Energy Economics & Optimization: Project 3

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ABSTRACT

This study presents a two-stage stochastic optimization framework designed to explore portfolio decisions about energy procurement contracts that serve campus needs while minimizing costs. By integrating 15-minute interval demand, price and capacity factor data, the model leverages Conditional Value-at-Risk (CVaR) analysis to find robust cost estimation under uncertainty. The study further examines the feasibility of renewable energy investments, such as expanding solar capacity and battery storage, and accounts for projected costs of CO2. This work provides actionable insights for energy portfolio management, offering a scalable approach to informed decision making and long-term sustainability planning.

Keywords: MILP, BiLevel, CVaR, Solar+Storage

INTRODUCTION

In the context of rising energy costs and the global push towards sustainability, this project addresses the challenge of optimizing a college campus's energy portfolio in upstate New York. The campus relies on a mix of renewable and non-renewable energy sources, including at-risk wind contracts, natural gas generator contracts, on-site solar power, and real-time spot market purchases. The objective is to minimize operational costs while considering potential pathways towards fully renewable energy reliance.

The problem (see **Methodology Algorithm**) is framed as a flattened two-stage stochastic optimization to determine the optimal mix of energy contracts under five equally probable demand scenarios. A robust optimization approach is employed to identify strategies that minimize costs in the worst-case scenario, leveraging Conditional Value-at-Risk (CVaR) analysis.

1. **Scenario Modeling**: Demand, price, and capacity factor profiles are simulated at 15-minute intervals for five scenarios to capture variability in energy needs and generation potential. The **real-time dispatch portfolio must meet expected demand**, but is **allowed to over-generate** at no specific over-generation cost.

2. **Optimization Framework**: Decision variables for contract capacities (wind, baseload, peak load, load-following) are optimized using CVXPY, subject to operational constraints. Throughout constraint and variable modeling, convexity is maintained for global solution convergence.

3. **Cost Minimization**: Fixed costs for contracts are minimized alongside weighted real-time operational costs from the spot market and load-following generators. Two primary methods of realtime cost valuation are investigated; an evenly-weighted average cost as well as a Conditional Variance-at Risk formulation parametrized for worst-case cost; both these methods and their implications are discussed in **Results**.

4. **Renewable Integration Analysis**: Energy production for electricity demand makes up The feasibility of transitioning to renewable energy is evaluated by simulating extended solar and battery storage capacities, incorporating realistic costs amortized over their lifespan.
A predicted cost of CO2 emissions is also factored into our renewables study analysis to provide a parametrized understanding of the economic feasibility of renewable incorporation.

The results inform decision-making for cost-effective and sustainable energy management while providing insights into reducing the carbon footprint of campus operations.

METHODOLOGY

Algorithm 1: Optimization Methodology for Energy Generation Planning

Input: Load scenario data for multiple scenarios
Input: Define time intervals and cost parameters
Input: Set capacity limits for different energy generation types
Initialize decision variables:
  C_{wind}: Installed wind capacity (MW)
  C_{baseload}: Installed baseload capacity (MW)
  C_{peak}: Installed peak capacity (MW)
  $C_{\text{load-following}}$: Installed load-following capacity (MW)
  for *each scenario s* **do**
    for *each time step t* **do**
      $G_{\text{load-following},s,t}$: Load-following generation
      $G_{\text{spot},s,t} \geq U_{s,t}$: Spot-mkt purchases
  Define capacity constraints:
    $0 \leq C_{\text{wind}} \leq C_{\text{wind,max}}$
    $0 \leq C_{\text{baseload}}$
    $0 \leq C_{\text{peak}}$
    $0 \leq C_{\text{load-following}}$
    $C_{\text{baseload}} + C_{\text{peak}} + C_{\text{load-following}} \leq C_{\text{generator,max}}$
  for *each scenario s* **do**
    for *each time step t* **do**
      Retrieve scenario-specific data:
        Demand $D_{s,t}$, Real-time price $p_{s,t}$
        Wind factor $f_{\text{wind},s,t}$, Solar factor $f_{\text{solar},s,t}$
      Calculate renewable generation:
      $G_{\text{solar},t} \leftarrow C_{\text{solar}} \times f_{\text{solar},s,t}$
      $G_{\text{wind},t} \leftarrow C_{\text{wind}} \times f_{\text{wind},s,t}$
      Determine peak generation availability:
      if *t is during peak hours* **then**
        $G_{\text{peak},t} \leftarrow C_{\text{peak}}$
      else
        $G_{\text{peak},t} \leftarrow 0$
      Compute total generation:
      $G_{\text{total},s,t} \leftarrow G_{\text{solar},t} + G_{\text{wind},t} + C_{\text{baseload}} + G_{\text{peak},t}$
      Calculate unmet demand:
      $U_{s,t} \leftarrow \max\left(0, D_{s,t} - G_{\text{total},s,t}\right)$
      Determine additional generation or purchases:
      $0 \leq G_{\text{load-following},s,t} \leq C_{\text{load-following}}$
      $G_{\text{load-following},s,t} + G_{\text{spot},s,t} \geq U_{s,t}$
      $G_{\text{spot},s,t} \geq 0$
    Calculate total cost for scenario s:
    $C_s \leftarrow C_{\text{fixed}} + \sum_t \left(G_{\text{load-following},s,t} \times c_{\text{lf,ex}} + G_{\text{spot},s,t} \times (p_{s,t} + c_{\text{service}})\right) \times \Delta t$
  Compute expected cost:
  $C_{\text{avg}} \leftarrow \frac{1}{N}\sum_{s=1}^{N} C_s$
  Compute cost variability:
  $\sigma_C \leftarrow \sqrt{\frac{1}{N}\sum_{s=1}^{N}(C_s - C_{\text{avg}})^2}$
  Define optimization objective:
  $\min \quad C_{\text{avg}} \quad \text{or} \quad \min_{\alpha,M,x_s,y} \quad \alpha + \frac{1}{N(1-\beta)}\sum_{s=1}^{N} M_s$
  Solve the optimization problem using an appropriate solver (CBC or GUROBI)
  if *Optimal solution is found* **then**
    Output optimal capacities and expected costs:
    Optimal wind capacity C^*_{wind}
    Optimal baseload capacity C^*_{baseload}
    Optimal peak capacity C^*_{peak}
    Optimal load-following capacity $C^*_{\text{load-following}}$
    Emissions Information ...
    Expected cost C^*_{avg}
  else
    Report no feasible solution found

RESULTS & DISCUSSION

Standard Optimization

In the standard case, the commitment portfolio is optimized for the minimum expected cost in five evenly weighted environment and demand scenarios. An example power dispatch for scenario 5 is shown in Figure 1. This suggests that without external stimulates, under average cost assumption, the system favors traditional natural-gas generator capacity at lowest possible cost. The moderate standard deviation of costs (51.5343) indicates some variability between scenarios, but is not a significant driver of potential edge case load issues; regardless, the next section will discuss a more robust method of optimization for variance-conditioned optimization.

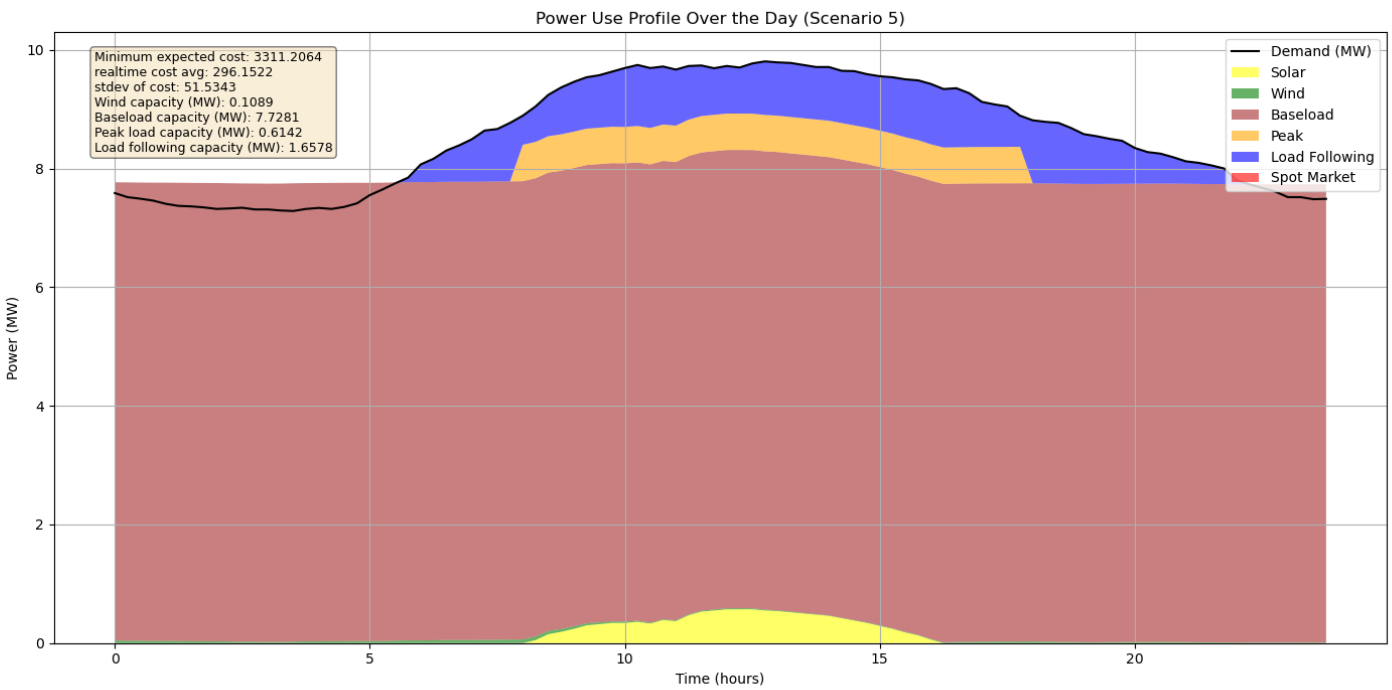

Figure 1. Average Cost - Focus Power Dispatch

Robust Optimization with CVaR

In addition to minimizing expected costs, this project also uses Conditional Value at Risk (CVaR) to account for potential high-cost severe scenarios.

Setting $\alpha = 0.8$ (which means that we consider the worst 20% of the scenarios), CVaR optimization effectively identifies and minimizes the expected cost in the worst α tail of the distribution.

The CVaR formulation can be written as:

$$\min_{\alpha, M, x_s, y} \quad \alpha + \frac{1}{N(1-\beta)} \sum_{s=1}^{N} M_s \tag{3}$$

$$\text{subject to: } M_s \geq R^T y + Q_s^T x_s - \alpha \tag{4}$$

$$M_s \geq 0 \tag{5}$$

This is equivalent to introducing an auxiliary variable M and writing:

$$\min_{x \in A} M \quad \text{subject to } M \geq 0 \text{ and } M \geq x. \tag{7}$$

Where N is the number of scenarios, M_s represents the amount by which the cost in scenario s exceeds the VaR-level cost α. The term $R^\top y + Q_s^\top x_s$ gives the realized cost for scenario s. Here, α can be interpreted as the VaR threshold, and each M_s measures how much the scenario s surpasses this threshold.

The CVaR result incorporates extreme unfavorable tail risk, ensuring that the possibility of cost spikes under the worst conditions is controlled. Compared to the previous optimization (3,311.2064), the CVaR optimization introduces a slightly higher total cost (3,370.2448). Both solutions rely heavily on stable baseload capacity; however, the CVaR approach slightly increases wind capacity, makes limited use of the spot market, and adjusts peak and load-following capacities. Nevertheless, the CVaR-based solution remains relatively conservative with respect to renewables, employing minimal amounts of solar and wind power.

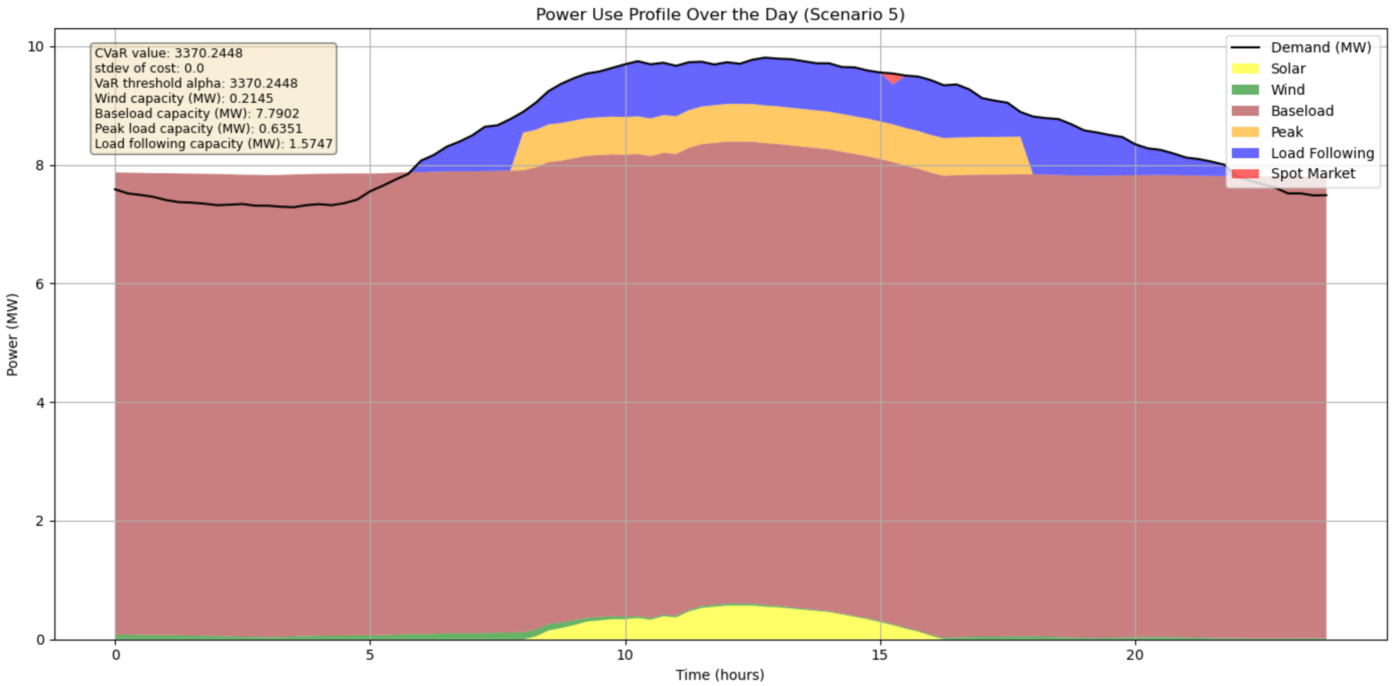

Figure 2. CVaR-Optimized Power Dispatch

RENEWABLE ENERGY FEASIBILITY

In the US, 40% of energy production is used for electricity, and 60% of this electricity is generated through CO2-emitting resources like coal and natural gas (**USEnergyFacts**). In light of climate damage and associated taxation involving rising atmospheric CO2 levels, this report provides a holistic cost and useage analysis of renewable resource utilization.

The feasibility study evaluates renewable energy resource use by allowing increased solar generation and battery storage for a campus-scale energy system. The system is modeled to include solar, storage, and traditional energy sources (base load, peak load, and load-following). Decision variables such as solar capacity and battery storage are constrained by physical and technical limits, including maximum capacities and charge/discharge rates. Costs include fixed infrastructure costs, real-time operational costs, and CO_2 taxes. Simulations are conducted across scenarios that capture demand variations, renewable generation profiles, and energy prices. Optimization ensures energy balance at every time step, with renewable sources and storage reducing reliance on CO_2-emitting energy. Constraints ensure operational feasibility, such as maintaining storage state-of-charge within allowable limits.

Renewables Variable Definitions

Solar Cost Parameters

- $solar\_fixed\_cost = 0$ (Upfront cost).
- $solar\_cost\_per\_mw = 770,000$ (Cost per MW of solar capacity) (**solar˙reviews**).
- $solar\_cost\_per\_mw = 1.25 \times solar\_cost\_per\_mw$ (Adjusted to 1.25 million per MW of solar generation with offsite transmission).
- $solar\_lifespan\_years = 30$ (Lifespan over which to amortize the cost).
- $max\_solar\_capacity = 100$ (Maximum solar capacity, limited by surface area).
- $solar\_capacity$ (Decision variable, nonnegative).

Storage Cost Parameters

- $storage\_fixed\_cost = 0$ (Upfront cost).
- $storage\_cost\_per\_mwh = 350,000$ (Cost per MWh of storage capacity) (**nrel˙report**).
- $storage\_lifespan\_years = 20$ (Lifespan over which to amortize the cost).
- $max\_storage\_capacity = 150$ (Maximum storage capacity, limited by space).
- $storage\_capacity$ (Decision variable, nonnegative).
- $storage\_cd\_rate = 0.20 \times storage\_capacity$ (20% of storage capacity, in MW, assuming 8-hour charge/discharge time).

CO2 Cost Premium

- $MWh\_to\_kgCO2 = 185$ (US average kg CO_2 per MWh) **eia˙emissions**.
- $co2\_cost\_perkg = 0.27$ (Cost per kg of CO_2 generation).
- $Emissions\_threshold\_MWh = 0.85$ (CO_2 cap in MWh).

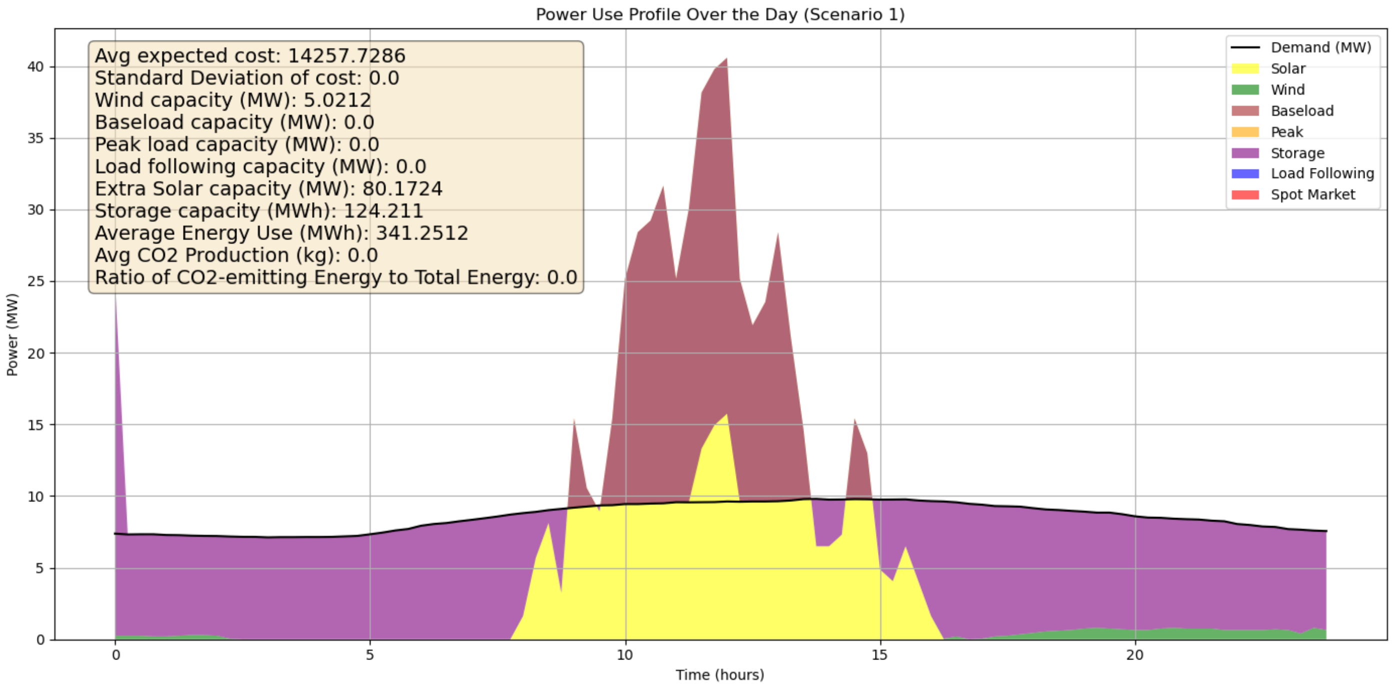

Figure 3. Exclusive Renewable Energy Resource Use & Characteristics

Renewables Discussion

Optimization ensures energy balance at every step by reducing CO_2 -emitting energy dependence with renewable sources and storage. In Figure 3 we provided power allocate using full renewable energy. Generator energy allowance is set to zero, enforcing wind, solar power and battery storage energy supply domination. The zero CO_2 emissions and great use of solar capacity highlight the viability of a sustainable energy mix for the given circumstances. Yet the total expected cost reaches more than high comparing to the coming two scenarios with set CO_2 tax threshold.

In NYC, carbon-emitting resource use is progressively more dis-incentivized by excess-use CO2 taxes, with threshold use determined by specific building/site allowances. Appendix Figure 4 shows a sensitive relationship between CO2 tax and nonrenewable energy use ratio; with a $0.27/kg tax (applied in NYC by 2025, see **NYCAcceleratorLL97**) applied to CO2 emissions above a parametrized energy use ratio threshold, the optimization heavily prioritizes renewables at cost to make up energy demand differences.

With a realistic CO_2 tax threshold(around 85% as in Appendix Figure 5), there will be a compensatory match in base-load capacity; total cost($4250) is still increased from base case($3300) due to the comparatively high operation cost of using renewable energy. With very low thresholds (see 25% case in Appendix Figure 6), this usage trend continues to track, indicating the relative power of CO2 taxation in renewable adoption, with associated cost increase from renewables.

As seen in Appendix Figure 7, solar+storage use begins to dominate over CO2-emitting resources at about 65% total cost. The overall feasibility study, at the current cost structures, show high realistic cost of significant transition to renewables. In the future study we need to focus on a more reliable and economical renewable energy systems to reduce the dependence on fossil fuels to achieve sustainability. Optimized portfolio costs are heavily dependent on storage and solar costs.

CONCLUSION

The results of this study indicate that transitioning to renewable energy sources is feasibility often comes at a higher cost, driven by the infrastructure and operational expenses associated with solar and storage systems. However, the sensitivity analysis shows the powerful influence of CO taxation in encouraging renewable adoption, suggesting that policy measures can play a crucial role in balancing cost efficiency with sustainability goals. Future research should prioritize the development of more cost-effective renewable technologies and explore innovative strategies to optimize energy storage and generation, ultimately reducing reliance on fossil fuels and achieving long-term sustainability.

APPENDIX

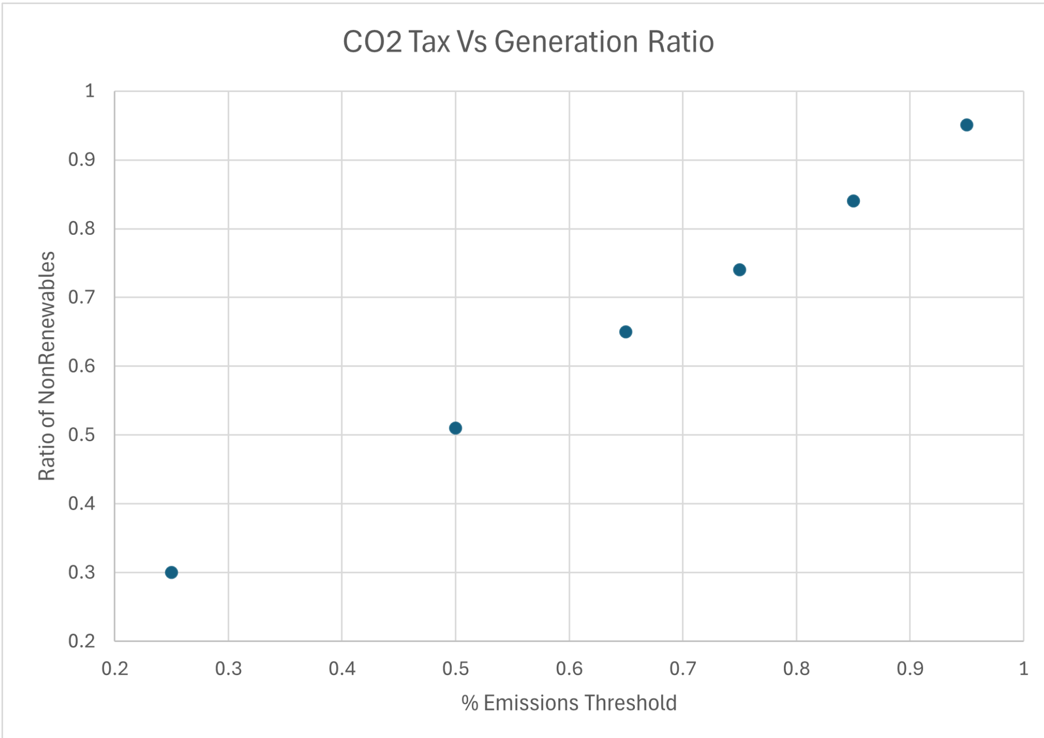

Figure 4. Energy Tax Performance: Tax($0.27/kg) Has Strong Effect on CO_2 Production

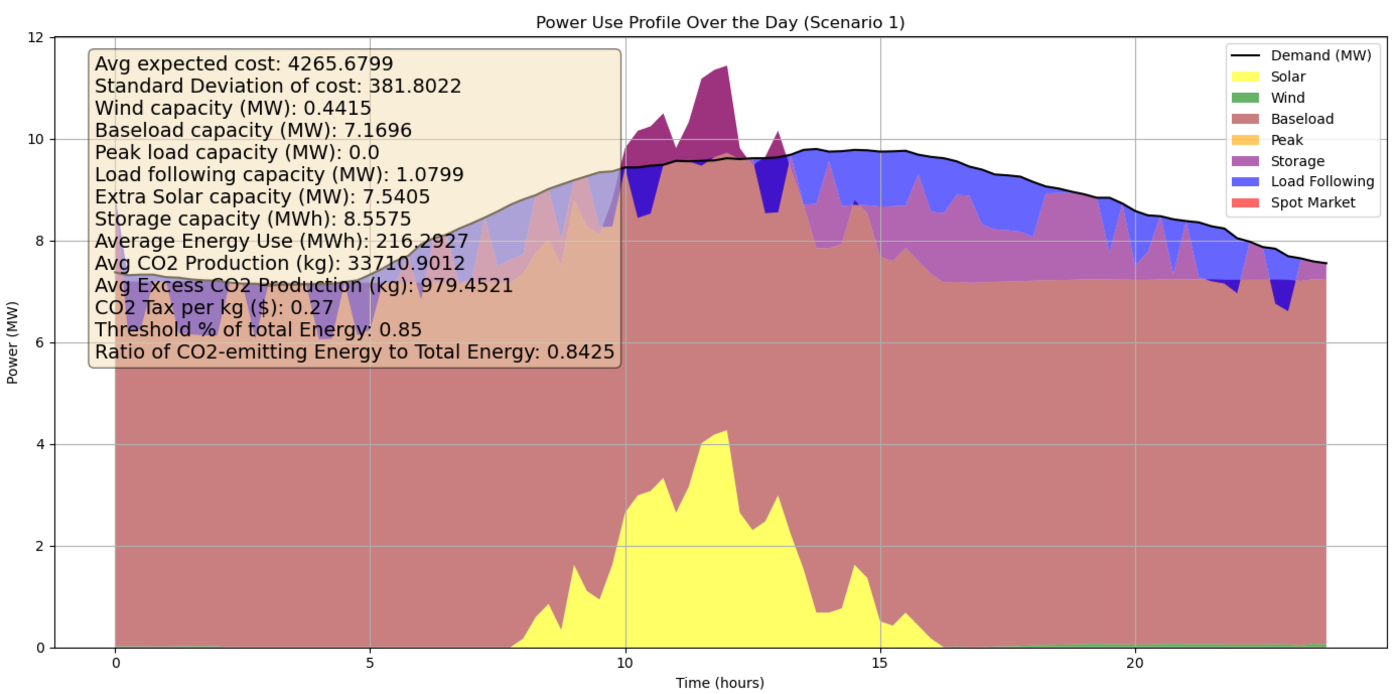

Figure 5. Power Use at 85% CO_2 Production Excess Tax Threshold

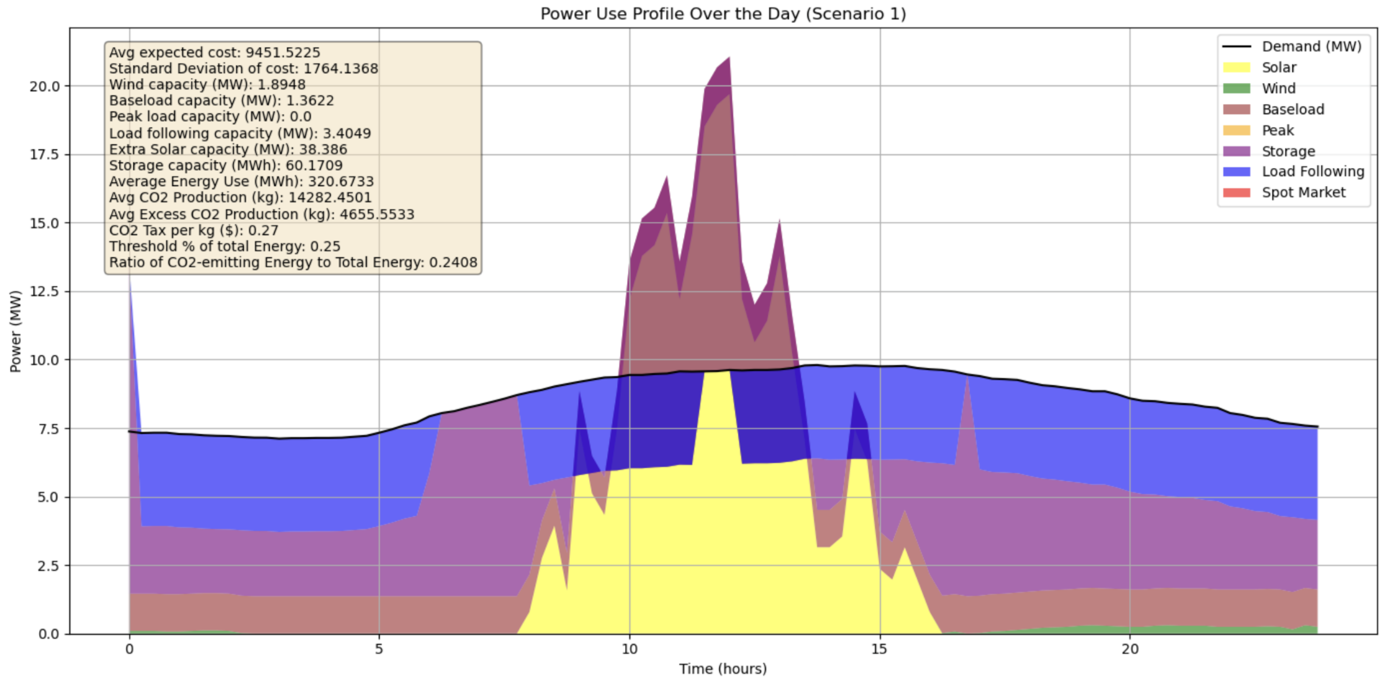

Figure 6. Power Use at 25% CO_2 Production Excess Tax Threshold

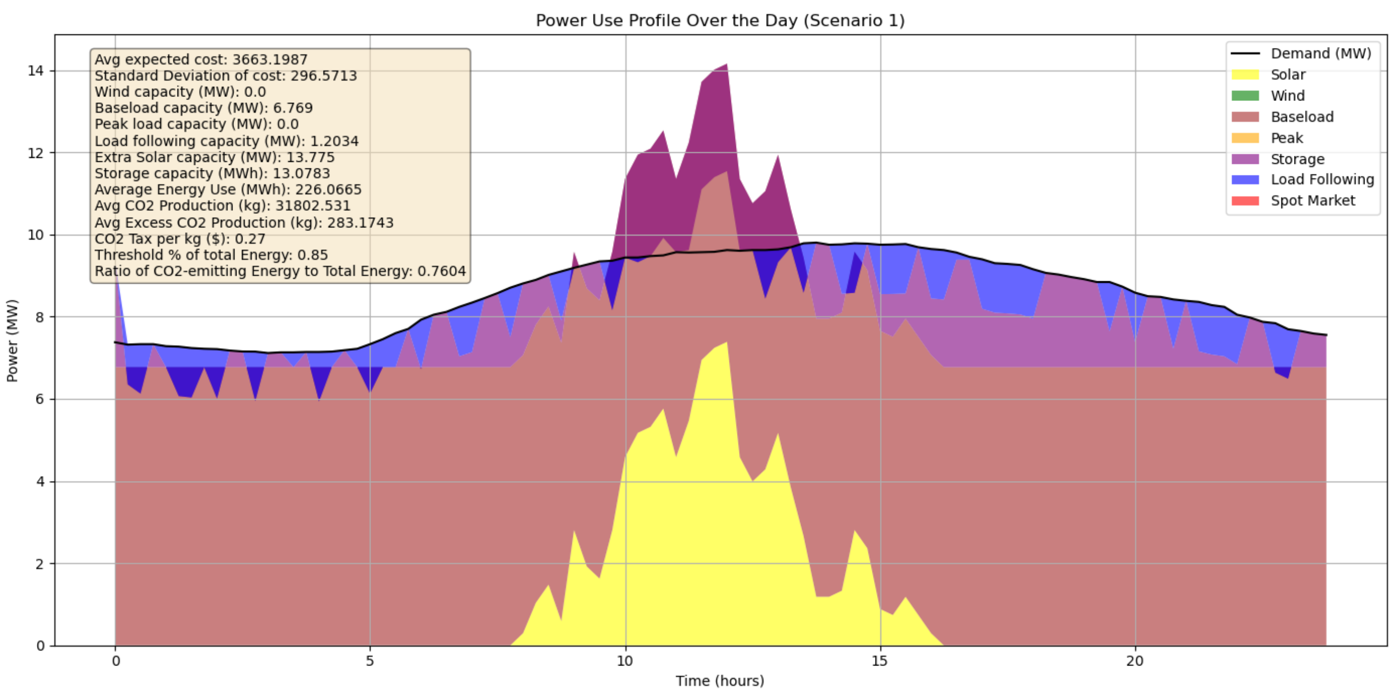

Figure 7. Power Dispatch - 65% Expected Solar, Storage Costs

REFERENCES

NRELReportNational Renewable Energy Laboratory, ”2023 Storage Cost Report,” *NREL*, 2023. [Online]. Available: https://www.nrel.gov/docs/fy23osti/85332.pdf. [Accessed: Dec. 13, 2024].

NYCAcceleratorLL97NYC Accelerator, ”Local Law 97”, *NYC Accelerator*, 2024. [Online]. Available: https://accelerator.nyc/ll97. [Accessed: Dec. 13, 2024].

SolarReviewsSolarReviews, ”How does utility-scale solar work?” *Solar Reviews*, 2024. [Online]. Available: www.solarreviews.com/blog/how-does-utility-scale-solar-work. [Accessed: Dec. 13, 2024].

EIAEmissionsU.S. Energy Information Administration, ”How much carbon dioxide is produced per kilowatthour of U.S. electricity generation?” *Energy Information Administration*, 2024. [Online]. Available: https://www.eia.gov/tools/faqs/faq.php?id=74&t=11. [Accessed: Dec. 13, 2024].

USEnergyFactsU.S. Energy Information Administration, ”U.S. Energy Facts Explained,” *Energy Explained*, 2023. [Online]. Available: https://www.eia.gov/energyexplained/us-energy-facts/. [Accessed: Dec. 13, 2024].