2nd Place Smart Energy Supply Scheduling for Green Telecom Challenge by ITU

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Abstract

With the fast pace of change in the telecom industry and the growing need for energy efficiency, finding smarter ways to manage energy has become essential. This project explores a new approach using machine learning to create an optimized strategy for powering mobile networks. By analyzing real-time data from sources like solar, grid, and diesel, it helps predict and manage energy use more effectively. This not only reduces costs but also supports the industry's goal of achieving net-zero emissions by 2050, making a meaningful impact on both sustainability and operational efficiency.

1 Overview and Objectives

As the telecom industry grapples with rising energy costs and the urgent need to reduce its carbon footprint, innovative solutions have become essential to sustain mobile network operations efficiently. Our approach brings a fresh perspective by applying machine learning to manage and optimize energy use across multiple sources, such as the electricity grid, solar power, and diesel generators, all with a focus on reducing costs and enhancing sustainability.

At the heart of this approach is a simple yet powerful idea: predicting solar energy generation and creating a smart energy management strategy that not only ensures the network stays online but also minimizes energy expenses. This estimation helps solve a few major challenges:

- **Unpredictable Energy Costs**: Energy availability and prices can vary significantly, especially in areas where the electricity grid is unreliable, making it tough to plan energy use effectively.
- **Sustainability Pressures**: With the telecom industry committed to achieving net-zero emissions by 2050, there's a growing need to find greener ways to power mobile networks while keeping them running smoothly.
- **Battery Management**: Ensuring that battery storage is used wisely is crucial to avoid excessive reliance on costly energy sources, like diesel generators, which are both expensive and harmful to the environment.

This approach aims to address these challenges and more, with key objectives such as:

- **Cutting Energy Costs**: By making smarter decisions about when to use solar, grid, or diesel energy, the approach helps bring down overall energy expenses.
- **Promoting Sustainability**: It reduces reliance on diesel generators by maximizing the use of cleaner energy sources, such as solar power, contributing to a greener telecom industry.
- **Ensuring Reliable Network Operation**: Even in regions where the electricity supply is unreliable, this strategy helps maintain uninterrupted network service by seamlessly switching between energy sources as needed.

In terms of outcomes, we anticipate:

- **Lowered Energy Bills**: A significant drop in the costs associated with running mobile networks, achieved through efficient energy use.
- **Reduced Carbon Emissions**: A meaningful reduction in the telecom sector's carbon footprint, helping to meet sustainability targets.
- **Increased Network Reliability**: Enhanced stability and reliability in mobile networks, even in areas with challenging power conditions, thanks to intelligent energy management.

This solution brings a new level of intelligence to energy management in the telecom industry, offering a future where cost savings and environmental responsibility go hand-in-hand. By leveraging machine learning and real-time data, it opens up opportunities for more efficient and sustainable mobile networks.

2 Materials & Methods

2.1 Exploratory Data Analysis

2.1.1 Univariate Analysis

In this section,I will examine the distribution of individual variables within the dataset. Our focus will be on visualizing the distributions of essential columns, including **Energy Output (kWh)** [Solar Power] and **Total Energy (kWh)** [Demand].

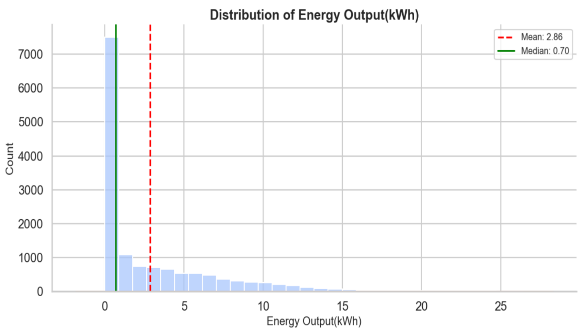

Figure 1: Distribution of Energy Output (kWh)

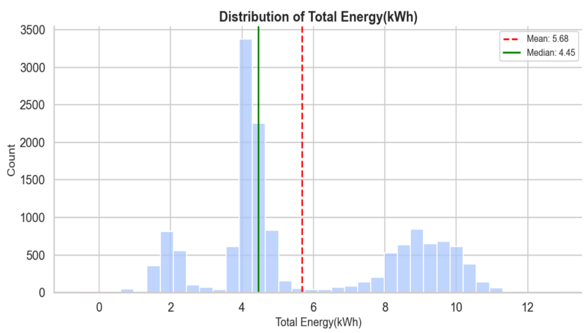

Figure 2: Distribution of Total Energy (kWh)

2.1.2 Time Series Analysis

In this section,I will examine the temporal patterns inherent in the solar power generation and energy consumption data. Through visualizing these variables over time,I aim to identify trends, periodicities, and other temporal behaviors that may enhance forecasting and optimization efforts.

We start by analyzing the variations in average solar power generation and energy consumption across all monitored sites. This analysis provides insights into how solar energy production correlates with energy consumption patterns, allowing us to better understand the dynamics of energy usage and generation in diverse contexts.

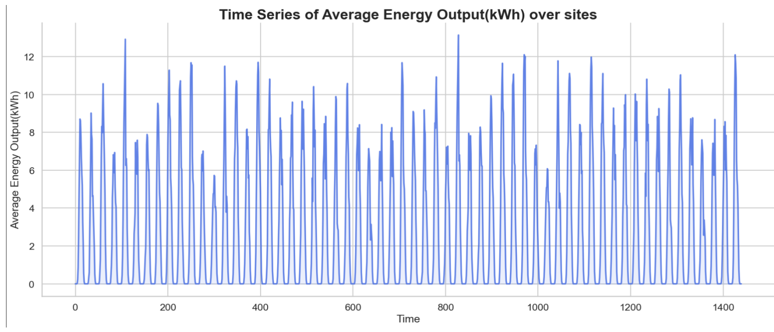

Figure 3: Average Solar Power Generation Across Sites

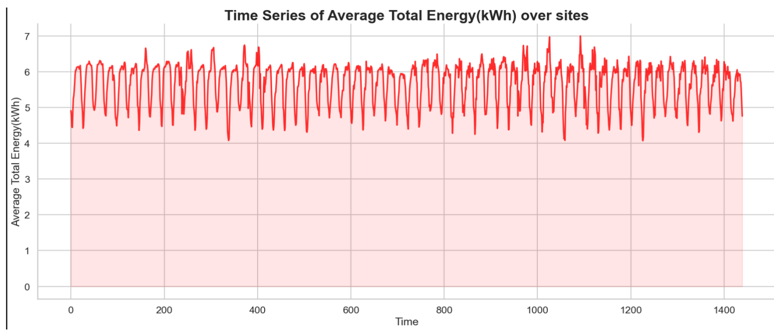

Figure 4: Average Energy Consumption Across Sites

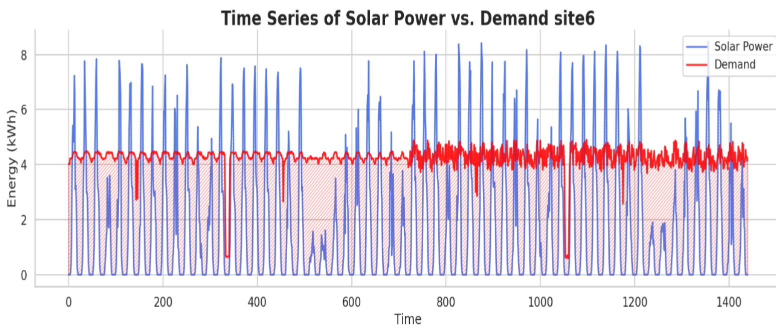

Figure 5: Solar power vs Energy Consumption Site 6

Furthermore, I begin by analyzing the variations in solar power generation and energy consumption data across each site. Understanding how solar power fluctuates over time is crucial for predicting energy availability, especially in scenarios where renewable energy sources significantly contribute to the energy mix. Through this analysis, I aim to address several key questions: How does solar power generation change over different days and weeks? Are there discernible trends or periodic patterns within the data? When does solar power effectively meet energy demand? Additionally, I will explore the balance of power and the availability of the grid.

2.2 Predictions

Given the constraint of keeping inference time under 1 second and the unpredictability of total energy consumption, I focused on refining the prediction strategy. I approximated the values for Total Energy (kWh) and Energy Output (kWh) for each hour of the test week by using the mean of historical energy data from the past two months. This method provides a reasonable estimate while maintaining the required performance speed.

2.2.1 Energy Output (kWh)

Table 1: Energy Output (kWh) for the First and Second Cycles

Cycle [Month]	Mean (kWh)	Std Dev (kWh)
First Cycle		
Week 1	2.66	3.93
Week 2	2.73	4.08
Week 3	3.01	3.97
Week 4	2.70	4.04
Second Cycle		
Week 1	2.85	4.14
Week 2	2.84	4.18
Week 3	3.12	4.09
Week 4	2.83	4.16

2.2.2 Total Energy (kWh)

The hourly approximation of solar energy and energy consumption is calculated by averaging the energy output during the same hour across the first three weeks of each cycle. It is important to note that the last week has been excluded from this analysis due to its lowest mean and highest standard deviation, which render it less reliable for estimating consistent solar energy.

Table 2: Total Energy (kWh) for the First and Second Cycles

Cycle [Month]	Mean (kWh)	Std Dev (kWh)
First Cycle		
Week 1	5.70	2.70
Week 2	5.75	2.63
Week 3	5.66	2.67
Week 4	5.65	2.70
Second Cycle		
Week 1	5.67	2.74
Week 2	5.75	2.66
Week 3	5.66	2.70
Week 4	5.66	2.74

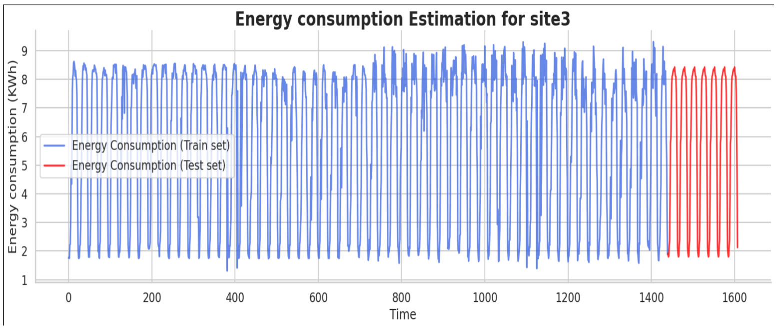

Figure 6: Energy Consumption Estimation for Site 3: Train vs. Test Set Comparison

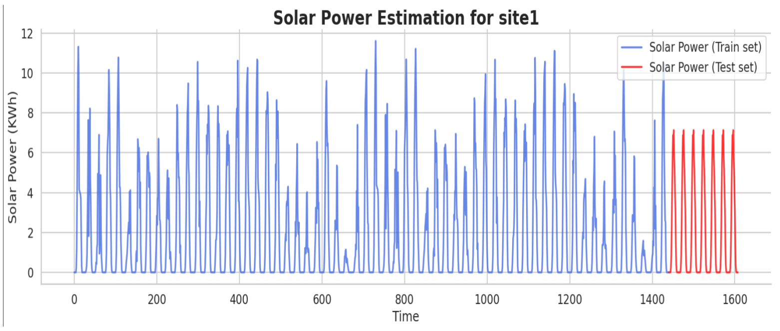

Figure 7: Solar Power for Site 3: Train vs Test Set Comparison

In Conclusion , The **approximation method** utilized in this study demonstrated remarkable resilience against the unpredictable and noisy fluctuations typically encountered in energy consumption data. These variations pose significant challenges, as any modeling errors that lead to unrecognized demand peaks could severely jeopardize the feasibility of solutions submitted in competitive settings, such as the private leaderboard. To address these challenges, I adopted a cautious and methodical approach characterized by two key strategies: first, an emphasis on maximum loss minimization rather than merely focusing on overall loss reduction. This strategy prioritized minimizing the maximum loss at each time step, helping to manage peak demands and avoid drastic mispredictions.

Second, I implemented a compensatory battery utilization mechanism, ensuring that any prediction error at a given moment could be offset through battery usage. This method provides an additional layer of reliability, acting as a safeguard to ensure that unexpected fluctuations do not lead to a failure in demand fulfillment. Ultimately, this methodology reflects a commitment to maintaining the feasibility of energy consumption predictions, even if it necessitates a trade-off in achieving marginal improvements in aggregate accuracy.

2.3 Strategy

2.3.1 Dynamic programming Limitations

I initially considered using a dynamic programming (DP) approach, which can be thought of as an optimized brute force method. The first step was to identify the states that define my problem, which can be represented by four variables:

- **Time**: 168 time steps, each divided into 4 intervals.
- **Grid availability**: Binary variable (available or not).
- **Diesel status in the previous time step**: Binary variable (on or off).
- **Battery level**: Approximated to integers by scaling values, with a maximum of 40,000.

While this approach would have allowed me to compute the minimum energy needed, I realized that the complexity, $O(2 \times 2 \times 168 \times 4 \times 40,000)$, would result in 104,960,000 operations, which take more than 1 second. This would exceed my time constraints. Additionally, tracking the optimal sequence of decisions (i.e., the path leading to minimum energy) would have added further complexity. Given my need to prioritize both performance and the ability to trace decision paths, I chose to abandon this method.

Instead,I adopted a different approach, which, while sacrificing some precision, allowed me to significantly reduce complexity and meet the required time constraints.

2.3.2 Proposed heuristic solution

After determining the limitations of the dynamic programming method,I opted for a **heuristic energy management strategy** to solve the energy management problem. This strategy allows for quicker decision-making while navigating the constraints of time and complexity. The heuristic approach prioritizes immediate benefits in energy allocation based on current conditions rather than exploring all potential future scenarios.

The state representation in the heuristic strategy is defined by several variables: the current time step, which ranges from 1 to 168; grid availability, which is a binary check to see if the grid is providing energy during the current time step; the diesel generator status, which keeps track of whether the diesel generator was on or off in the previous time step; and the battery level, represented as an integer value scaled appropriately for easy calculations.

2.3.3 First Phase

At each time step, the algorithm evaluates the available resources and makes decisions based on a priority order:
1. Solar power
2. Electricity Grids
3. Battery than Diesel [If Possible]

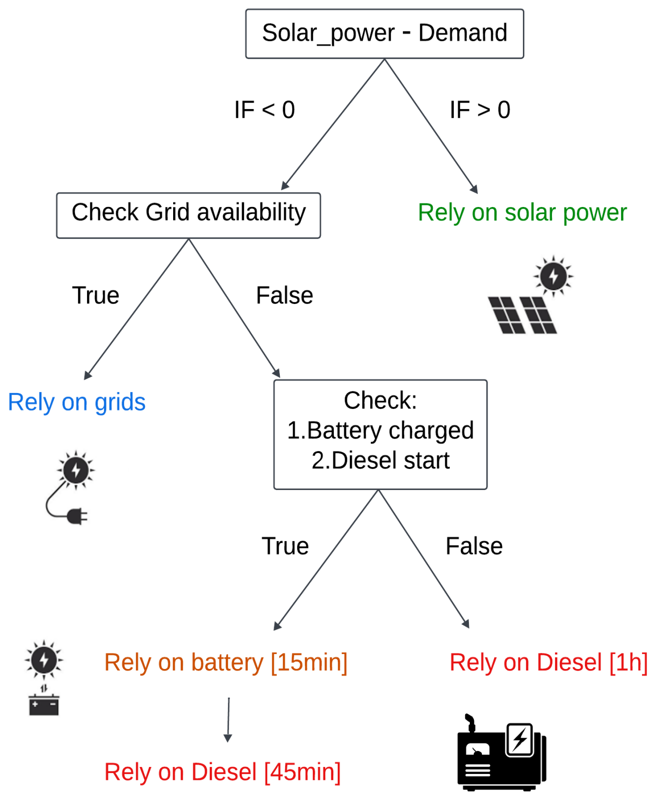

Figure 8: First Phase of the strategy

After making decisions at each time step, the battery level is updated according to the energy drawn, and the status of the diesel generator is adjusted based on whether it was used during that time step. Throughout the execution of the heuristic algorithm, the total energy consumption from all sources is tracked, providing insights into the efficiency of the energy management strategy.

2.3.4 Second Phase

The second phase of the method is tracking the Diesel starts and cuts [Intervals] and use the scoring function to decide whether to merge two diesel intervals or not:

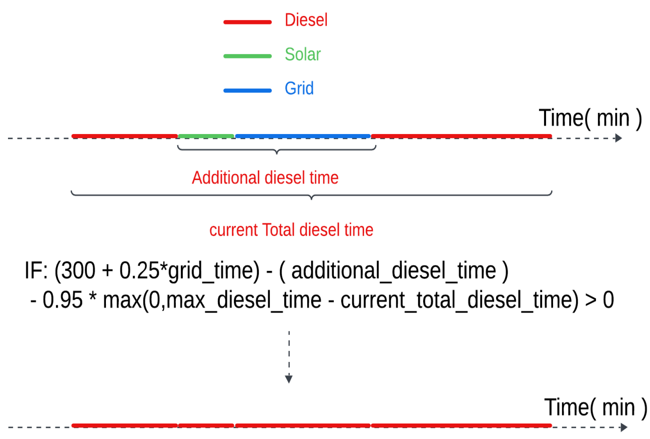

Figure 9: Second Phase of the strategy

The complexity of the heuristic approach is $O(T \times I)$, where T is the number of time steps (168) and I is the number of intervals (4), resulting in manageable operations compared to the dynamic programming method. This allows the algorithm to execute efficiently within the required time constraints. By employing this strategy,I ensured that the energy management decisions made at each step were both timely and effective, allowing for a practical balance between immediate operational needs and overall energy efficiency.

2.4 Strategy Performance Summary

The table below provides a comprehensive overview of the performance of a solar power strategy across multiple sites. It includes key metrics such as minimum State of Charge (SOC), average SOC, solar usage, grid usage, diesel usage, diesel starts, and total costs. Each site exhibits different characteristics, indicating how effectively solar energy is utilized and the associated operational costs.

- **Site ID**: Identifies each site where the strategy is implemented.
- **Min SOC**: Represents the minimum State of Charge observed, indicating the lowest level of battery charge during the operational period.
- **Avg SOC**: Indicates the average State of Charge, reflecting the overall efficiency of energy storage across the duration.
- **Solar Usage**: Quantifies the amount of energy generated and utilized from solar power.

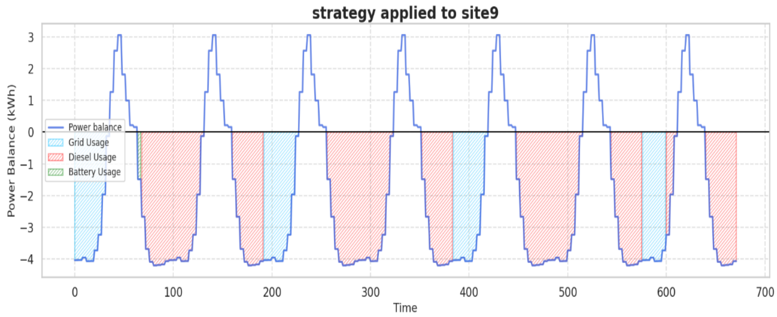

Figure 10: Strategy applied to site 9

- **Grid Usage**: Measures the energy drawn from the grid, showcasing reliance on external energy sources.
- **Diesel Usage**: Indicates the amount of energy produced from diesel generators, which can suggest inefficiencies in solar utilization.
- **Diesel Starts**: Counts the number of times diesel generators were started, reflecting their operational necessity.
- **Total Cost**: Represents the total financial expenditure incurred for energy generation at each site.

The average cost across all sites is noted to provide a benchmark for evaluating cost-effectiveness.

Table 3: Strategy Performance Summary

Site ID	Min SOC	Avg SOC	Solar Usage	Grid Usage	Diesel Usage	Diesel Starts	Total Cost
1	0.4943	0.9957	504	76	428	8	10131.00
2	0.2777	0.9780	504	256	416	5	10524.00
3	0.2928	0.9811	476	220	340	9	9765.00
4	0.2448	0.9644	476	144	356	8	9249.00
5	0.3619	0.9921	448	280	336	8	9630.00
6	0.3161	0.9860	448	100	460	8	10815.00
7	0.4379	0.9943	448	216	260	8	8079.00
8	0.3462	0.9892	448	184	208	8	7008.00
9	0.2642	0.9742	448	132	340	8	8964.00
10	0.4327	0.9940	448	168	280	7	7842.00
Average Cost							**9200.70**

Conclusion

In conclusion, I believe that my approach exemplifies the effective fusion of innovative technology and energy management expertise. By implementing sophisticated predictive algorithms and real-time data analysis, I have established a resilient framework that not only optimizes energy consumption but also responds proactively to fluctuations in energy availability. My commitment to continuous improvement and adaptive strategies ensures that the system evolves, aligns, and enhances the sustainability of mobile networks. As I move forward, I remain dedicated to advancing my methodologies, ensuring my approach remains a pivotal force in achieving cost-effective and environmentally responsible telecom operations.

Future Work

Proposed Two-Phase Enhancement for Energy Optimization

A potential continuation for this solution: In a third phase, a reinforcement learning (RL) agent could be initialized using supervised fine-tuning (SFT) or offline RL on the designed strategy. This would enable the agent to learn the dynamics of the energy supply environment effectively. Subsequently, the agent could further explore the action space using online reinforcement learning, maximizing the long-term reward function.

The reward function for the energy optimization can be expressed as:

$$\text{Reward} = \alpha \times (\text{solar\_usage} + \text{battery\_efficiency}) - \beta \times (\text{cost\_diesel} + \text{cost\_grid} + \text{penalty}) \quad (1)$$

where:

- α and β are scaling factors to balance the importance of minimizing costs and maximizing clean energy usage.
- **solar_usage**: The total amount of energy generated and used from solar power.
- **battery_efficiency**: The efficiency of battery usage in the system.
- **cost_diesel**: The cost incurred from using the diesel generator.
- **cost_grid**: The cost incurred from using grid electricity.
- **penalty**: Any penalty associated with the system's inefficiencies or excessive diesel/grid usage.

This reward function aims to maximize clean energy usage while minimizing costs related to diesel and grid usage. While this approach holds significant promise, implementing few-shot reinforcement learning strategies would require careful tuning to ensure it does not exceed the 1-second inference time constraint. Due to the computational resources available during the competition, this method was not fully explored. However, it is worth investigating in future developments for its potential to optimize the energy supply strategy further.

Acknowledgements

I extend my heartfelt gratitude to the Zindi platform and the International Telecommunication Union (ITU) for their invaluable contribution to the success of this project. Zindi's commitment to fostering a collaborative environment has not only provided me with rich datasets but also the opportunity to engage with a vibrant community of data scientists and energy management experts. Their support has been instrumental in enabling me to harness the power of advanced technologies for optimizing energy use in the telecom industry. I look forward to continued collaboration with Zindi as I further my endeavors in this field.