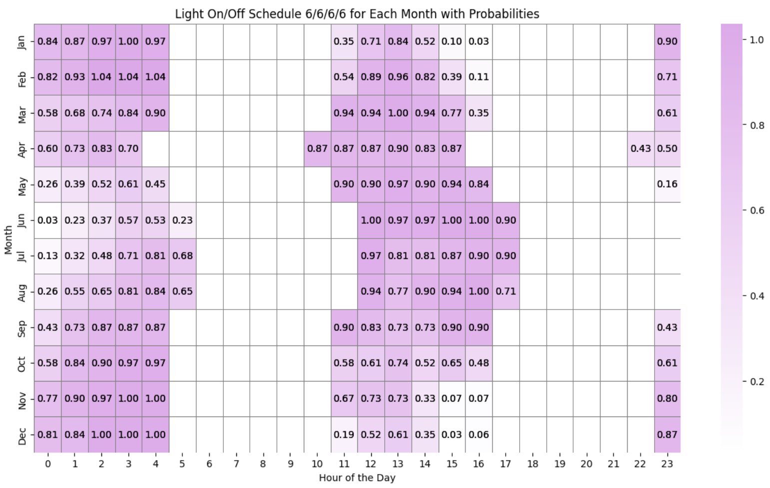

Figure A.22: Ideal Hours for 6/6/6/6 Based on Probabilities

The 9/6/3/6 Light Schedule

Figure A.23 shows the 9/6/3/6 light schedule, again the total probabilities were calculated to find the best start hours. Again, a mask is created over the original probabilities plot. The schedule closely resembles the original probability distribution, suggesting that this light schedule might be the most effective. The similarity indicates that this schedule aligns well with the periods of high solar PV generation and low energy costs, optimizing energy use and cost efficiency.

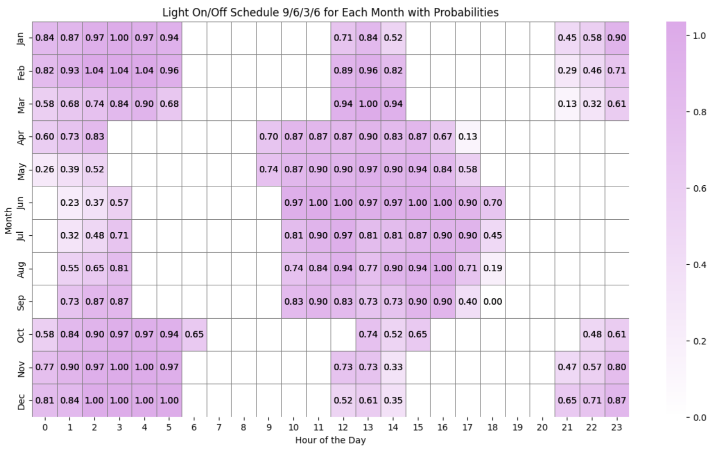

Figure A.23: Ideal Hours for 9/6/3/6 Based on Probabilities

During the winter months, the lights are primarily on at night and early morning, similar to the 6/6/6/6 schedule, to take advantage of lower grid energy costs. In the summer months, the light periods shift to daylight hours, maximizing the use of solar PV generation and minimizing reliance on the grid.

A.2.3. Results Fixed Light Schedules with and without Energy Management

Figure A.24 shows the results of the model for the fixed light schedule without energy management for the first week of July. Figure A.25 shows the average hourly results per month.

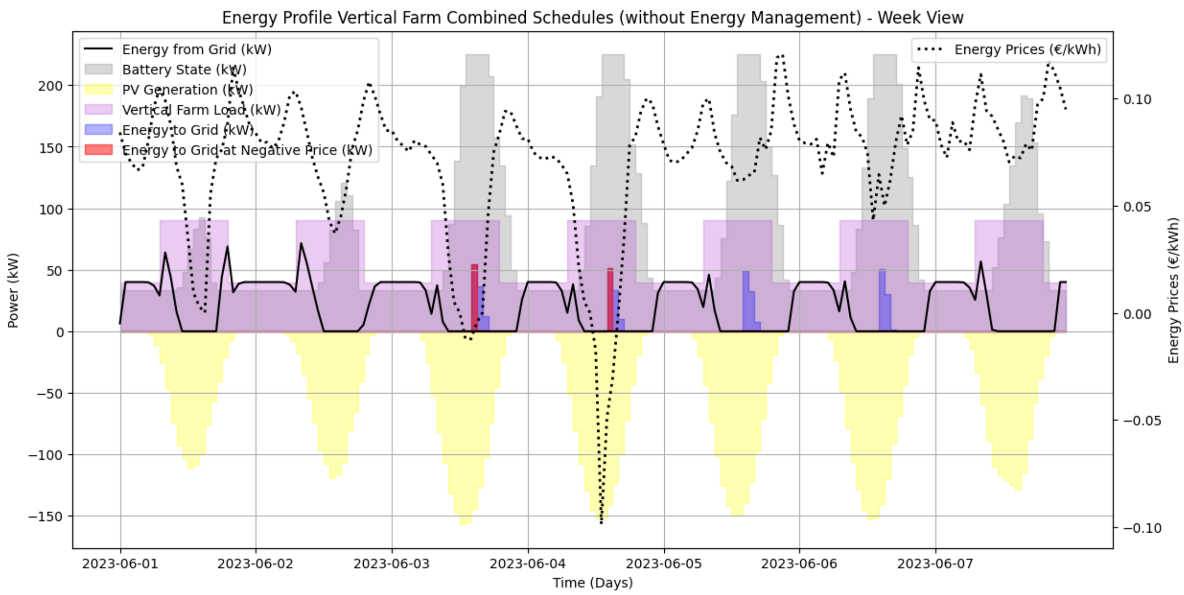

Figure A.24: Results Fixed Light Schedule without Energy Management

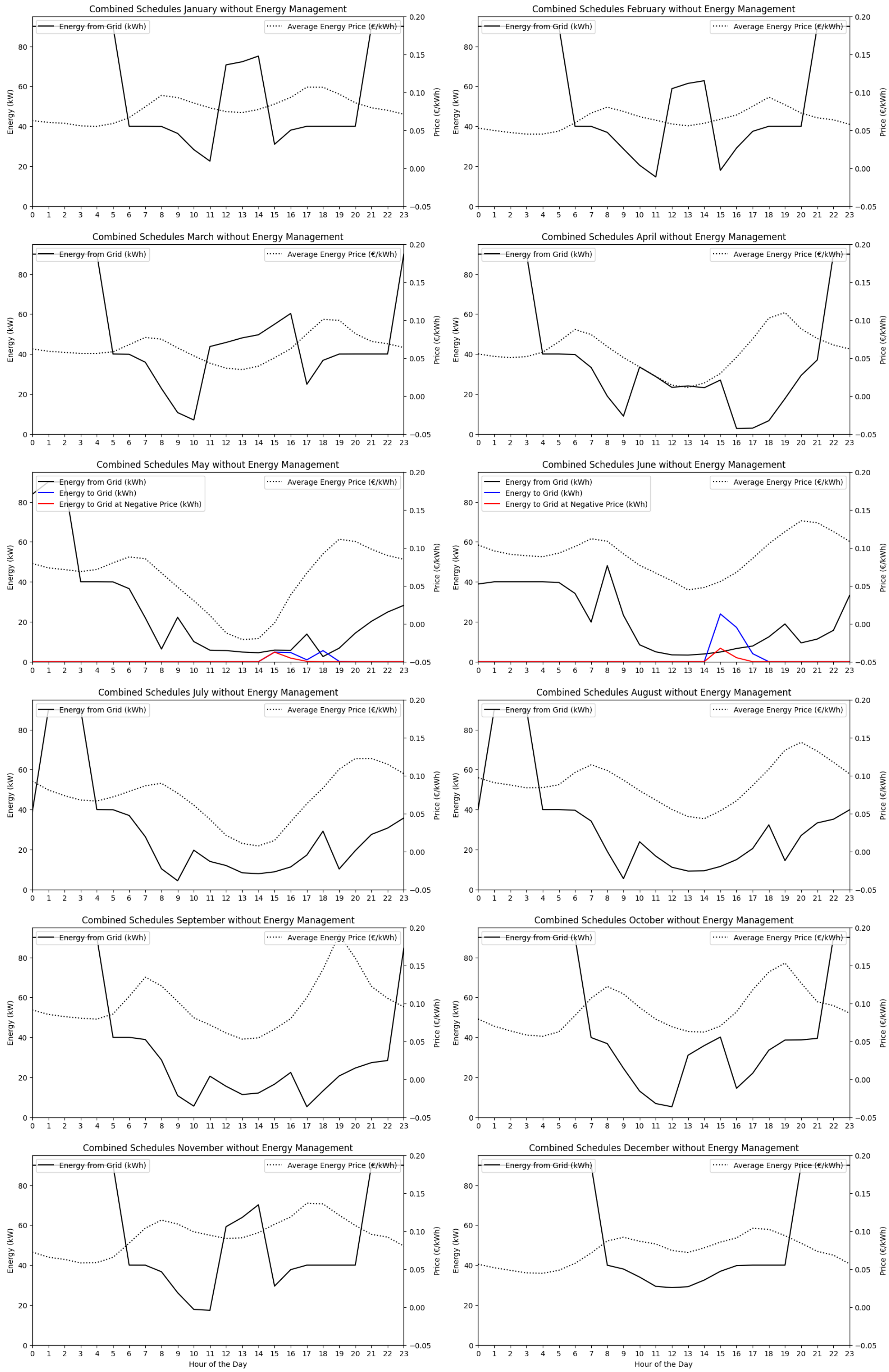

Figure A.25: Results Fixed Light Schedule without Energy Management

Figure A.26 shows the results of the model for the fixed light schedule without energy management for the first week of July. Figure A.27 shows the average hourly results per month.

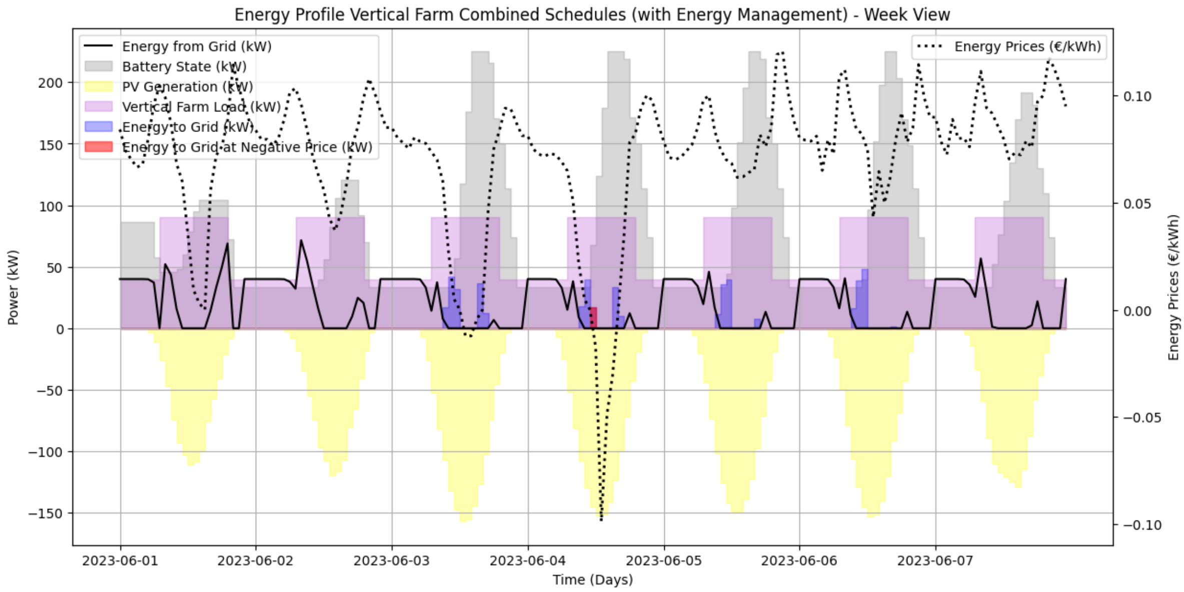

Figure A.26: Results Fixed Light Schedule with Energy Management

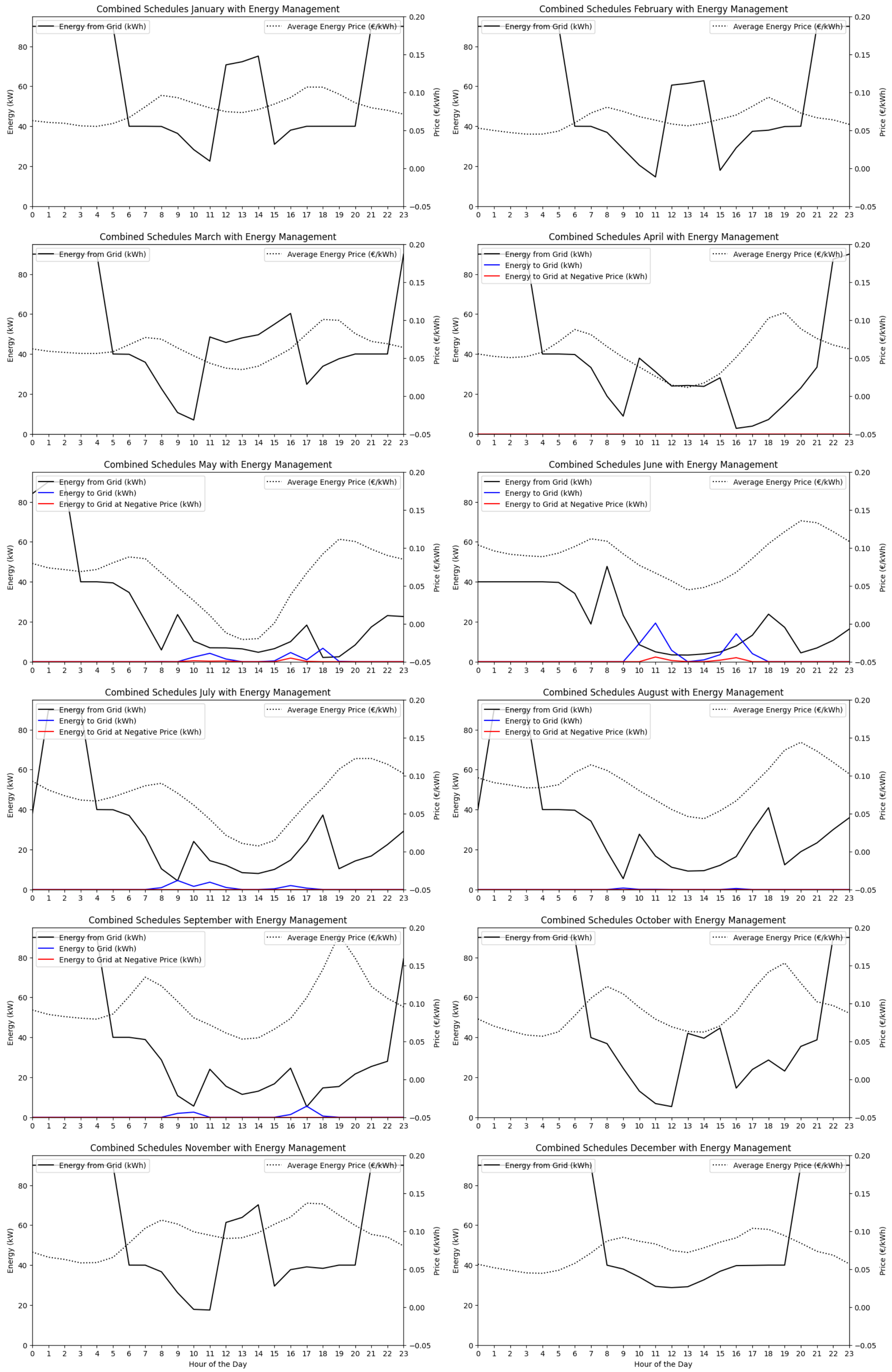

Figure A.27: Results Fixed Light Schedule with Energy Management

A.2.4. Summarized Results

Table A.1 below shows the results for all the scenarios in numbers.

Scenario	Energy to Grid (kWh)	Energy to Grid Negative Prices (kWh)	Costs (€)	Energy from Grid (kWh)
Baseline without Battery	20692.42	4536.36	32710.91	401878.64
Baseline with Battery	2321.60	595.49	31127.37	387495.21
Combined Schedules (no Energy Management)	2449.61	465.64	29547.59	387830.20
Combined Schedules (Energy Management)	3179.94	262.70	29083.88	386190.00
Grid & Costs Optimization	2420.73	262.70	27957.95	386225.19

Table A.1: Comparison of all Scenarios

B
Source Code

B.1. Code for Optimization with Gurobi

Below is the Python code for the optimization with costs and grid objectives, with the weekly results output, the probabilities output and the hourly results per month. Optimizing for only costs of grid would only alter the code for one line so these are excluded from the source code. Comments are included in the code to provide clarity about the steps taken.

```python

#!pip install gurobipy

import pandas as pd
import gurobipy as gp
from gurobipy import GRB
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from matplotlib.colors import ListedColormap

# Define the charging and discharging efficiencies
charging_efficiency = 0.9
discharging_efficiency = 0.9

# Optimization model function
def optimize_energy_usage(energy_prices, solar_data, battery_capacity, charge_power, discharge_power, base_load_fixed, initial_battery_state):
    model = gp.Model("Optimized_Energy_Management_Grid_Costs")
    model.setParam('OutputFlag', 0)  # Set OutputFlag to 1 to get solver output for debugging

    # Define decision variables for the 24 hours
    vars = {
        'battery_charge': model.addVars(24, vtype=GRB.CONTINUOUS, lb=0, ub=charge_power, name="BatteryCharge"),
        'battery_discharge': model.addVars(24, vtype=GRB.CONTINUOUS, lb=0, ub=discharge_power, name="BatteryDischarge"),
        'battery_state': model.addVars(25, lb=0, ub=battery_capacity, name="BatteryState"),
        'grid_energy': model.addVars(24, vtype=GRB.CONTINUOUS, lb=0, name="GridEnergy"),
        'energy_to_grid': model.addVars(24, vtype=GRB.CONTINUOUS, lb=0, name="EnergyToGrid"),
        'light_on': model.addVars(24, vtype=GRB.BINARY, name="LightOn"),
        'pv_used_for_load': model.addVars(24, vtype=GRB.CONTINUOUS, lb=0, name="PVUsedForLoad"),
        'surplus_pv': model.addVars(24, vtype=GRB.CONTINUOUS, lb=0, name="SurplusPV"),
        'demand': model.addVars(24, vtype=GRB.CONTINUOUS, name="Demand"),
        'negative_price_energy_to_grid': model.addVars(24, vtype=GRB.CONTINUOUS, lb=0, name="NegativePriceEnergyToGrid"),
    }

    # Set initial battery state
    model.addConstr(vars['battery_state'][0] == initial_battery_state, "InitialBatteryState")

```

```
    # Constraint for minimum 12 hours of lights on
    model.addConstr(vars['light_on'].sum() == 12, "MinLightHours")

    # Constraint for minimum battery state
    min_battery_state = 0.15 * battery_capacity  # 15% of battery capacity

    for i in range(24):
        # Load and demand constraints
        model.addConstr(vars['demand'][i] == base_load_fixed + vars['light_on'][i] * 50, "Demand_%d" % i)
        model.addGenConstrMin(vars['pv_used_for_load'][i], [solar_data[i], vars['demand'][i]], name="MinPVUsage_%d" % i)
        model.addConstr(vars['surplus_pv'][i] == solar_data[i] - vars['pv_used_for_load'][i], "SurplusPV_%d" % i)

        # Ensure surplus PV energy is handled: either stored in battery or sent to grid
        model.addConstr(vars['surplus_pv'][i] == vars['battery_charge'][i] + vars['energy_to_grid'][i], "HandleSurplusPV_%d" % i)

        # Battery state transitions with efficiency
        model.addConstr(vars['battery_state'][i + 1] == vars['battery_state'][i] + charging_efficiency * vars['battery_charge'][i] - vars['battery_discharge'][i] * discharging_efficiency, "BatteryState_%d" % i)

        model.addConstr(vars['battery_charge'][i] <= charge_power, "BatteryChargeLimit_%d" % i)
        model.addConstr(vars['battery_discharge'][i] <= discharge_power, "BatteryDischargeLimit_%d" % i)
        model.addConstr(vars['battery_discharge'][i] <= vars['battery_state'][i], "BatteryDischargeLimit2_%d" % i)

        # Grid and additional energy sources
        model.addConstr(vars['grid_energy'][i] + discharging_efficiency * vars['battery_discharge'][i] + vars['pv_used_for_load'][i] == vars['demand'][i], "TotalEnergyAvailability_%d" % i)

        # Ensure battery state does not fall below the minimum
        model.addConstr(vars['battery_state'][i + 1] >= min_battery_state, "MinBatteryState_%d" % i)

        # Ensure surplus PV is never negative
        model.addConstr(vars['energy_to_grid'][i] >= 0, "NonNegativeEnergyToGrid_%d" % i)

        # Track when energy price is negative and energy is fed back to grid
        model.addConstr(vars['negative_price_energy_to_grid'][i] == vars['energy_to_grid'][i] * (energy_prices[i] < 0), "NegativePriceEnergyToGrid_%d" % i)

    # Define primary objective to minimize energy fed to grid
    primary_objective = gp.quicksum(vars['energy_to_grid'][i] for i in range(24))

    # Define secondary objective to minimize cost
    secondary_objective = gp.quicksum(energy_prices[i] * vars['grid_energy'][i] - energy_prices[i] * vars['energy_to_grid'][i] for i in range(24))

    # Set the multi-objective
    model.ModelSense = GRB.MINIMIZE
    model.setObjectiveN(primary_objective, index=0, priority=1, name="MinimizeEnergyToGrid")
    model.setObjectiveN(secondary_objective, index=1, priority=0, name="MinimizeCost")

    model.optimize()

    if model.status == GRB.OPTIMAL:
        return {var_name: [var.X for var in var_dict.values()] for var_name, var_dict in vars.items()}
    else:
        print("Optimization was stopped or is infeasible with status:", model.status)
        return None

# Function to simulate an entire year with summarized output
def simulate_year(energy_prices_df, solar_data_df, battery_capacity, charge_power, discharge_power, base_load_fixed):
```

```python
    results_year = []
    initial_battery_state = 0.15 * battery_capacity  # Start with the battery at 15% capacity

    for day in range(365):  # Loop for 365 days
        date = pd.to_datetime(energy_prices_df.iloc[day * 24]['datetime'])
        daily_energy_prices = energy_prices_df.loc[day * 24:(day + 1) * 24 - 1, 'price_kwh'].tolist()
        daily_solar_data = solar_data_df.loc[day * 24:(day + 1) * 24 - 1, 'generation_pv'].tolist()

        # Check if data for the day is complete
        if len(daily_energy_prices) != 24 or len(daily_solar_data) != 24:
            print(f"Data missing for {date}: {len(daily_energy_prices)} prices, {len(daily_solar_data)} solar data points found")
            continue

        results = optimize_energy_usage(daily_energy_prices, daily_solar_data, battery_capacity, charge_power, discharge_power, base_load_fixed, initial_battery_state)
        if results:
            results_year.append(results)
            initial_battery_state = results['battery_state'][-1]

    return results_year

# Function to calculate hourly light-on probabilities per month
def calculate_hourly_light_probabilities(results_year):
    # Create array to hold counts of light being on for each hour of each month
    hourly_light_counts = np.zeros((12, 24))

    # Iterate over the results and populate the counts
    for day_index, daily_results in enumerate(results_year):
        date = pd.to_datetime(energy_prices_df.iloc[day_index * 24]['datetime'])
        month = date.month - 1  # Convert to 0-based index

        for hour in range(24):
            if daily_results['light_on'][hour] > 0.5:  # Light is on (binary variable)
                hourly_light_counts[month, hour] += 1

    # Convert counts to probabilities
    days_per_month = [31, 28, 31, 30, 31, 30, 31, 31, 30, 31, 30, 31]
    hourly_light_probabilities = hourly_light_counts / np.array(days_per_month)[:, None]

    return hourly_light_probabilities

# Function to plot the hourly light-on probabilities
def plot_hourly_light_probabilities(hourly_light_probabilities):
    # Create custom colormap with varying alpha values
    colors = [(186/255, 85/255, 211/255, alpha) for alpha in np.linspace(0, 0.5, 256)]
    custom_cmap = ListedColormap(colors)

    plt.figure(figsize=(14, 8))
    sns.heatmap(hourly_light_probabilities, annot=True, fmt=".2f", cmap=custom_cmap, cbar=True,
                xticklabels=[f'{hour}:00' for hour in range(24)],
                yticklabels=['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'],
                linewidths=.5, linecolor='gray', annot_kws={"color": "black"})  # Set text color to black
    plt.xlabel('Hour of the Day')
    plt.ylabel('Month')
    plt.title('Hourly Probability of Light Being On per Month (Optimized for Grid & Costs)')
    plt.show()

# Function to plot aggregated weekly results
def plot_aggregated_weekly_results(results_week, energy_prices_df, solar_data_df, start_date):
    fig, ax1 = plt.subplots(figsize=(14, 7))
    ax2 = ax1.twinx()

    # Initialize lists to hold data
```

```
    grid_energy_week = []
    battery_state_week = []
    solar_generation_week = []
    building_load_week = []
    energy_prices_week = []
    excess_pv_to_grid_week = []
    negative_price_energy_to_grid_week = []

    # Process each day's results
    for i, daily_results in enumerate(results_week):
        date = start_date + pd.Timedelta(days=i)
        daily_solar_data = solar_data_df.loc[solar_data_df['datetime'].dt.date == date.date(), 'generation_pv'].tolist()
        daily_energy_prices = energy_prices_df.loc[energy_prices_df['datetime'].dt.date == date.date(), 'price_kwh'].tolist()

        if len(daily_solar_data) == 24 and len(daily_energy_prices) == 24:
            grid_energy_week.extend(daily_results['grid_energy'])
            battery_state_week.extend(daily_results['battery_state'][1:])  # Skip the first value to maintain sequence length
            solar_generation_week.extend([-val for val in daily_solar_data])  # Make solar generation negative for visual distinction
            building_load_week.extend(daily_results['demand'])
            energy_prices_week.extend(daily_energy_prices)
            excess_pv_to_grid_week.extend(daily_results['energy_to_grid'])
            negative_price_energy_to_grid_week.extend(daily_results['negative_price_energy_to_grid'])

    # Time axis in hours across the week
    hours = np.arange(24 * 7)

    # Plotting variables
    ax1.plot(hours, grid_energy_week, label='Energy from Grid (kW)', color='black')

    ax1.fill_between(hours, 0, battery_state_week, color='grey', step='pre', alpha=0.3, label='Battery State (kW)')
    ax1.fill_between(hours, 0, solar_generation_week, color='yellow', step='pre', alpha=0.3, label='PV Generation (kW)')
    ax1.fill_between(hours, 0, building_load_week, color='mediumorchid', step='pre', alpha=0.3, label='Vertical Farm Load (kW)')
    ax1.fill_between(hours, 0, excess_pv_to_grid_week, color='blue', step='pre', alpha=0.3, label='Energy to Grid (kW)')
    ax1.fill_between(hours, 0, negative_price_energy_to_grid_week, color='red', step='pre', alpha=0.5, label='Energy to Grid at Negative Price (kW)')

    ax1.set_xlabel('Time (Days)')
    ax1.set_ylabel('Power (kW)')
    ax1.set_xticks(np.arange(0, 24*7, 24))  # Set x-ticks to be every 24 hours
    ax1.set_xticklabels([(start_date + pd.Timedelta(days=i)).strftime('%Y-%m-%d') for i in range(7)])
    ax1.legend(loc='upper left')
    ax1.grid(True)

    # Plot energy prices on a second y-axis
    ax2.plot(hours, energy_prices_week, 'k:', label='Energy Prices €(/kWh)', linewidth=2)
    ax2.set_ylabel('Energy Prices €(/kWh)')
    ax2.legend(loc='upper right')

    plt.title('Energy Profile Vertical Farm (Optimized for Grid & Costs) - Week View')
    plt.show()

# Function to calculate monthly costs and energy sent to grid
def calculate_monthly_metrics(results_year, energy_prices_df):
    monthly_costs = np.zeros(12)
    monthly_energy_to_grid = np.zeros(12)
    monthly_grid_energy = np.zeros(12)
    monthly_negative_price_energy_to_grid = np.zeros(12)

    for day_index, daily_results in enumerate(results_year):
        date = pd.to_datetime(energy_prices_df.iloc[day_index * 24]['datetime'])
        month = date.month - 1  # Convert to 0-based index
```

```python

        daily_costs = sum(energy_prices_df.iloc[day_index * 24 + hour]['price_kwh'] * daily_results['grid_energy'][hour] for hour in range(24))
        daily_energy_to_grid = sum(daily_results['energy_to_grid'][hour] for hour in range(24))
        daily_grid_energy = sum(daily_results['grid_energy'][hour] for hour in range(24))
        daily_negative_price_energy_to_grid = sum(daily_results.get('negative_price_energy_to_grid', [0] * 24)[hour] for hour in range(24))

        monthly_costs[month] += daily_costs
        monthly_energy_to_grid[month] += daily_energy_to_grid
        monthly_grid_energy[month] += daily_grid_energy
        monthly_negative_price_energy_to_grid[month] += daily_negative_price_energy_to_grid

    # Print the results for each month
    for month in range(12):
        print(f"Month {month + 1}: Energy to Grid at Negative Prices = {monthly_negative_price_energy_to_grid[month]:.2f} kWh")

    return monthly_costs, monthly_energy_to_grid, monthly_grid_energy

# Load data
energy_prices_df = pd.read_csv('/content/drive/MyDrive/Energiedata/energyprice.csv')
solar_data_df = pd.read_csv('/content/drive/MyDrive/Energiedata/pv_data_new.csv')

# Convert 'datetime' column to datetime objects
energy_prices_df['datetime'] = pd.to_datetime(energy_prices_df['datetime'])
solar_data_df['datetime'] = pd.to_datetime(solar_data_df['datetime'])

# Simulate entire year
results_year = simulate_year(energy_prices_df, solar_data_df, battery_capacity=225, charge_power=125, discharge_power=125, base_load_fixed=40)

# Calculate monthly costs, energy sent to grid, and grid energy usage
monthly_costs, monthly_energy_to_grid, monthly_grid_energy = calculate_monthly_metrics(results_year, energy_prices_df)

# Print monthly costs, energy sent to grid, and grid energy usage
for month in range(12):
    print(f"Month {month + 1}: Cost = {monthly_costs[month]:.2f} €, Energy to Grid = {monthly_energy_to_grid[month]:.2f} kWh, Grid Energy = {monthly_grid_energy[month]:.2f} kWh")

# Calculate hourly probabilities
hourly_light_probabilities = calculate_hourly_light_probabilities(results_year)

# Plot hourly probabilities
plot_hourly_light_probabilities(hourly_light_probabilities)

# Function to select a week based on a start date
def get_week_results(start_date_str, results_year):
    start_date = pd.to_datetime(start_date_str)
    start_day_index = (start_date - energy_prices_df['datetime'].min()).days

    # Ensure the start_day_index is valid and within range
    if start_day_index < 0 or start_day_index + 7 > len(results_year):
        raise ValueError("Start date out of range or not enough data for a full week.")

    return results_year[start_day_index:start_day_index + 7], start_date

# Select a specific week for visualization, e.g., starting from 2023-06-16
week_start_date_str = '2023-06-01'
week_results, week_start_date = get_week_results(week_start_date_str, results_year)

# Plot aggregated results for the selected week
plot_aggregated_weekly_results(week_results, energy_prices_df, solar_data_df, week_start_date)

# Function to calculate hourly metrics per month
def calculate_hourly_metrics(results_year, energy_prices_df):
    hourly_energy_to_grid = np.zeros((12, 24))
```

```python
    hourly_negative_price_energy_to_grid = np.zeros((12, 24))
    hourly_grid_energy = np.zeros((12, 24))
    hourly_costs = np.zeros((12, 24))
    hourly_counts = np.zeros((12, 24))
    hourly_prices = np.zeros((12, 24))  # New array for storing prices

    for day_index, daily_results in enumerate(results_year):
        date = pd.to_datetime(energy_prices_df.iloc[day_index * 24]['datetime'])
        month = date.month - 1  # Convert to 0-based index

        for hour in range(24):
            price = energy_prices_df.iloc[day_index * 24 + hour]['price_kwh']
            grid_energy = daily_results['grid_energy'][hour]
            energy_to_grid = daily_results['energy_to_grid'][hour]
            negative_price_energy_to_grid = daily_results.get('negative_price_energy_to_grid', [0] * 24)[hour]

            hourly_grid_energy[month, hour] += grid_energy
            hourly_energy_to_grid[month, hour] += energy_to_grid
            hourly_negative_price_energy_to_grid[month, hour] += negative_price_energy_to_grid
            hourly_costs[month, hour] += price * grid_energy if price > 0 else -price * grid_energy
            hourly_counts[month, hour] += 1
            hourly_prices[month, hour] += price  # Sum the prices

    avg_hourly_grid_energy = hourly_grid_energy / hourly_counts
    avg_hourly_energy_to_grid = hourly_energy_to_grid / hourly_counts
    avg_hourly_negative_price_energy_to_grid = hourly_negative_price_energy_to_grid / hourly_counts
    avg_hourly_costs = hourly_costs / hourly_counts
    avg_hourly_prices = hourly_prices / hourly_counts  # Compute average prices

    return avg_hourly_grid_energy, avg_hourly_energy_to_grid, avg_hourly_negative_price_energy_to_grid, avg_hourly_costs, avg_hourly_prices

# Calculate hourly metrics
avg_hourly_grid_energy, avg_hourly_energy_to_grid, avg_hourly_negative_price_energy_to_grid, avg_hourly_costs, avg_hourly_prices = calculate_hourly_metrics(results_year, energy_prices_df)

# Create plots
months = ['Flex January Grid & Costs Optimization', 'Flex February Grid & Costs Optimization', 'Flex March Grid & Costs Optimization', 'Flex April Grid & Costs Optimization', 'Flex May Grid & Costs Optimization', 'Flex June Grid & Costs Optimization',
          'Flex July Grid & Costs Optimization', 'Flex August Grid & Costs Optimization', 'Flex September Grid & Costs Optimization', 'Flex October Grid & Costs Optimization', 'Flex November Grid & Costs Optimization', 'Flex December Grid & Costs Optimization']
hours = np.arange(24)

fig, axes = plt.subplots(6, 2, figsize=(20, 30))

price_ylim = (-0.05, 0.2)  # Set price range
energy_ylim = (0, 95)  # Set energy from grid range between 0 and 90

for month in range(12):
    ax = axes[month // 2, month % 2]

    # Plotting the lines
    ax.plot(hours, avg_hourly_grid_energy[month], color='black', label='Energy from Grid (kWh)')
    if np.any(avg_hourly_negative_price_energy_to_grid[month] != 0):
        ax.plot(hours, avg_hourly_energy_to_grid[month], color='blue', label='Energy to Grid (kWh)')
    if np.any(avg_hourly_negative_price_energy_to_grid[month] != 0):
        ax.plot(hours, avg_hourly_negative_price_energy_to_grid[month], color='red', label='Energy to Grid at Negative Price (kWh)')

    # Twin axis for costs and average prices
    ax2 = ax.twinx()
```

```
    ax2.plot(hours, avg_hourly_prices[month], color='black', linestyle=':', label='Average Energy Price €(/kWh)')  # New line for average prices

    # Set x-ticks and x-tick labels for each subplot
    ax.set_xticks(hours)
    ax.set_xticklabels([f"{hour}" for hour in range(24)])  # Label every hour with rotation for clarity
    ax.set_ylabel('Energy (kW)')
    ax2.set_ylabel('Price €(/kWh)')
    ax.set_title(months[month])

    # Set same energy & prices scale for all plots
    ax2.set_ylim(price_ylim)
    ax.set_ylim(energy_ylim)

    # Add legends
    ax.legend(loc='upper left')
    ax2.legend(loc='upper right')

    # Set limits to make space for the third bar
    ax.set_xlim([0, 23])

axes[-1, 0].set_xlabel('Hour of the Day')
axes[-1, 1].set_xlabel('Hour of the Day')

# Adjust layout to make space for the suptitle
fig.subplots_adjust(top=0.95)

# Add title above all plots
fig.suptitle('All months flex scenario optimized for Grid & Costs', fontsize=16)
plt.suptitle('')
plt.show()
```

B.2. Code for Ideal Start Hours

Start hours are identified with the code below, the example code below is for the 12/12 scenario. This code is used after the initial optimization model above.

```
# Calculate the hourly probabilities
hourly_light_probabilities = calculate_hourly_light_probabilities(results_year)

# Function for ideal start hour
def calculate_ideal_start_hour_12_12(hourly_light_probabilities):
    results = []
    for month in range(12):
        monthly_probs = hourly_light_probabilities[month]
        total_probs = []

        for start_hour in range(24):
            # Calculate the total probability for the 12/12 light/dark pattern
            total_prob = sum([monthly_probs[(start_hour + i) % 24] for i in range(12)])
            total_probs.append(total_prob)

        # Determine the ideal start hour for the current month
        ideal_start_hour = np.argmax(total_probs)
        results.append((month + 1, total_probs, ideal_start_hour, total_probs[ideal_start_hour]))

    return results

# Calculate ideal start hours
ideal_start_hours_12_12 = calculate_ideal_start_hour_12_12(hourly_light_probabilities)

# Extract the ideal start hour and probability for each month
filtered_results = []
for month, total_probs, ideal_start_hour, ideal_prob in ideal_start_hours_12_12:
    filtered_results.append([month, ideal_start_hour, ideal_prob])

# Create DataFrame to display filtered results
df_filtered_results = pd.DataFrame(filtered_results, columns=['Month', 'Ideal Start Hour', 'Probability'])

# Display table
print(df_filtered_results)

# Prepare data for heatmap
heatmap_data = np.zeros((12, 24))
probability_data = hourly_light_probabilities

for month, total_probs, ideal_start_hour, ideal_prob in ideal_start_hours_12_12:
    for i in range(12):
        hour = (ideal_start_hour + i) % 24
        heatmap_data[month - 1, hour] = 1  # Light on

# Create heatmap
#plt.figure(figsize=(15, 8))
#ax = sns.heatmap(heatmap_data, cmap=['white', 'mediumorchid'], cbar=False, yticklabels=[
    #'Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'], xticklabels=range(24), alpha=0.2, linewidths=0.5, linecolor='gray')

# Create mask for the values outside the 12-hour blocks
mask = np.ones_like(heatmap_data, dtype=bool)

for month, total_probs, ideal_start_hour, ideal_prob in ideal_start_hours_12_12:
    for i in range(12):
        hour = (ideal_start_hour + i) % 24
        mask[month - 1, hour] = False  # Light on

# Create custom colormap with varying alpha values for medium orchid
colors = [(186/255, 85/255, 211/255, alpha) for alpha in np.linspace(0, 0.5, 256)]
custom_cmap = ListedColormap(colors)

# Create masked heatmap
plt.figure(figsize=(15, 8))
```

```
ax = sns.heatmap(probability_data, mask=mask, cmap=custom_cmap, cbar=True, yticklabels=[
    'Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'], xticklabels=range(24), linewidths=0.5, linecolor='gray', annot=True, fmt=".2f", annot_kws={"color": "black"})

# Add probabilities inside the light blocks
for month in range(12):
    for hour in range(24):
        if not mask[month, hour]:
            prob = probability_data[month, hour]
            ax.text(hour + 0.5, month + 0.5, f'{prob:.2f}', ha='center', va='center', color='black')

plt.xlabel('Hour of the Day')
plt.ylabel('Month')
plt.title('Light On/Off Schedule 12/12 for Each Month with Probabilities')
plt.show()
```

B.3. Code for the Fixed Light Schedule

To implement the fixed light schedule after determining the ideal hours the following code is used.

```python
def get_light_schedule(date):
    schedule = [0] * 24

    if date.month in [1, 2, 11]:
        for hour in range(21, 24):
            schedule[hour] = 1
        for hour in range(0, 6):
            schedule[hour] = 1
        for hour in range(12, 15):
            schedule[hour] = 1
    elif date.month == 3:
        for hour in range(11, 17):
            schedule[hour] = 1
        for hour in range(23, 24):
            schedule[hour] = 1
        for hour in range(0, 5):
            schedule[hour] = 1
    elif date.month == 4:
        for hour in range(10, 16):
            schedule[hour] = 1
        for hour in range(22, 24):
            schedule[hour] = 1
        for hour in range(0, 4):
            schedule[hour] = 1
    elif date.month == 5:
        for hour in range(9, 18):
            schedule[hour] = 1
        for hour in range(0, 3):
            schedule[hour] = 1
    elif date.month == 6:
        for hour in range(8, 20):
            schedule[hour] = 1
    elif date.month in [7, 8]:
        for hour in range(10, 19):
            schedule[hour] = 1
        for hour in range(1, 4):
            schedule[hour] = 1
    elif date.month == 9:
        for hour in range(11, 17):
            schedule[hour] = 1
        for hour in range(23, 24):
            schedule[hour] = 1
        for hour in range(0, 5):
            schedule[hour] = 1
    elif date.month == 10:
        for hour in range(22, 24):
            schedule[hour] = 1
        for hour in range(0, 7):
            schedule[hour] = 1
        for hour in range(13, 16):
            schedule[hour] = 1
    elif date.month == 12:
        for hour in range(20, 24):
            schedule[hour] = 1
        for hour in range(0, 8):
            schedule[hour] = 1

    return schedule
```