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Electricity Cost Savings in Energy-Intensive Companies: Optimization Framework and Case Study

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Abstract: In recent years, there has been an increasing urgency among energy-intensive companies to find innovative ways of mitigating the negative financial impacts of rising fuel and electricity prices. Consequently, companies are exploring new technological solutions to lower electricity costs, such as investing in their own power generation sources or storage systems. In this context, this article presents a data-driven optimization-based framework to manage and optimize the operation of a hybrid energy system within industries characterized by substantial power requirements. The framework encompasses several key aspects: electricity generation, self-consumption, storage, and electric grid interaction. The case of an energy-intensive company specializing in wood processing and office furniture production is evaluated. This study explored two system configurations of hybrid energy systems within an energy-intensive company. The result of the analyzed case shows that the system's flexibility is enhanced by its ability to store energy, resulting in electricity cost savings of nearly 72% and total operating cost savings of 20%.

Keywords: hybrid energy systems; optimization; electricity; energy-intensive sectors

Citation: Benalcazar, P.; Malec, M.; Kaszyński, P.; Kamiński, J.; Saługa, P.W. Electricity Cost Savings in Energy-Intensive Companies: Optimization Framework and Case Study. *Energies* **2024**, *17*, 1307. https://doi.org/10.3390/en17061307

Academic Editor: Meysam Khojasteh

Received: 8 February 2024
Revised: 2 March 2024
Accepted: 7 March 2024
Published: 8 March 2024

1. Introduction

Electricity prices are among the most significant cost drivers in the operation of energy-intensive companies in sectors such as cement, paper, steel, and chemical [1]. In recent years, the financial results of these enterprises have been impacted by the rise and high volatility of electricity prices—mainly caused by the COVID-19 pandemic and the conflict in Ukraine. The increasing urgency among enterprises to mitigate this negative impact on operational costs is a response to the surge in fuel and electricity prices, as well as the risk of further volatility in commodity markets.

For this purpose, companies are exploring innovative solutions to lower electricity costs, such as investing in their own power generation sources (preferably renewables) or storage systems. Strategies like integrating dispatchable power generation units with renewable energy sources (RES) and energy storage technologies into a single hybrid system or integrated system are becoming widely accepted [2]. Moreover, energy management systems that promote energy self-sufficiency are gaining traction in energy clusters and energy cooperatives [3].

A fundamental problem and research challenge lie in effectively managing such systems to either minimize energy consumption costs within a company or maximize the profit related to the operation of the entire system, including energy generation, consumption, purchase, and storage. In this context, decision-support tools such as mathematical models to optimize the operation of hybrid energy systems in energy-intensive companies emerge as promising solutions. Using these models, it is possible to reduce electricity costs by optimizing energy production, purchase, self-consumption, and storage.

2. Literature Review

Developing optimization models to support decisions regarding the management of energy generation, purchase, and storage systems is a complex task. In recent years, researchers have directed their attention to the development of decision-support tools for integrated distributed energy resources like local microgrids. Numerous articles in this area explore the optimal control of integrated systems like microgrids in small energy cooperatives. Kriett and Salani proposed one such model in [4]. They employed a mixed integer linear programming approach to minimize system operating costs. The microgrid was modeled as a grid-connected system and included solar energy installations, distributed generators (micro gas turbines, diesel generators), energy storage units, and load control devices (controlled-load home appliances and electric vehicles).

A similar problem was solved by Su et al. in [5]. The authors described a two-step stochastic model for managing a local microgrid in a grid-connected mode. The proposed model considered the intermittency and variability of renewable energy sources (i.e., wind and solar). Moreover, it minimized operating costs while reducing power losses via an optimal storage operation and scheduling of controllable sources. A similar approach was taken by Zhang et al. in [6]. Their study proposed a stochastic energy management model for a microgrid. It was formulated as a quadratic mixed integer (MIQP) programming problem and further applied within a stochastic model predictive control (SMPC) framework. Renewables, controllable power generation units, energy storage, and variable load devices were considered. RES production, demand, and electricity price forecasts were treated as uncertain parameters and generated using Monte Carlo simulation methods. In [7], Mansour Lakouraj et al. proposed a model for supporting decision-making in microgrids. The model aimed to minimize energy costs in the day-ahead market and was formulated as a mixed integer linear programming problem (MILP). The microgrid included controllable units, energy storage systems, wind turbines, and demand response capabilities. In the study, the microgrid operator could purchase active and reactive power from the local distribution market. To ensure the optimal operation of the microgrid, an effective short-term scheduling was implemented.

Subsequent publications have concentrated on models that support energy consumption management. Ottesen and Tomasgard [8] proposed a model for energy consumption management in a university college building, introducing the concept of an energy hub. The system included multiple energy carriers, converters, and storage units to increase the system's flexibility. The study presented two models (one deterministic and one stochastic) and emphasized the role of the retail side in the electricity market. A similar approach was proposed by Brahman et al. in [9].

A critical issue that arises in the effective management of controllable units involves the careful planning of startup and shutdown procedures, taking into account the dynamics of ramping and the technical restrictions of the units. This problem was considered by Liu et al. [10], who proposed a decision-support tool that integrates dynamic temperature and startup/shutdown modeling. Similar issues were considered by Correa-Posada CM et al. in [11] and Jin et al. in [12]. Srilakshmi and Singh proposed a social micro-network management model in [13]. The authors developed a model for the optimal operation of the social microgrid with photovoltaics (PV), energy storage systems (ESS), and electric vehicles (EV) as alternative energy sources. In their work, the surplus energy stored in electric vehicles can be transferred to the grid or consumed locally (two-way energy flow strategy). The EV charging/discharging schedules were modeled as a MILP problem.

Soares et al. [14] proposed a model for integrated energy management that accounts for several sources of uncertainty. The uncertainties in power demand, wind and photovoltaic (PV) energy, the demand for electric vehicles, and the volatility of market prices were considered. The proposed method was based on stochastic programming. The authors formulated a two-stage stochastic problem for energy resource scheduling to address the challenge posed by the demand, renewable sources, electric vehicles, and market price uncertainty.

Recent articles also describe models that support the decision-making process in local electricity grids, accompanied by relevant case studies. Carli et al. [15] delved into the energy scheduling of a smart microgrid problem with shared photovoltaic panels and storage, using the Ballen Marina in Samsø, Denmark, as an example. The case study demonstrates energy scheduling in a system with non-controllable and controllable electrical devices, as well as photovoltaic (PV) panels and a battery energy storage system (BESS). By utilizing a model predictive control, the self-supply increased by 1.6%, resulting in 8.2% savings in yearly energy costs. Another example concerns the optimization of the operation of multiple micro-energy systems in a science and education park in Guangzhou, China [16]. The study demonstrated that Shared Energy Storage Systems (SESS) for different local systems can help reduce up to 10% of the capital investments in energy storage units and operating costs. The case of a microgrid aggregator that manages microturbines, wind and photovoltaic systems, energy storage, electric vehicles, and usage of energy was explored by Gomes et al. in [17]. They proposed a microgrid support management system based on a stochastic mixed-integer linear programming formulation. The cases concerned the application of demand response and the associated risks of participating in the electricity market.

Other applications of decision-support tools for energy management involve stand-alone rural electrification systems based on photovoltaic technologies, including both microgrids and individual supply configurations. The results of using mathematical models for these purposes are illustrated, among others, in the examples of Bolivia [18], Ecuador's Amazon Region [19], and the Galapagos Region [20]. The abovementioned studies offer various approaches for determining optimal system configurations and propose decision-support tools based on linear and mixed integer linear programming models, with economic, technical, and social aspects integrated as model constraints.

Examples of decision-support tools for energy-efficiency planning in production systems powered by renewable energy can also be found in the literature. Materi et al. [21] proposed an optimization solution that incorporated manufacturing parameters as inputs. The decision-support tool aimed to optimize the production planning while aligning it with the availability of renewable energy. Wang et al. [22] formulated a two-stage multi-objective stochastic MILP for production planning. In the first stage, optimal schedules were generated to minimize the total production completion time. The second stage determined the energy supply decisions to minimize energy costs under a time-of-use electricity pricing scheme. Although the approaches reviewed in this section contribute to the optimal operation of the grid and off-grid energy systems, there is a noticeable gap in the literature regarding computational frameworks and computable models specifically designed for energy-intensive companies. In particular, there is a deficiency in models that optimize the purchasing process of electricity, self-generation, and energy storage within enterprises that exhibit high levels of fuel and electricity price risk exposure.

In this context, this study contributes to the literature by describing an integrated computational approach for the minimization of energy acquisition costs by combining machine learning methods and mathematical programming. The approach presented in this work aims to provide optimal schedules for a wide range of system configurations and local system components, including local conventional (steam turbine, gas engine, etc.) and renewable generation sources (PV, wind turbine, etc.), charging and discharging energy storage units, as well as purchasing and selling electricity from and to the grid. Moreover, it takes into account the operational limitations of these generation sources, energy storage units, price volatility in the electricity market within the planning horizon, and demand-side response interventions. The approach also accounts for the variable electricity demand of the enterprise, determining the potential volume of power reduction, as well as the maximum duration of this reduction in a given period with fluctuating electricity prices. It is worth highlighting that the proposed approach is demonstrated using the case study of an energy-intensive company specializing in wood processing. Additionally, it is important to note that the approach can be adapted to incorporate additional technologies and be applied to assess other industries and companies in different countries.

In summary, this work contributes to the existing literature via the following:

(1) Proposing a data-driven optimization-based framework to manage and optimize the operation of a hybrid energy system within industries characterized by significant energy demands.
(2) Developing a framework architecture that integrates a mixed-integer linear programming model aimed at minimizing the total operating costs of the system. In addition, it provides the ability to obtain critical input data using additional modules based on machine learning methods.
(3) Showcasing the benefits and applicability of the optimization model via a case study of an energy-intensive company specializing in wood processing and office furniture production.

With this scope in mind, the remainder of this paper is structured as follows. Section 3 describes the proposed tool and the main assumptions adopted in its construction. Section 4 presents a case study and two research scenarios—a system without energy storage (Case A) and a system with energy storage (Case B). Section 5 discusses the main research results. Concluding remarks are provided in Section 6.

3. Decision-Support System for Energy-Intensive Enterprises

This section describes a model designed to support the operations management of electricity production assets in energy-intensive companies. The decision-support tool has been built with universality in mind, allowing its application across various energy-intensive companies. Its primary function is to optimize the operation of generating units (dispatchable sources), non-dispatchable generating units (renewable energy technologies), and energy storage systems and to minimize the costs of electricity generation within the enterprise.

3.1. Mathematical Model

In recent years, several research works have investigated and compared the effects of the selection of linear and non-linear optimization approaches on the operation management of energy system technologies. Although the choice of the optimization approach depends on a number of conditions, numerous studies have showcased that the advantages of convex optimization outweigh the overall errors that could be caused by linear approximations [23]. Moreover, there is an increasing number of works that suggest that techniques based on mixed-integer linear programming offer significant advantages for cost minimization, such as global solutions, shorter computation times, and model trackability, when compared to non-linear or rule-based techniques [24]. Therefore, a mixed-integer linear programming approach was adopted to develop the mathematical model described in this section. The model was implemented in the General Algebraic Modeling System (GAMS), and a simplified scheme of the model is shown in Figure 1. The goal of this model, represented by its objective function, is to minimize the total operating costs of the hybrid energy system. Cost components incorporated in the objective function include fuel costs, fixed and variable operation costs, maintenance costs, costs from purchasing power from the grid, startup and shutdown costs, and storage operational costs. In addition to costs, the model considers revenues from the sale of electricity to the grid and additional revenues from demand-side response (DSR) interventions. This study adopts a similar approach to the breakdown of cost components often employed by independent system operators [25], where variable costs depend on the level of output of a generation unit (excluding fuel), and fixed costs remain constant regardless of the electrical production.

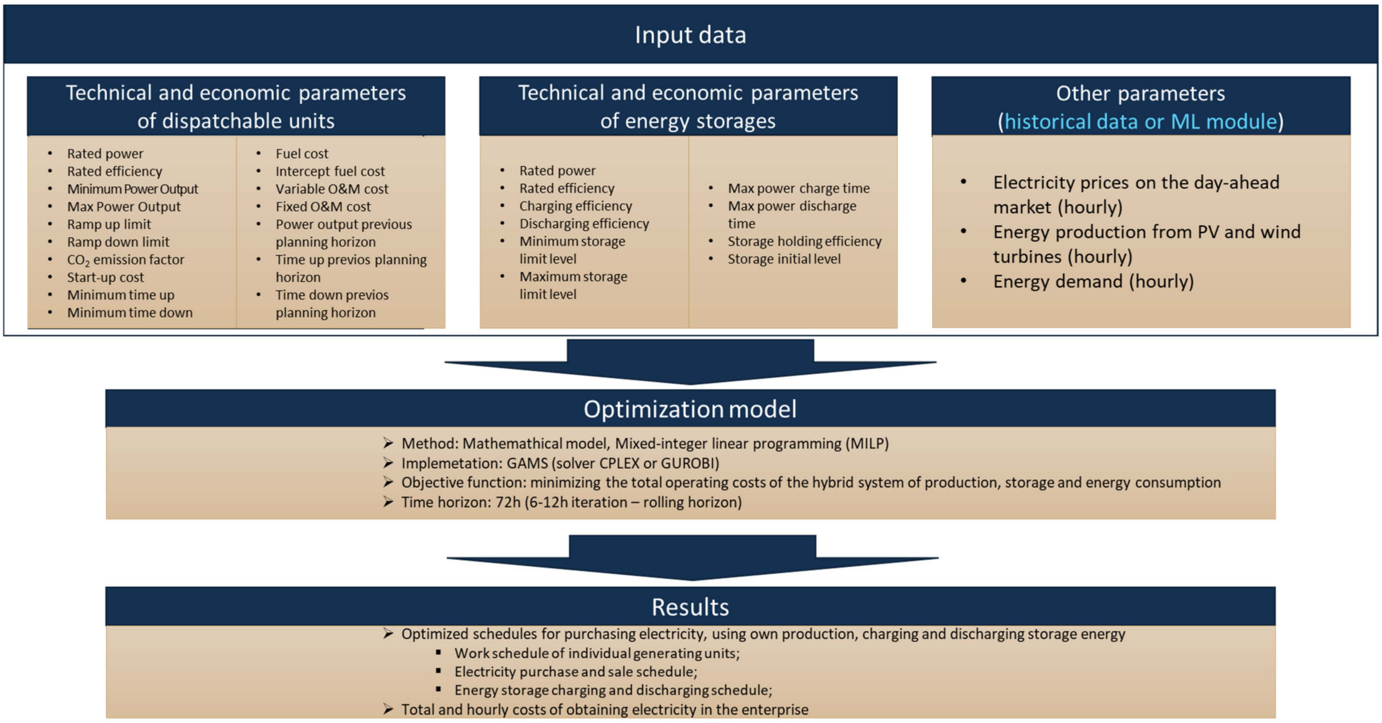

Figure 1. Block flow diagram of the proposed framework. Source: own elaboration.

The model's temporal resolution is hourly, and the optimization horizon can be selected flexibly in the range of 3–7 days. The calculations can be performed in planning intervals using a rolling horizon approach. The rolling horizon method in decision-making processes allows users to utilize updated forecasts (electricity prices, wind, or PV generation profiles) or information from unexpected events (e.g., unplanned increase/decrease in demand).

The framework's architecture assumes the possibility of obtaining critical input data using additional modules based on machine learning methods. For example, an additional module that uses specific data to forecast demand could be incorporated into the workflow (e.g., outdoor temperature, when using electricity to heat rooms, or the number of orders). The model can also utilize real-time or historical data provided by energy-intensive companies, enabling energy consumption analyses focused on the seasonality of the production process.

The input data may also include forecasted electricity generation estimates from non-dispatchable sources. These forecasts can be provided using external wind and solar production forecasts or be the result of machine learning methods. The machine learning module for renewable generation forecasts may use temperature, insolation, and wind speed for a given location. The application of such methods enables the framework to account for intermittency and variability in renewable sources and dynamically adjust the generation levels of dispatchable technologies, mitigating the impact of forecasting errors. Furthermore, unlike heuristic models that employ strategies to maximize the utilization of renewable energy sources, the optimization model prioritizes the utilization of renewables due to their low or nearly negligible variable costs.

Similarly, in the case of input data regarding electricity price forecasts, one may use external forecasts or machine learning methods. In this work, the model uses electricity prices from the Polish Balancing Market (spot) [26]. Forecasting models used by companies can also serve as sources of input data [27]. It is important to note that the prices at which electricity is bought and sold significantly impact the decisions concerning the operation of dispatchable sources and energy storage; therefore, the data used in the mathematical model should have a high degree of reliability—as they entail financial consequences. Figure 2 presents a block flow diagram illustrating the structure of the data input.

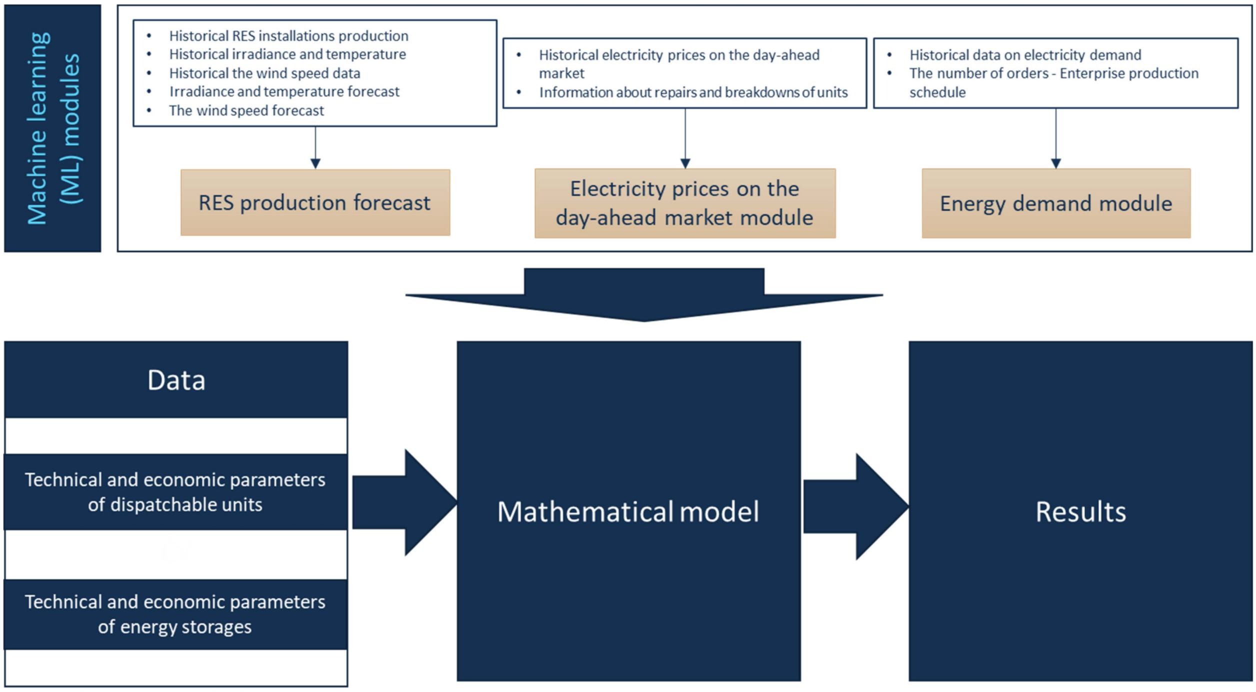

Figure 2. Block flow diagram of the proposed computational approach. Source: own elaboration.

Incorporating machine learning methods offers three main benefits. First, machine learning methods can provide real-time forecasted values to the optimization network, allowing for dynamic adjustments to the generation levels of dispatchable technologies and better utilization of energy storage units. Second, the system can adapt to changing demand patterns and allocate resources optimally, resulting in enhanced efficiency in resource allocation and minimized system costs. Third, the use of forecasting tools improves grid reliability by proactively responding to fluctuations in energy production and consumption, enhancing the overall system stability. This integration can be achieved by soft-linking different programming environments, such as establishing communication between optimization models implemented in GAMS version 42.4.0 and machine learning models programmed in Python version 3.10.10).

As previously mentioned, the model's objective function assumes the minimization of all system operating costs. These costs include fuel, fixed and variable costs of generating units, startup and shutdown costs, costs of purchasing electricity from the grid, and storage maintenance costs. The system cost balance equation also incorporates revenues that can be obtained from the sale of electricity to the grid or those associated with demand side response.

The constraint that defines the power balance in each time step is a crucial equation implemented in the model. This equation ensures that the total generation of dispatchable units, PV and wind turbines, energy discharged from the battery storage, and the total volume of purchased electricity minus the amount of energy sold and the amount of energy allocated to charging the battery storage and demand reduction is equal to the expected demand in a given time step.

This study assumes that the system is connected to the main grid and the power balance can be satisfied using local energy sources as well as energy from the main grid. Therefore, the following constraints associated with the operation of the grid interaction were defined:

- Maximum power purchased in a given time step;
- Minimum power purchased in a given time step;

- Maximum power sold in a given time step;
- Minimum power sold in a given time step;
- Binary variable constraint that determines if the system is importing or exporting power in a given time step.

Additional constraints in the model are related to the operation of the generation sources. For dispatchable units, the following constraints were defined:

- Maximum power output in a given time step;
- Minimum power output in a given time step;
- Maximum ramp-up in a given time step;
- Maximum ramp-down in a given time step;
- Minimum up times (number of operating hours after starting the unit);
- Minimum down times (number of hours the unit is off);
- Fuel cost calculation in a given time step;
- Binary variable constraints that represent the operating status of the units at a given time step.

Moreover, the model includes additional constraints that specify the ramp-up and ramp-down limits of the dispatchable unit in the first hour of the time horizon, utilizing information about the unit's operational state at the beginning of the analyzed period. Similarly, constraints for non-dispatchable sources have been implemented in the model. Because of the intermittency of these sources, the primary constraint focuses on the production balance of solar PV and wind generation technologies.

The operation of energy storage was also characterized using a set of equations. The equations consider three fundamental elements for the mathematical representation of a generic battery energy storage system: parameters, decision variables, and operational constraints, which are based on the exact-MILP representation of a BESS discussed in [28]. These constraints employ binary and positive variables to reflect the operational plan of the battery storage at an hourly resolution. Each state (charging, holding, and discharging) is characterized by the appropriate variable 0 (on)/1 (off). Additional constraints are associated with the maximum storage capacity, minimum and maximum state of charge, and the storage's maximum charge and discharge levels in one hour. Similar to the case of dispatchable sources, various technical limitations have been added for the first hour of the time horizon. These limitations include information on the battery's state of charge at the beginning of the analyzed period. It is worth noting that the rolling horizon approach allows for the monitoring of the battery's state of charge over time. It also records the charging and discharging profiles, capturing the continuous-time coupled battery dynamics. Similar approaches have been discussed in [29]. The following constraints were defined:

- Energy storage inventory balance in a given time step;
- Energy storage capacity limits in a given time step;
- Energy storage charge and discharge limits in a given time step;
- Binary variable constraints that represent the operating status of the energy storage units at a given time step.

The implementation of the model elements, such as sets, parameters, variables, and the objective function within the modeling system, allows one to determine the optimal values of the decision variables while considering the various scenario assumptions. The main outputs of the model include the following:

- Power output of dispatchable technologies in a given time step;
- Power purchased from the external grid in a given time step;
- Power sold to the external grid in a given time step;
- Battery state of charge in a given time step;
- Energy charged to the storage unit in a given time step;
- Energy discharged from the storage unit in a given time step;
- Total system operating costs;
- Fuel cost of dispatchable technologies in a given time step;

- Fixed and variable costs of dispatchable and non-dispatchable technologies in a given time step;
- Startup and shutdown costs of dispatchable and non-dispatchable technologies;
- Costs of grid interaction (power purchase from the grid and power sold to the grid costs) in a given time step.

The tool developed in this study can be employed to optimize the operation of an energy-intensive company with different configurations of generating units. Furthermore, the analyses can be used to support planning and investment decisions regarding the purchase of new generation or storage units.

The primary outcomes of the model, which are valuable for decision-makers in enterprises, consist of optimized schedules for purchasing electricity, utilizing local generation sources, and charging and discharging energy storage units. This capability makes it possible to minimize operating costs in hybrid energy systems. The fast solution times (typically a few seconds to several minutes) facilitate the analysis of several scenarios, including, for example, changes in forecasted electricity prices, unexpected unavailability of local power generation units, and the reduction in local system demand.

3.2. Model Implementation

The model was implemented in the General Algebraic Modeling System (GAMS). The optimization was carried out using GAMS version 42.4.0 (64-bit/MS Windows platform). The solvers (a) IBM ILOG CPLEX version 22.1.1.0 and (b) Gurobi Optimizer version 10.0.0 build v10.0.0rc2 (win64) were used to evaluate the case study. All calculations were conducted on a desktop computer with a 12th Gen Intel(R) Core(TM) i9-12900K 3.20 GHz, with a thread count of 16 physical cores, 24 logical processors, and 128 GB of RAM.

The model was verified and validated via a two-step process in line with the standards commonly used in the development of optimization models for optimization-based decision-support tools [30]. First, a series of sensitivity analyses were performed to assess the robustness of the model. Second, various scenario analyses were conducted to validate the model's performance under different operating conditions. The sensitivity analysis was performed by adjusting individual parameters, such as fuel price, electricity price, battery capacity, and others, one at a time by a specified percentage. The sensitivity analysis indicated that changes in electricity prices had the most significant impact on the model results.

4. Case Study

The model was used to optimize the operation of local electricity generation sources in an energy-intensive company specializing in wood processing and office furniture production. The primary cost parameter in its operation, aside from the price of wood and materials, is electricity consumption. The electricity demand depends on the time of day and the number of orders. The company operates from 6:00 to 22:00, six days a week. In exceptional cases, when there is an increase in the number of orders, the company shifts to a 24 h, seven-days-a-week schedule.

The company's operational goal is to generate electricity from its local power sources, but it also possesses the flexibility to purchase electricity from the grid and sell any surplus back to the grid. The operational strategy established by the plant manager is to minimize the total costs of production and energy purchases while maximizing the revenues from electricity sales. In the context of the high volatility of energy prices in the Polish market, activities related to the energy management and optimization of its purchase and sale are particularly important [31]. The company owns two generating units, a 200 kW diesel engine and a 400 kW gas engine. Additionally, it integrates a photovoltaic installation with a capacity of 100 kWp and a wind turbine with a capacity of 100 kW.

This study assesses the financial and operational effects of incorporating a battery unit into the system. Therefore, this study analyses two possible scenarios: one where the company operates without a battery energy storage (Case A) and the second with a 200 kW battery energy storage (Case B).

The highest energy consumption in the energy-intensive company occurs between 8:00 and 22:00. The demand profile for the next three days (72 h) was provided by the company, as shown in Figure 3. The figure shows that the peak demand is 120 kWh, and the minimum is 25 kWh.

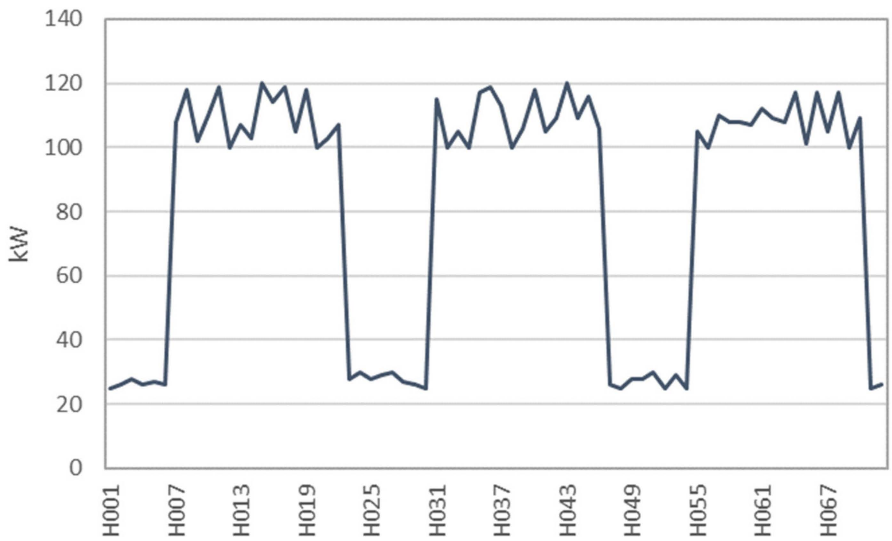

Figure 3. Company demand profile. Source: own elaboration.

Technical parameters of dispatchable and energy storage units are presented in Tables 1–3. The technical data for the generation sources were made available by the company.

Table 1. Technical parameters of dispatchable units (part 1). Source: own elaboration.

Dispatchable Technologies	Rated Power or Rated Energy [kW]	Rated Efficiency [%]	Min. Output Power [% of IC]	Max. Power Output [% of IC]	Ramp Up Limit [kW]	Ramp Down Limit [kW]	CO_2 Emission Factor [$kgCO_2$/kWh]	Minimum Time Up [h]	Minimum Time Down [h]
Diesel	200	0.45	0.05	0.8	10	10	0.76	1	1
Gas engine	400	0.42	0.05	1	50	50	0.48	2	2

Table 2. Technical parameters of dispatchable units (part 2). Source: own elaboration.

Dispatchable Technologies	Fuel Cost [EUR/kWh]	Intercept Fuel Costs [EUR]	Variable O&M Costs [EUR/kWh]	Fixed O&M Costs [EUR]	Startup Costs [EUR]	Shutdown Costs [EUR]	Power Output from the Previous Planning Horizon (Horizon-1) [kW]	Time UP from the Previous Planning Horizon (Horizon-1) [h]	Time Down from the Previous Planning Horizon (Horizon-1) [h]
Diesel	0.6	50	16.3	5	5	5	0	0	0
Gas engine	0.5	120	13	0.3	13.2	0	0	0	0

Table 3. Technical parameters of the battery energy storage (only Case B). Source: own elaboration.

Storage Technologies	Rated Power or Rated Energy [kWh]	Rated Efficiency [%]	Charging Efficiency [%]	Dis-Charging Efficiency [%]	Min. Storage Limit Level [% of IC]	Max. Storage Limit Level [% of IC]	Max. Power Charge Time [h]	Max. Power Discharge Time [h]	Storage Initial Level [kWh]	Storage O&M Costs [EUR/kWh]
Battery	200	100	98	98	0	100	4	4	0.1	0

The generation profiles of the wind turbine and photovoltaic installation are shown in Figure 4. The case study employs historical data on the production of non-dispatchable units provided by the company and historical electricity prices published by the Polish Power Exchange (TGE) [26] (Figure 5). To ensure the tractability of the model results for both scenarios, the option of obtaining additional revenues from demand-side response interventions was excluded.

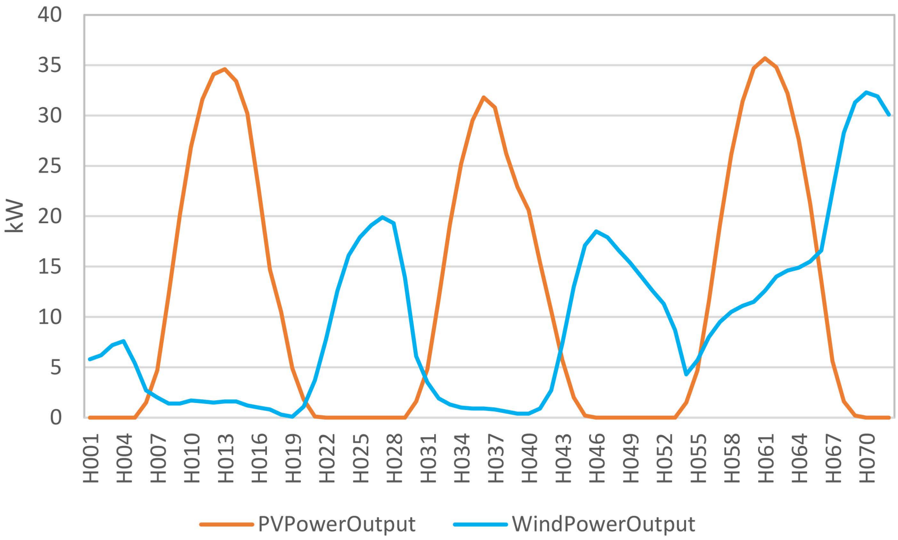

Figure 4. Production of non-dispatchable (RES) sources. Source: own elaboration.

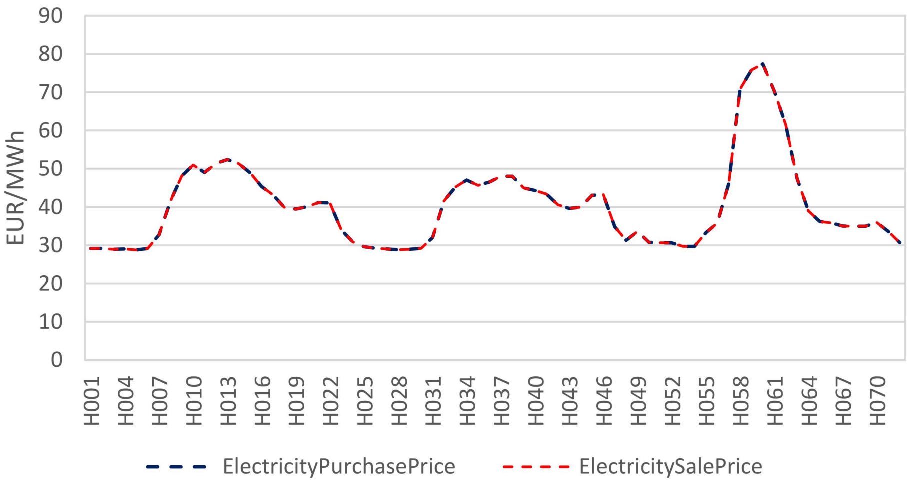

Figure 5. Electricity price on the balancing market. Source: [26].

5. Result and Discussion

The calculations were executed using the proposed model for optimizing the operation of a local energy-intensive company and the assumptions and input data outlined in Section 4. The results were compared for two scenarios. In the first scenario (referred to as Case A), the system operated without an energy storage unit, while in the second case (referred to as Case B), the system incorporated a battery energy storage unit with a capacity of 200 kWh.

Consequently, the results for both scenarios are presented in three subsections. Section 5.1 provides the results of electricity production and interaction with the grid—information on purchasing and selling electricity in individual hours. Section 5.2 presents detailed results of the operation of the energy storage for Case B. Section 5.3 compares the total system costs, considering the revenues from electricity sales.

It is worth noting that the total computation time with the CPLEX solver ranged from 0.07 s for case A to 0.13 s for case B. Although alternative solvers such as GUROBI or

HIGHS may yield different computation times, the results obtained are satisfactory for the operational planning process in energy intensive companies.

5.1. Electricity Generation Mix

The company's detailed electricity production structure from individual sources is shown in Figure 6 (Case A) and Figure 7 (Case B). The black line indicates the demand for electricity in the analyzed system. The low cost of the system forces the controlled unit (GasEngine1) to operate continuously throughout the entire time horizon. The minimum production level is 63 kW, and the maximum is 339 kW. The genset (Diesel1) operates at specific time steps of the analyzed period, with a maximum production level of 50 kW. The periods of energy sale to the grid, most often related to the generation of wind energy during low demand, are shown in the diagram above the black line. The total volume of energy sold to the grid in the analyzed period is 1040 kWh. Hours in which electricity is purchased from the grid are shown in green. The total purchase of energy in the analyzed period amounted to 1658 kWh.

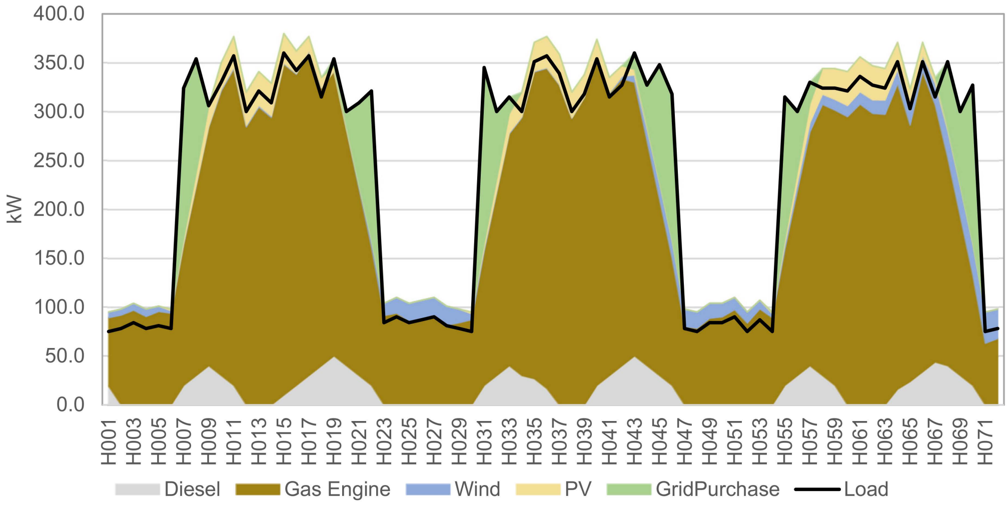

Figure 6. Model results for scenario A—electricity production structure in the enterprise. Source: own elaboration.

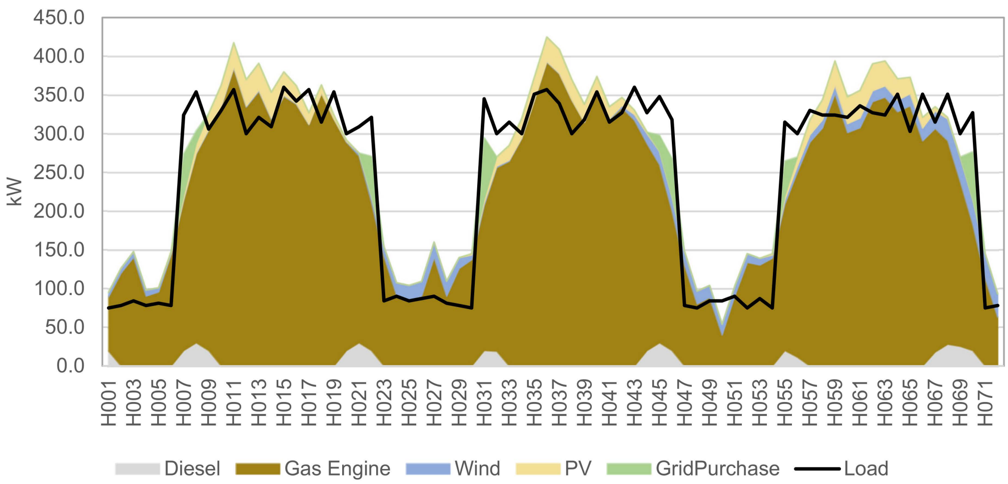

Figure 7. Model results for scenario B—electricity production structure in the enterprise. Source: own elaboration.

In Case B, there are periods when the local electricity production either exceeds or falls significantly below the energy demand. This is mainly due to the operation of energy storage. Overall, for Case A and B, the electricity generated by the conventional technologies (Diesel1 and GasEngine1) was at a similar level. The most significant difference is noticeable in the volume of electricity purchased.

Figures 8 and 9 show the detailed results of purchasing and selling electricity by the system. During the hours when the sale of electricity was possible, the model sought to increase its profit by selling it to the grid. Electricity was purchased from the grid when the local generating assets could not satisfy the demand. Scenario A (without storage) shows that electricity was purchased from the grid in 20 time periods of the analyzed horizon (accounting for over 25% of the time). The highest purchased volume in a time step amounted to approximately 160–180 kWh. In Case B (with storage), the highest volumes were lower (approx. 60–80 kWh), and the number of hours needed to purchase electricity was only 8.

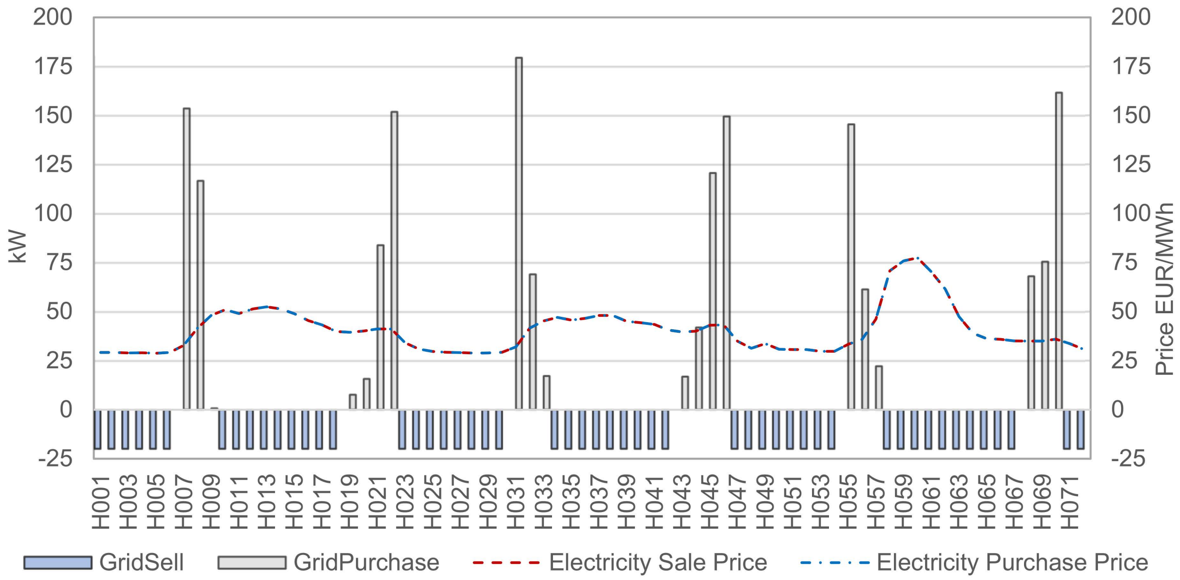

Figure 8. Results for scenario A—purchase and sale of electricity.

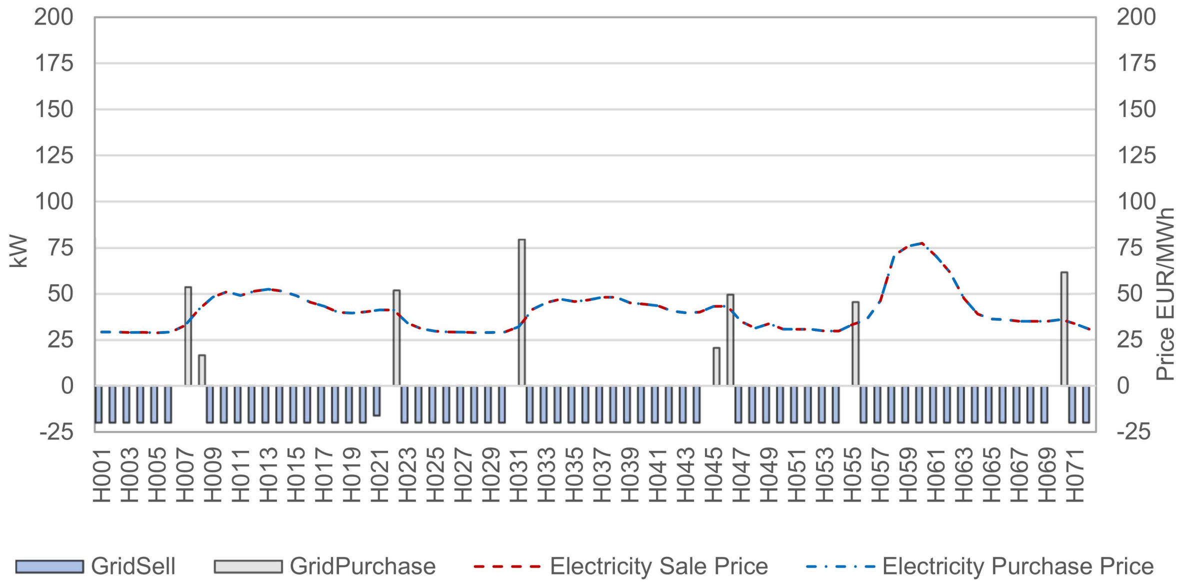

Figure 9. Results for scenario B—purchase and sale of electricity.

5.2. Battery Energy Storage Integration

The decision to charge and discharge the battery energy storage is influenced by factors such as energy purchase and sale prices, the generation level of dispatchable sources, and the capacity of the storage unit. Figure 10 illustrates the charging and discharging periods of the energy storage in relation to the purchase and sale price of electricity (for Case B). During the analyzed period (72 h), the storage was charged for 30 h, discharged for 25 h, and energy was stored for 17 h. Figure 11 shows the production from non-dispatchable sources in relation to the battery storage state of charge (SOC). When energy production from non-dispatchable sources is high, the storage (charging) operation is visible. Conversely, periods in which energy production from non-dispatchable sources is low often coincide with the discharging of the battery storage.

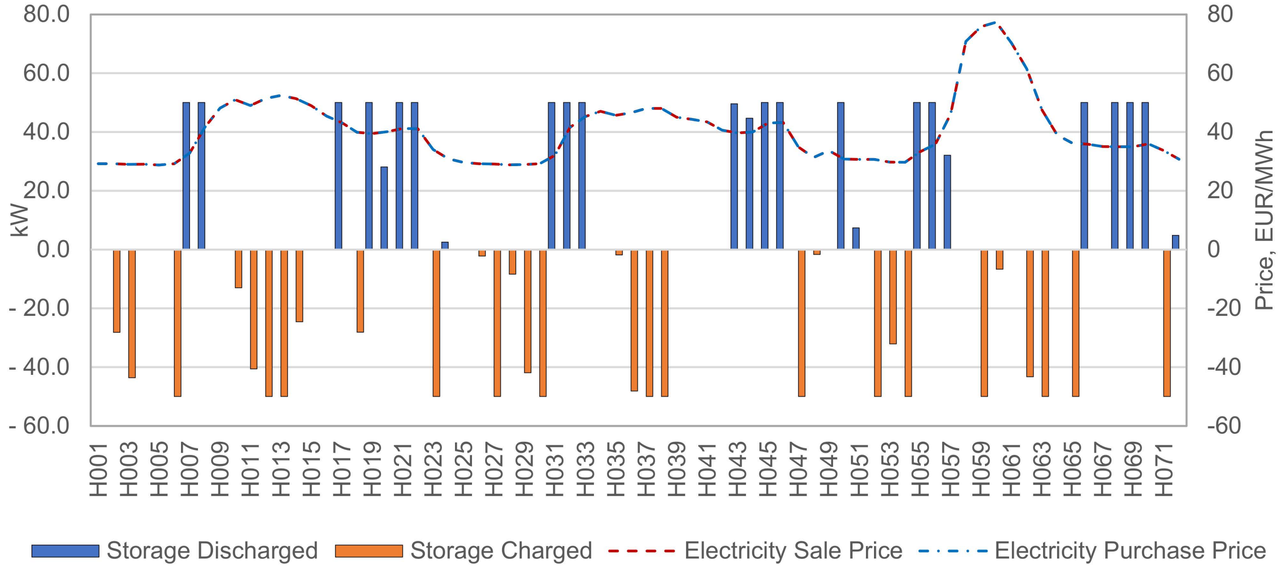

Figure 10. Model results for scenario B—energy storage charging and discharging cycles in relation to energy purchase and sale prices.

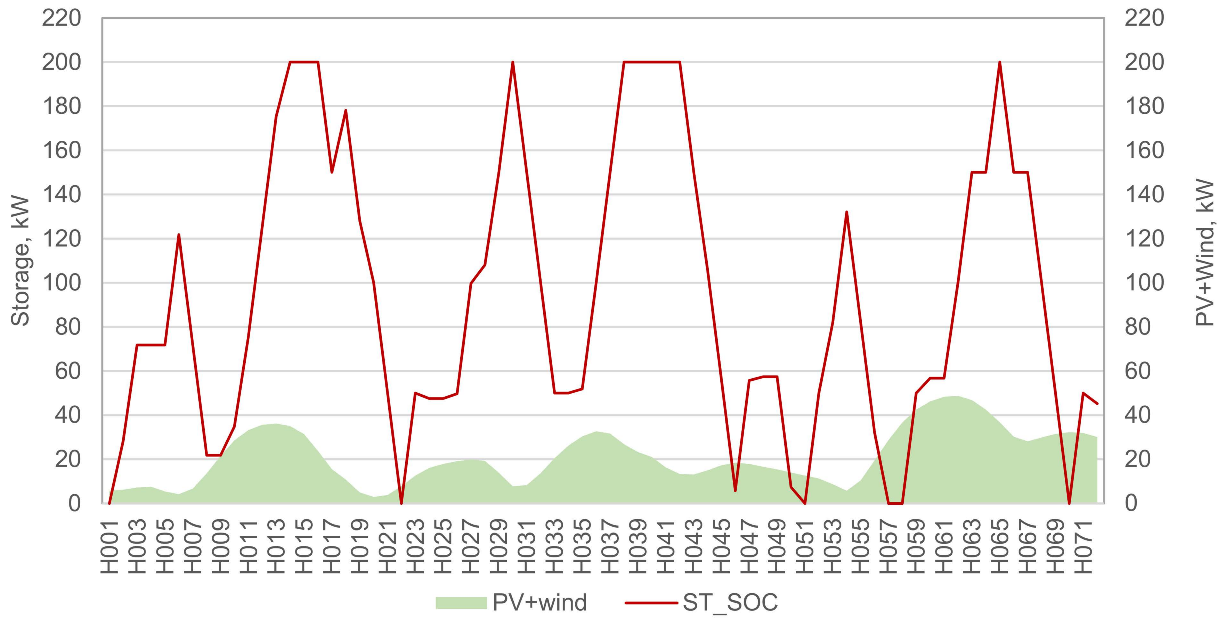

Figure 11. Simulation results for scenario B—state of charge of the storage in relation to the production of energy from non-dispatchable sources.

5.3. System Operating Costs

Table 4 compares the cost components for both scenarios: Case A and Case B. The upper section of the table distinguishes between the cost components related to the production of electricity in individual dispatchable units and non-dispatchable units, as well as the costs of operating the energy storage and purchasing electricity from the grid. The lower section presents the revenues from the sale of electricity to the grid and the total system costs for the analyzed horizon.

Table 4. Model results for scenarios A and B—system operating costs [EUR]. Source: own elaboration.

Cost Category	Cost Component	Case A [EUR]	Case B [EUR]
Variable operations and maintenance costs (non-fuel portion)	Dispatchable technologies VOM costs	205,685.5	223,504.2
	Dispatchable technologies startup costs	48.2	48.2
	Dispatchable technologies shutdown costs	35.0	35.0
	PV VOM costs	9.5	9.5
	Wind VOM costs	14.7	14.7
	Storage VOM costs	0.0	0.0
Fixed operations and maintenance costs	Dispatchable technologies FOM costs	216.6	111.6
Fuel costs	Fuel costs	18,470.3	18,125.8
Electricity costs	Costs of purchasing electricity from the grid	62,782.2	13,860.5
Electricity revenues	Revenue from selling electricity to the grid	−42,397.0	−51,982.2
	Total System Cost [EUR]	244,865.0	203,727.3

The total cost of operating the system for Case A (without storage) is EUR 244,865.0. The most significant cost components are the variable costs (amounting to EUR 205,685.5) and the cost of purchasing electricity from the grid (EUR 62,782.2). Revenues from the sale of electricity to the grid amounted to EUR 42,397.0. The system's flexibility is enhanced by its ability to store energy, which results in lower operating costs. As a result, in the second scenario (Case B, with storage), fuel and variable costs are slightly higher. However, the cost of purchasing energy from the grid dropped almost four times, and the revenues from the sale of electricity doubled. Consequently, the operating cost of the entire system amounts to EUR 203,727.3 (approximately EUR 40,000 lower than Case A).

6. Conclusions

This article proposes an optimization-based framework that can be widely used by energy-intensive companies specializing in various economic activities. It can be applied to optimize the generation, purchase, and sale of electricity in an enterprise on an ongoing basis, as well as to support management decisions regarding the integration or the purchase of new power generation and storage technologies.

The developed tool demonstrates that innovative configurations of technological installations are necessary for energy-intensive companies. These systems may include local generation units (conventional and renewable), electricity storage facilities, and smart loads or smart energy devices. The framework's architecture assumes the possibility of obtaining critical input data using additional modules based on machine learning methods. Moreover, the model was used to optimize the operation of local electricity generation sources in an energy-intensive company specializing in wood processing and office furniture production. The optimization-based framework proposed in this study is highly generalizable, flexible, and scalable. Therefore, it could be applied to other energy-intensive companies operating in various economic activities and located in different regions, such as industrial processes, agriculture, microgrids, mining and extractive industries, and commercial buildings, among others.

The results from the case study show that the total cost of operating the system for Case A (without storage) is EUR 244,865.0, with the most significant cost components being the variable costs (amounting to EUR 205,685.5) and the cost of purchasing electricity from the grid (EUR 62,782.2). Adding a battery to the system enhanced its flexibility, resulting in lower operating costs. The cost of buying electricity from the grid dropped almost four times, and the revenues from the sale of electricity doubled.

Possible paths for future research worth exploring are integrating smart energy devices and potentially increasing the temporal resolution adopted in the rolling horizon to

15 min. Additionally, the optimization framework could be expanded to include emerging technologies, such as electrolyzers and electric vehicles, and analyze their financial impact on current hybrid energy systems. While the framework is designed for optimal operational scheduling of the hybrid energy systems, it could also be used to perform techno-economic analyses using capital budgeting methods such as payback period (PBP), return on investment (ROI), net present value (NPV), and internal rate of return (IRR).

Author Contributions: Conceptualization. P.B., M.M., P.K., J.K. and P.W.S.; methodology. P.B., P.K. and J.K.; software. P.B., P.K. and J.K.; formal analysis. P.B., M.M., J.K. and P.W.S.; data curation. P.B., P.K. and M.M.; writing—original draft. P.B., M.M., P.K., J.K. and P.W.S.; writing—review and editing. P.B., M.M., P.K., J.K. and P.W.S.; visualization P.B., P.K. and M.M. All authors have read and agreed to the published version of the manuscript.

Funding: The project is co-financed by the European Union from the European Regional Development Fund under the Operational Program Smart Growth 2014–2020. Project carried out as part of the competition by the National Center for Research and Development, Poland: (1/1.1.1/2021—Fast track "Industrial research and development work carried out by enterprises"). Grant number: POIR.01.01.01-00-0709/21.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are contained within the article.

Acknowledgments: This study was conducted within the statutory research activity of the Mineral and Energy Economy Research Institute of the Polish Academy of Sciences.

Conflicts of Interest: The authors declare no conflicts of interest.

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