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Optimizing Electric Vehicle Fleet Operations by using Mixed Integer Linear Programming: A BESS Scheduling Approach

OPTIMIZATION IN QUANTITATIVE MANAGEMENT

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Optimizing Electric Vehicle Fleet Operations by using Mixed Integer Linear Programming: A BESS Scheduling Approach

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Abstract: Amidst the sustainable shift in energy systems, Battery Energy Storage Systems (BESS) have become instrumental in integrating renewable sources into the grid, particularly within the electric vehicle (EV) sector. This paper presents an optimization framework for BESS in EV operations, utilizing a Mixed Integer Linear Programming (MILP) model executed through IBM's CPLEX solver. Our work is distinguished by its dual focus: theoretical development of BESS scheduling and practical application within EV fleet management. We have crafted a user-friendly application interface that allows for the customization of BESS parameters, catering to diverse EV models and operational demands. The MILP model aims to minimize total daily electricity costs, accounting for dynamic pricing, EV energy requirements, and BESS operational limits. The application's efficacy is underscored by a cost reduction from $1396.10 to $1313.02, saving $83.09 daily. The model identifies optimal charging during low-price midday periods, and strategic discharging during high-price intervals, thereby ensuring operational efficiency and energy cost savings. This paper emphasizes the real-world applicability of our MILP approach to BESS management, providing a scalable tool for EV companies to navigate the evolving landscape of energy consumption and optimize fleet operations sustainably.
Keyword: Battery Energy Storage Systems, Electric Vehicle Fleet Management, Mixed Integer Linear Programming, IBM CPLEX Solver, Optimization Problem

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1. Background and Practical Problem Statement

1.1. *Context and Importance of Battery Energy Storage Systems*

The contemporary energy landscape is undergoing a transformative shift towards sustainability, necessitating innovative solutions to address the intermittency inherent in renewable energy sources. Central to this evolution is the role of Battery Energy Storage Systems (BESS), offering a pivotal means to store and regulate energy. BESS not only facilitates grid balance but also enables the seamless integration of renewable energy sources, contributing substantially to the reduction of carbon footprints in line with global sustainability goals. [1]

In this dynamic context, our study focuses on the strategic utilization of BESS within the specific domain of electrical transportation, a sector emblematic of the evolving commitment to sustainable practices. The proliferation of electric vehicles (EVs) in various industries marks a paradigm shift towards cleaner and more energy-efficient modes of transportation. In such a scenario, BESS emerges as a linchpin technology, playing a crucial role in optimizing energy usage, minimizing costs, and ensuring the reliability of electrical transportation fleets. [2]

1.2. *Practical Problem of Scheduling Battery Storage Systems*

In the context of advanced enterprises engaged in the domain of electric transportation, the operational framework prominently features a fleet of electric vehicles (EVs) as an integral facet of its daily activities. A pertinent pragmatic issue confronted by this enterprise pertains to the optimization of Battery Energy Storage Systems (BESS) within the context of the dynamic temporal nuances inherent in time-of-use electricity rates. Given the inherent variability in electricity costs dictated by supply and demand dynamics over the course of the day, the enterprise endeavors to strategically orchestrate the charging and discharging cycles of the BESS. This strategic manipulation is designed not only to minimize the daily expenditure on electricity but also to ensure the smooth and uninterrupted functioning of the electric transportation fleet.

This intricate optimization process necessitates the consideration of technical and operational constraints inherent in electrical transportation systems. The goal is to achieve cost efficiency while ensuring the smooth operational integration of BESS. This involves navigating complex decision-making processes to determine optimal charging and discharging cycles, factoring in BESS charging and discharging rates, EV energy demand, and the evolving electricity price landscape.

In this real-world scenario, the business endeavors to harness the economic benefits of BESS deployment. The optimal scheduling of charging and discharging cycles becomes instrumental in offsetting high electricity prices during peak demand and capitalizing on lower prices during periods of reduced demand. The practical problem thus lies in managing an electric transportation fleet while concurrently optimizing BESS utilization to strike a delicate balance between economic gains and operational efficiency. [3]

2. Review of Related Works

2.1. *Existing Literatures*

The landscape of research surrounding Battery Energy Storage Systems (BESS) has witnessed notable contributions, with two seminal works deserving close examination for their insights into optimal scheduling and the broader implications of battery adoption in the prosumer era.

This study delves into the intricate domain of optimizing the scheduling of Battery Energy Storage Systems. By employing a Mixed Integer Linear Programming (MILP) model, the research seeks to determine the most efficient daily operation of BESS to minimize electricity costs. Noteworthy in its methodology, the study focuses on the overarching economic aspects of BESS utilization, striving to find the optimal balance between charging, discharging, and energy costs.

Energy Systems and Energy Storage Lab - Optimal scheduling of battery energy storage systems (2018).

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While the study provides a comprehensive model for overall BESS optimization, it primarily emphasizes economic considerations without specific attention to the nuances of daily scheduling within distinct timeframes. The absence of a focused exploration into time-of-use dynamics limits its applicability in scenarios where businesses, particularly those in the electrical transportation sector, seek to fine-tune BESS operations within specific daily timeframes.

Projecting battery adoption in the prosumer era Paper.

This work navigates the complex terrain of solar photovoltaic (PV) systems and their integration with energy storage. By analyzing smart meter data from 369 consumers across diverse regions in the U.S., the study assesses the economic benefits of PV and coupled PV-battery systems. A significant facet of this research is its consideration of real demand data, actual PV generation, and the optimization of individual consumer battery operations to minimize electricity bills. [5]

While the study makes substantial contributions to understanding the economic viability of PV-battery systems, it predominantly underscores the challenges and advantages at a macro level. The focus on economic benefits and self-sufficiency enhancement provides a broad overview, yet the absence of a granular examination into daily scheduling dynamics may leave certain gaps in addressing specific operational challenges faced by businesses reliant on electrical transportation.

2.2. *Contribution of Our Work*

In addressing the evolving landscape of Battery Energy Storage Systems (BESS), our study stands out by making significant contributions, both theoretically and practically, with a distinct focus on the electric transportation sector. Our research not only delves into the theoretical aspects of BESS optimization but also presents a tangible application within the realm of electric vehicles (EVs). This nuanced approach sets the stage for a comprehensive exploration of daily scheduling intricacies, bringing to light a crucial yet underexplored facet of BESS utilization.

Within the expansive field of BESS, our work distinctly narrows its focus to the electric transportation sector, particularly EVs. In doing so, we unravel the intricacies of optimizing BESS operations within specific daily timeframes. By showcasing detailed charging and discharging schedules, we illuminate the path toward minimizing electricity costs - a paramount concern for the burgeoning EV industry. The precision with which our study navigates the time-sensitive charging and discharging cycles underscores its practical relevance and real-world applicability.

A pioneering aspect of our contribution lies in the development of a user-centric interface - an application tailored to the unique requirements of businesses operating in the electric transportation domain. Recognizing the diverse parameters associated with different EV models, our research provides a customizable platform. This interface empowers end-users to swiftly adapt the optimization tool to specific product types, offering a seamless and efficient solution. In doing so, we bridge the gap between theoretical advancements and practical usability, catering to the specific needs of businesses in the electrical transportation sector.

In conclusion, our study not only advances the theoretical discourse surrounding BESS optimization but also addresses a significant gap in practical application. By concentrating on the electric transportation sector and providing a tool with a customizable interface, we present an optimal solution for minimizing electricity costs in the day-to-day operations of EV fleets. The emphasis on sustainability and cost-efficiency positions our work as a pioneering effort toward building a more resilient and energy-efficient future for large-scale enterprises. As the global push for sustainable practices intensifies, our research offers a timely and pertinent contribution to the ongoing dialogue on optimal solutions for the electrical transportation industry.

3. Modeling

In our pursuit of addressing the real-world challenge posed by the dynamic nature of energy markets, we formulate a comprehensive mathematical model for optimizing the daily operation of a Battery Energy Storage System (BESS). The paramount objective is the minimization of electricity costs for consumers, acknowledging the inherent complexities and uncertainties within the energy landscape.

Our model centers around a time-of-use electricity rate environment, where the consumer, equipped with a BESS, aims to strategically schedule charging and discharging activities. The intricacy lies in finding the optimal schedule that not only aligns with fluctuating electricity prices but also adheres to technical and operational constraints imposed by the BESS.

Mathematical problem specification

An electric vehicle company is equipped with a BESS and is subject to time-of-use electricity rates, which fluctuate throughout the day based on supply and demand dynamics. Hence, The company seeks to minimize their daily electricity cost by optimally deciding when to charge and discharge the BESS. The challenge lies in determining the optimal charging and discharging schedule that aligns with electricity price fluctuations while adhering to technical and operational constraints.

The variables our model can manage include:

- **Parameters and Variables:**
  - **Time (T):** Discretized into 24 hours, representing a typical day.
  - **Electricity Prices (P_t):** Varying prices of electricity for each hour t.
  - **Energy Demand (D_t):** The consumer's energy demand at each hour t.

- **Battery Specifications:**
  * **Capacity (C):** The total energy capacity of the battery.
  * **Charging Rate (CR):** Maximum power input to the battery per hour.
  * **Discharging Rate (DR):** Maximum power output from the battery per hour.
  * **Charging Efficiency (η_c):** Efficiency factor during charging.
  * **Discharging Efficiency (η_d):** Efficiency factor during discharging.

- **Decision Variables:**
  - **Charging Power (x_t^c):** The amount of energy to charge the battery at time t.
  - **Discharging Power (x_t^d):** The amount of energy to discharge from the battery at time t.
  - **State of Charge (SOC_t):** The amount of energy in the battery at the end of time t.

- **Objective Function:** Minimize Total Daily Cost:

$$\min \sum_{t \in T} P_t \cdot (D_t - x_t^d + x_t^c)$$

Subject to the following constraints:

- **Power Balance:** Ensuring that the demand is always met

$$D_t = x_t^d - x_t^c + D_t^{\text{grid}}$$

- **Battery Capacity:** The SOC must not exceed the battery's physical limits

$$0 \leq \text{SOC}_t \leq \text{C}$$

- **Charging/Discharging limits:** The battery can only charge or discharge within its rated power

$$0 \leq x_t^c \leq \text{CR}$$

$$0 \leq x_t^d \leq \text{DR}$$

- **SOC Dynamics:** The SOC evolves based on charging and discharging activities, accounting for efficiencies.

- **Initial and Final SOC:** Typically set to ensure the battery has a certain charge at the beginning and the end of the day.

4. Introduce/Explain Algorithm/Solution methods/Solvers for the mathematical problem above

4.1. Introduce/Explain about Mixed Integer Linear Programming (MILP)

In this project, we attempt to formulate a Mixed Integer Linear Programming (MILP) model to optimize BESS. Unlike Linear Programming (LP), MILP incorporates integer decision variables, adding a layer of precision that proves important in solving the complexity of real-world optimization problems. [6] MILP's ability to handle both continuous and discrete variables makes it particularly suitable for situations where the constraints require more complexity and practicality.

MILP assumes a central role by strategically determining the charging and discharging schedule. The inclusion of integer variables in MILP becomes pivotal when discrete decisions, such as when to charge or discharge the battery, significantly impact the optimization outcome.

The primary aim is to minimize the total daily cost, a linear function defined by the sum of electricity prices multiplied by the difference between energy demand and the net effect of charging and discharging actions.

The formulation of the objective function encapsulates MILP's ability to handle mixed types of decision variables, addressing the intricate nature of BESS optimization in the dynamic energy landscape. Through the synergistic integration of continuous and integer variables, MILP provides a sophisticated and effective tool for minimizing daily electricity costs while navigating the constraints and fluctuations inherent in energy management. [7]

4.2. *Introduce/Explain about our CPLEX (and solving Mixed Integer Linear Programming by using CPLEX)*

CPLEX stands out as a leading optimization solver developed by IBM. Known for its versatility and efficiency, CPLEX excels in tackling complex mathematical programming problems. In practical terms, CPLEX proves invaluable in solving optimization problems across different industries. Its application extends to areas such as logistics, finance, and energy systems. For instance, in logistics, CPLEX can efficiently optimize supply chain and transportation networks. In finance, it aids in portfolio optimization and risk management. Furthermore, CPLEX's utility extends to optimizing energy systems, where it plays a pivotal role in enhancing resource allocation and efficiency. This is particularly evident in the realm of optimizing Battery Energy Storage Systems (BESS), where the application of IBM's CPLEX optimizer is instrumental. The objective of BESS optimization is to determine the most efficient charging and discharging schedules, considering dynamic electricity prices, energy demand fluctuations, and stringent technical constraints. This endeavor is formulated as a Mixed-Integer Linear Programming (MILP) problem, where the decision variables encompass the charging and discharging actions, as well as the state of charge of the battery at discrete time intervals. [8]

The fundamental components of the optimization problem include the definition of decision variables, the formulation of an objective function aimed at minimizing the total daily cost, and the imposition of various constraints to ensure operational feasibility. Notably, these constraints encompass power balance, battery capacity limitations, charging and discharging rate limits, and the dynamical evolution of the state of charge over time. The comprehensive model is then translated into the programming environment using the CPLEX library in Python, interfacing seamlessly with IBM's powerful CPLEX optimizer.

CPLEX employs sophisticated algorithms, including the Branch & Bound method, to navigate through the intricate solution space, addressing both continuous and discrete decision variables. It plays an important role in systematically exploring potential solutions, striving to identify the optimal charging and discharging schedules that minimize the total cost over the course of a day. The resulting solution provides insights into the optimal power actions at each hour, shedding light on how to intelligently operate the BESS to achieve cost savings while satisfying technical constraints.

The advantages of employing CPLEX in this context lie in its computational efficiency and precision. CPLEX excels at handling complex MILP problems, ensuring a balance between speed and accuracy. This systematic and accurate approach is essential for deriving meaningful insights into BESS optimization, enabling users to make informed decisions that align with their economic and operational objectives.

5. Experiments

5.1. *Gather/generate data*

In the context of optimizing the scheduling of an electric vehicle (EV) battery to minimize electricity costs, it is crucial to understand and characterize the data that drives the optimization model. The data used in this optimization problem includes information on electricity prices and energy demand throughout a typical day. Below is a detailed explanation of how this data is gathered and generated:

Electricity Prices ($/kWh): The electricity price data is a composite of various elements, each reflecting different market dynamics:

- **Base Price:** Set at $0.1/kWh, this represents the average baseline cost of electricity.
- **Daily Variation:** Modeled using $0.05 \times \sin\left(\frac{2\pi t}{24}\right)$, this sinusoidal component reflects typical daily price fluctuations, peaking during expected high-demand periods.
- **Seasonal Variation:** Captured by $0.05 \times \cos\left(\frac{2\pi t}{\text{hours\_in\_day}}\right)$, this factor introduces variability associated with broader demand changes over seasons.
- **Random Variation:** Introduced through $0.01 \times$ np.random.randn(hours_in_day), this stochastic element adds unexpected fluctuations to account for unpredictable market changes.

The final electricity prices for each hour are synthesized by summing these components, offering a realistic portrayal of how real-world prices might vary over a single day.

Energy Demand (kW): The energy demand reflects the power required to charge the EV company's fleet:

- **Base Demand:** Set at 500 kW, it acts as the foundational demand level for the fleet.
- **Daily Demand Variation:** Defined by $200 \times \sin\left(\frac{2\pi t}{24}\right)$, this term models the expected rise in charging demand during off-peak hours, typically overnight.

The demand for each hour is the sum of the base demand and its variation, with negative values corrected to zero using `np.maximum(0, ...)`. This creates a realistic, variable demand profile that peaks when charging is most beneficial cost-wise.

Battery Parameters:

- **Battery Capacity:** Set at 1000 kWh, reflecting a large-scale BESS capable of meeting substantial daily demand variations.
- **Charge/Discharge Rates:** Both set at 100 kW, indicating the maximum power at which the BESS can either charge or discharge within an hour.
- **Charge/Discharge Efficiencies:** Both efficiencies are set at 0.9, accounting for a 10% loss in energy during the charge/discharge process.
- **Initial State of Charge (SOC):** Set at 50% of the battery's capacity, indicating that the BESS starts the day half-charged.

These parameters provide a detailed characterization of the BESS's capabilities and constraints, directly influencing the optimization's feasibility and strategy.

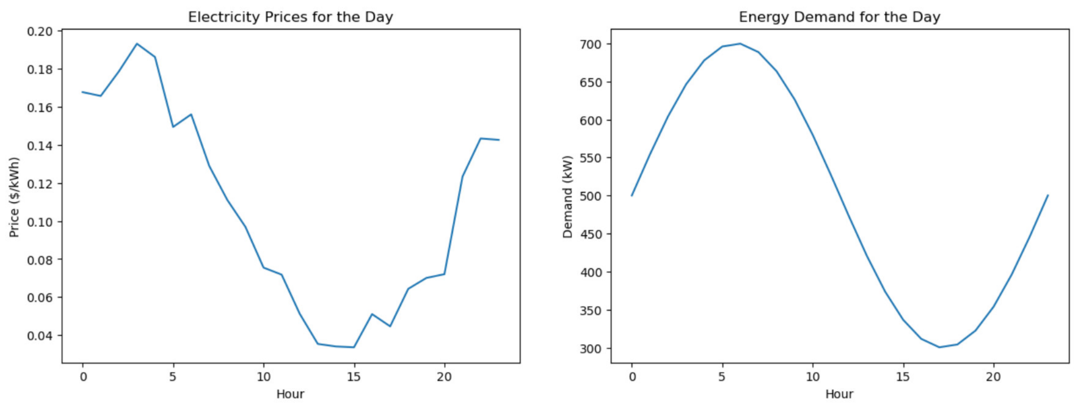

Figure 1:

The Data of Electricity prices, Energy demand for the Day

5.2. Write Code or Use Solvers Successfully

Below is a step-by-step explanation of the provided Python code for solving an optimization problem using a Mixed-Integer Linear Programming (MILP) model with CPLEX. This optimization problem involves scheduling the charging and discharging of an electric vehicle (EV) battery to minimize the cost of electricity consumption while meeting the energy demand throughout the day.

Step 1: Setting Up Your Environment & Importing Libraries

Initially, we establish our working environment by importing necessary libraries. NumPy is incorporated for its comprehensive mathematical functions, Matplotlib for its advanced plotting capabilities, and docplex.mp.model from CPLEX to define and solve optimization problems. This setup is crucial as it provides the tools needed for numerical calculations and visualizing data, forming the foundation for our optimization model.

```
import numpy as np
import matplotlib.pyplot as plt
from docplex.mp.model import Model
```

Step 2: Setting the Data

In this step, we initialize our data parameters, which are pivotal in simulating real-world conditions. We define a 24-hour day to represent the time horizon for our scheduling problem. We then set up a base price for electricity and superimpose daily, seasonal, and random variations to reflect the complex nature of real-world electricity pricing. Similarly, we establish a baseline for energy demand and introduce a sinusoidal variation to mimic daily changes. These parameters are visualized through plots, offering us a preliminary look at the patterns and variations our model will address.

```
hours_in_day = 24  # 24 hours in a day
np.random.seed(0)  # For reproducibility

# Electricity prices ($/kWh)
base_price = 0.1  # Base price
daily_variation = 0.05 * np.sin(np.linspace(0, 2 * np.pi, 24))  # Daily fluctuation
seasonal_variation = 0.05 * np.cos(np.linspace(0, 2 * np.pi, hours_in_day))
random_variation = 0.01 * np.random.randn(hours_in_day)  # Random noise
electricity_prices = base_price + daily_variation + seasonal_variation
+ random_variation

# Energy demand (kW)
base_demand = 500  # Average demand
daily_demand_variation = 200 * np.sin(np.linspace(0, 2 * np.pi, 24)
demand = np.maximum(0, base_demand + daily_demand_variation)

# Plotting the results
plt.figure(figsize=(15, 5))

# Plotting electricity prices for the day
plt.subplot(1, 2, 1)
plt.plot(electricity_prices[:24])  # Plot the entire day (24 hours)
plt.title('Electricity Prices for the Day')
plt.xlabel('Hour')
plt.ylabel('Price ($/kWh)')

# Plotting energy demand for the day
plt.subplot(1, 2, 2)
plt.plot(demand[:24])  # Plot the entire day (24 hours)
plt.title('Energy Demand for the Day')
plt.xlabel('Hour')
plt.ylabel('Demand (kW)')

plt.show()
```

Step 3: Defining the Parameters for the EV and Charging

Here, we delve into specifics by defining the characteristics of our battery and charging system. Parameters like battery capacity, charge and discharge rates, and efficiencies are set. We also determine the initial state of charge (SoC) for the battery, which is vital for understanding how the battery will behave and be utilized throughout the optimization process. These parameters are foundational for constructing a realistic and functional model.

```
# Defining Parameters for the EV and charging
battery_capacity = 1000  # kWh
charge_rate = 100  # kW
discharge_rate = 100  # kW
charge_efficiency = 0.9
discharge_efficiency = 0.9
initial_soc = battery_capacity * 0.5  # 50% initial charge
```

Step 4: Creating the MILP Model

We now begin constructing our Mixed-Integer Linear Programming (MILP) model using CPLEX. We introduce decision variables that will determine our charging and discharging strategies and the state of charge (SoC) for each hour. Binary variables are also created to indicate the on/off status of charging and discharging at any given time. This step is critical as it lays down the structure of our optimization problem, ready to be solved.

```
# Creating the MILP model
mdl = Model("Battery Scheduling_MILP")

# Decision variables
```

```
charging = [mdl.continuous_var(lb=0, ub=charge_rate, name='charge_{}'.format(t))
for t in range(hours_in_day)]
discharging = [mdl.continuous_var(lb=0, ub=discharge_rate, name='discharge_{}'.format(t)
for t in range(hours_in_day)]
soc = mdl.continuous_var_list(hours_in_day, name='soc', lb=0, ub=battery_capacity)

# Binary decision variables
charging_decision = mdl.binary_var_list(hours_in_day, name='charging_decision')
discharging_decision = mdl.binary_var_list(hours_in_day, name='discharging_decision')
```

Step 5: Setting the Objective Function

Our objective is to minimize the total cost of electricity while ensuring that energy demands are met at all times. The objective function we construct reflects the cost incurred for each hour, considering whether the system is charging, discharging, or idle. This function is the heart of our optimization problem, guiding the solver towards the most cost-effective solution.

```
# Objective
cost = mdl.sum(electricity_prices[t] * (demand[t] - discharging[t] + charging[t])
for t in range(hours_in_day))
mdl.minimize(cost)
```

Step 6: Adding Constraints

To ensure the model reflects real-world limitations and operates correctly, we impose various constraints. These include ensuring the energy demand is met at every hour, the state of charge is updated accurately after each charging or discharging activity, and the battery's state of charge at the beginning and end of the period remains constant. These constraints are crucial for maintaining the feasibility and reliability of our model's solutions.

```
for t in range(hours_in_day):
    mdl.add_constraint(demand[t] - discharging[t] + charging[t] >= 0)

for t in range(1, hours_in_day):
    mdl.add_constraint(soc[t] == soc[t - 1] + charging[t - 1] * charge_efficiency
    - discharging[t - 1] / discharge_efficiency)

mdl.add_constraint(soc[0] == initial_soc)
mdl.add_constraint(soc[-1] == initial_soc)
```

Step 7: Solving the Model and Analyzing the Results

Upon solving the model, we analyze the results if a solution is found. We calculate and compare the total costs with and without battery integration, highlighting the cost savings achieved. We also examine the optimal charging and discharging schedule, providing insights into how the battery should be operated throughout the day. Additionally, we observe the final state of charge, ensuring it aligns with our initial conditions and constraints.

```
solution = mdl.solve(log_output=True)
if solution:
    print("Solution found!")
    charging_schedule = solution.get_values(charging)
    discharging_schedule = solution.get_values(discharging)
    soc_schedule = solution.get_values(soc)

    # Detailed optimal solution insights
    total_cost_with_battery = solution.objective_value
    print(f"Total Cost with Battery: ${total_cost_with_battery:.2f}")

    # Calculate the cost without the battery
    total_cost_without_battery = sum(electricity_prices[t] * demand[t]
    for t in range(hours_in_day))
    print(f"Total Cost without Battery: ${total_cost_without_battery:.2f}")

    # Calculate and report the cost savings
```

```
    cost_savings = total_cost_without_battery - total_cost_with_battery
    print(f"Cost Savings with Battery: ${cost_savings:.2f}")

    # Optimal charging and discharging times
    print("\nOptimal Charging (kW) and Times:")
    for t, charge in enumerate(charging_schedule):
        if charge > 0:
            print(f"Hour {t}: Charge {charge:.2f} kW")

    print("\nOptimal Discharging (kW) and Times:")
    for t, discharge in enumerate(discharging_schedule):
        if discharge > 0:
            print(f"Hour {t}: Discharge {discharge:.2f} kW")

    # Final State of Charge
    print(f"\nFinal State of Charge: {soc_schedule[-1]:.2f} kWh")
else:
    print("No solution found.")
```

Step 8: Plotting the Results

Finally, we visualize our findings by plotting the charging and discharging schedules alongside the state of charge over the 24-hour period. These visualizations are not just illustrative but also offer an intuitive understanding of the battery's operational strategy and its impact on costs and energy usage.

```
# Plot the results
plt.figure(figsize=(15, 5))

# Plotting charging and discharging schedule for the day
plt.subplot(1, 2, 1)
plt.plot(charging_schedule, label='Charging')
plt.plot(discharging_schedule, label='Discharging')
plt.title('Charging and Discharging Schedule for the Day')
plt.xlabel('Hour')
plt.ylabel('Power (kW)')
plt.legend()

# Plotting state of charge for the day
plt.subplot(1, 2, 2)
plt.plot(soc_schedule)
plt.title('State of Charge for the Day')
plt.xlabel('Hour')
plt.ylabel('SOC (kWh)')

plt.show()
```

After executing the computational model, the analysis reveals the optimal solutions for the charging and discharging schedules, along with the State of Charge (SOC) throughout the day:

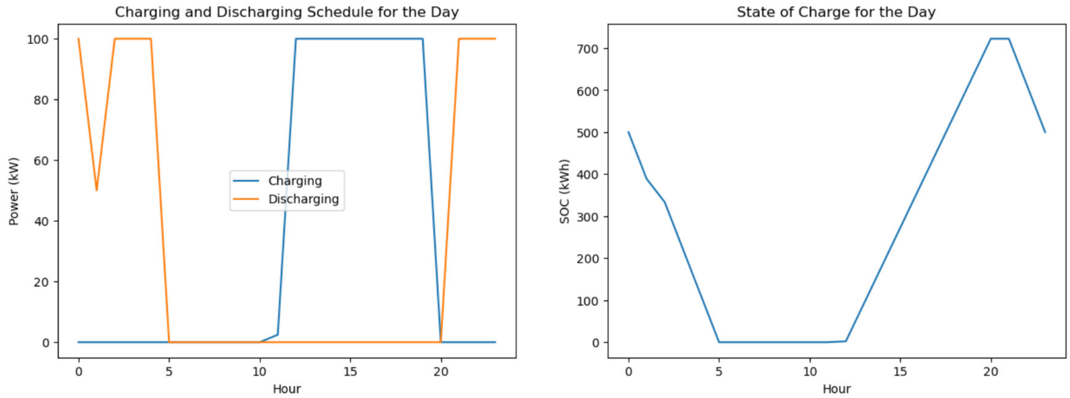

Figure 2:

The optimal outcome of Charging, Discharging Schedule, and SOC for the Day

6. Derive Findings

1. Enhanced Cost Management for EV Operations:

Actualized Energy Costs with Battery Integration ($1313.02): By implementing a battery system, our EV company reduces daily energy costs to $1313.02. This figure includes the strategic charging of electric vehicles (EVs) during hours with lower electricity rates and discharging the stored energy when rates peak. This approach not only minimizes the cost of electricity drawn from the grid but could also provide income through energy sold back during peak hours, assuming a rate of return that matches or exceeds the cost of electricity during off-peak hours.

Potential Costs Without Battery Utilization ($1396.10): In the absence of a battery system, the company faces a higher energy expenditure of $1396.10, purely purchasing grid energy to meet demand. This comparison underscores the immediate cost-saving benefits of a battery system, amounting to an $83.09 reduction in daily operational expenses.

2. Energy Utilization Strategies for Fleet Optimization:

Intelligent Charging Schedules: Data indicates optimal battery charging primarily takes place between 11 am and 7 pm, which may coincide with the lowest electricity pricing possibly due to peak solar energy generation. This knowledge empowers an EV company to align fleet charging times with these hours, thus benefiting from lower costs and contributing to a sustainable charging strategy.

Strategic Energy Disbursement: The battery is discharged during early morning (12 am to 4 am) and late evening (9 pm to 11 pm), which aligns with the anticipated high energy cost periods due to increased demand or reduced renewable generation. An EV company could leverage this pattern by powering facilities or charging vehicles during these times, mitigating the need for expensive grid power. The company can also explore opportunities to generate revenue by providing grid support services during these peak periods.

3. Battery Capacity and Fleet Readiness:

Maximized Charging Dynamics: Observing the battery's charging behavior at its full rate of 100 kW during the afternoon suggests that taking full advantage of available lower-cost energy is most beneficial. For an EV fleet operator, such data can inform the design of charging infrastructure to ensure that vehicles are charged rapidly and efficiently, preparing the fleet for peak service times without incurring high energy costs.

Optimized Discharging Rates: The battery's discharging at the maximum rate during specific high-demand hours indicates times when energy can be most profitably used or sold. An EV company can use this insight to schedule ancillary services or high-power-consuming activities, such as maintenance or vehicle pre-conditioning, during these times.

Calibrated State of Charge (Ending at 500 kWh): Concluding the day at a 50% state of charge provides a buffer that can accommodate unforeseen demand surges or exploit advantageous shifts in electricity pricing. For an EV company, maintaining such a strategic reserve is critical for operational flexibility, ensuring that vehicles can respond to immediate service demands or participate in grid services without the risk of energy deficits.

Incorporating these detailed data-driven strategies can lead to significant cost efficiencies, improved operational readiness, and potential new revenue streams for an EV company. By leveraging the insights from the optimization model, the company can make informed decisions that not only reduce operational costs but also support a sustainable and resilient energy management system.

7. Demo App Interface Development

Objectives of the App Interface: The primary objective of this app interface is to provide a user-friendly platform for EV companies and energy managers to optimize their battery charging and discharging schedules. The goal is to minimize electricity costs while meeting the energy demand by smartly leveraging time-of-use electricity rates. The interface allows for the input of variable electricity prices, demand profiles, and battery parameters, which are then processed by a sophisticated optimization algorithm.

How to Use the App Interface:

- **Input Electricity Prices and Demand Data:**
  - Use the Prices textarea to enter the electricity prices for each hour of the day. The prices should be entered as a comma-separated list.
  - In the Demand textarea, input the expected electricity demand for each hour, also as a comma-separated list.
- **Set Battery Parameters:**
  - Adjust the Capacity (kWh) slider to match the battery's total storage capacity.
  - Move the Charge Rate (kW) and Discharge Rate (kW) sliders to reflect the maximum rates at which the battery can be charged and discharged.
  - Use the Charge Efficiency and Discharge Efficiency sliders to set the efficiency at which the battery charges and discharges energy, respectively.
- **Run the Optimization:**
  - Click the Run Optimization button to start the optimization process. The algorithm will use the provided data to calculate the most cost-effective charging and discharging schedule.
- **Interpret the Results:**
  - Once the optimization is complete, the results will be displayed below the button. You'll see the total cost with the battery strategy applied.
  - The plotted graphs will show the optimal charging and discharging schedules, along with the state of charge (SoC) of the battery over the 24-hour period.
- **Analyzing Outcomes for Decision Making:**
  - Examine the Total Cost with Battery to assess the direct financial benefit of using the battery storage system.
  - Analyze the charging and discharging graphs to determine the best hours to charge and discharge the battery in future operations.
  - Utilize the SoC graph to understand how the battery's charge is being utilized and plan for capacity needs and battery life preservation.
- **Iterative Improvement:**
  - Adjust inputs and re-run the optimization as needed to explore different scenarios or to respond to changing electricity prices, demand forecasts, or operational strategies.

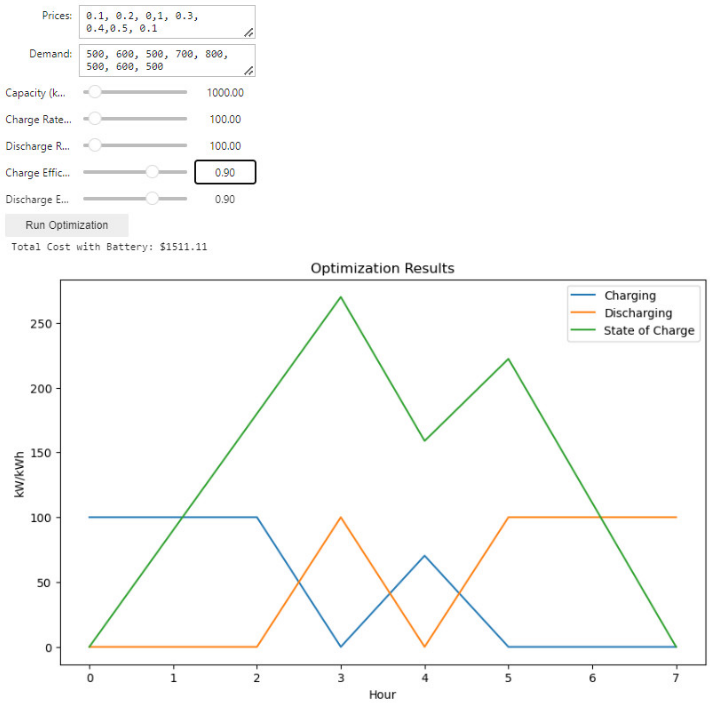

Figure 3:

The Demo of the App interface, illustrating its capability to customize input data for obtaining an optimal solution.

8. Conclusion

8.1. Summary of Work

In synthesis, our study undertook an exhaustive examination of the optimal scheduling dynamics for Battery Energy Storage Systems (BESS) in the realm of electric transportation, specifically focusing on minimizing daily electricity costs. Our approach effectively aligns charging and discharging cycles with fluctuating electricity prices, ensuring a delicate balance between economic gains and operational efficiency. The trajectory of our research unfolded through three discernible phases:

Theoretical Foundations: A meticulous scrutiny of extant BESS optimization literature illuminated critical lacunae, primarily the absence of a targeted exploration of daily scheduling intricacies within distinct timeframes. This preliminary analysis paved the way for our distinctive emphasis on the electric transportation sector, with a specific lens on electric vehicles (EVs).

Model Formulation: Recognizing the dynamic nuances of energy markets, we articulated a robust mathematical model firmly grounded in Mixed Integer Linear Programming (MILP). This model intricately navigated the intricacies of time-of-use electricity rates, offering a precise tool for strategically orchestrating BESS charging and discharging activities. The calibration of decision variables, constraints, and the objective function was a meticulous process, ensuring alignment with real-world operational complexities.

Implementation and Findings: Our study ventures beyond the theoretical realm into the practical landscape, showcasing substantial contributions to the optimization of Battery Energy Storage Systems (BESS) for electric vehicle (EV) operations. Through a nuanced Mixed Integer Linear Programming (MILP) approach and the employment of IBM's CPLEX solver, we've not only illuminated the path for enhanced cost management but also laid down a strategic roadmap for efficient energy utilization and fleet readiness.

The findings from our discussion are pivotal. We actualized a significant reduction in daily energy costs for an EV company, bringing it down to $1313.02 from a potential $1396.10 without battery utilization. This $83.09 saving per day is not merely a numerical victory but a testament to the BESS's capacity to transform energy management. By integrating strategic charging during low-cost periods and discharging during peak hours, our approach demonstrates a robust model for capitalizing on fluctuating electricity prices, promising substantial economic benefits and operational efficiencies.

Our insights into intelligent charging schedules and strategic energy disbursement are particularly compelling. The identification of optimal charging times exploits lower electricity costs and aligns with sustainable energy generation patterns. Concurrently, the strategic discharging during high-price periods opens avenues for both cost savings and potential revenue generation. This dual strategy underscores the adaptability and foresight our model offers to the EV industry.

Moreover, the nuances of battery capacity and fleet readiness discussed provide a clear direction for EV companies. The maximized charging dynamics and optimized discharging rates we've identified are not mere recommendations but actionable strategies that enhance operational efficiency and economic returns. Our findings on maintaining a calibrated state of charge offer a strategic buffer, ensuring resilience and flexibility in operations.

8.2. Limitations

However, our study, while extensive, acknowledges certain limitations. The model's reliance on predictable electricity pricing and demand patterns may not encapsulate the full spectrum of market volatility. Furthermore, it assumes a homogeneous BESS technology, which might not be universally applicable.

8.3. Promising Results and Future Work

The auspicious outcomes derived from our study pave the way for prospective research trajectories. A natural progression involves introducing a stochastic component into the model, augmenting its adaptability to dynamic and uncertain energy environments. Further exploration into the ramifications of battery degradation on cost-effectiveness holds potential for refining our comprehension of the long-term viability of BESS implementation. Extending our study's purview to encompass diverse consumer profiles, including different EV models and energy demand patterns, promises to enhance practical applicability. Moreover, investigating the integration of demand response strategies within the BESS optimization framework presents an avenue for unlocking additional economic advantages and fortifying grid resilience. Collaborative engagements with industry stakeholders could facilitate real-world validations, fostering the evolution of adaptive models responsive to dynamic energy market paradigms. In essence, our study initiates a continuum of scholarly dialogue, beckoning researchers and industry practitioners to collectively refine BESS optimization paradigms and propel innovations toward a sustainable and resilient energy future within the electric transportation sector. Future research should focus on incorporating more dynamic and stochastic elements into the model to reflect real-world complexities better. Exploring different BESS technologies and configurations will provide a more comprehensive understanding and broader applicability. Additionally, as policies and technologies evolve, further studies should consider these changes' impacts on the optimization strategy. Lastly, expanding the model to include environmental impact assessments will align the operational strategies with broader sustainability goals, providing a more holistic approach to BESS management in the EV sector.

In conclusion, our research marks a significant advancement in the theoretical and practical realms of Battery Energy Storage Systems (BESS) optimization, fostering a leap towards economically viable and sustainable solutions within the electric vehicle (EV) industry. As we navigate towards a future of cleaner energy and transportation, our study provides critical insights and strategies to enhance efficiency and resilience. This investigation is not merely an endpoint but the commencement of a promising journey toward sustainable transformation in the electric transportation domain, underscoring the imperative for continued innovation and collaboration in this evolving field.

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