Optimizing Solar Energy Utilization in Facilities Using Machine Learning-Based Scheduling Techniques: A Case Study

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Abstract

This study introduces an innovative approach to improving solar energy utilization in facilities by integrating advanced machine learning (ML) techniques into solar power scheduling. Traditional methods, often constrained by static schedules, fail to adequately adapt to the inherently dynamic and intermittent nature of solar energy. Our approach overcomes these limitations by employing ML algorithms to accurately predict solar generation patterns, enabling more efficient scheduling of electrical appliances. This methodology was applied to a facility equipped with a 5kW photovoltaic system, resulting in a significant reduction in grid dependency by more than 26%. This marked decrease in grid imports underscores the effectiveness of our approach in optimizing solar energy use, particularly in settings where traditional scheduling methods fall short. The study not only demonstrates the practical benefits of ML in managing solar energy resources, but also highlights its potential to reduce dependence on conventional power grids, thus contributing to more sustainable energy practices. The findings of this research have far-reaching implications, suggesting a paradigm shift in solar energy management towards more adaptive, data-driven solutions and paving the way for broader applications in various sectors seeking to maximize renewable energy use.

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1. Introduction

The demand for electricity has become a global concern, especially in light of the climate consequences of generating electric power from fossil fuels. Renewable energy sources have appeared as one of the leading solutions to meet the increasing demand for energy Lee and Cheng (2016). Solar energy is a key renewable source relied upon to produce electricity through photovoltaic (PV) solar panels Mas' ud (2022). However, despite their popularity, solar energy systems suffer from some obstacles that prevent their spread in a way that lessens reliance on nonrenewable sources. One of these obstacles is the fact that solar energy is intermittent and non-dispatchable Sharrma et al. (2021); Lee et al. (2020). To overcome this challenge, many solutions manifest themselves, such as energy storage Lee et al. (2020), combining solar with other renewable energy technologies (such as wind), and solar energy forecasting Harrou et al. (2020); Haupt et al..

An effective possible solution is to schedule the operational time of the loads to maximize the utilization of solar power systems Setlhaolo et al. (2014). It is known that the generated power from PV systems varies according to the weather conditions and the time of the day Pan et al. (2020). The conventional PV integration within the electric grid does not pay any attention to load scheduling, which results in higher dependency on importing from the electrical grid instead of maximizing the reliance on the solar system Goldman et al. (2010). Although research in the scheduling of PV systems is promising Bourhnane et al. (2020), the concept of scheduling is yet to be widely adopted. Deciding which electrical loads should be run based on continuous real-time assessment of current solar generation poses challenges preventing the adoption of scheduling Shariatzadeh et al. (2015). For appliances and applications that cannot be paused during operation (i.e., require continuous running time), such as ovens or pumps, the continuous shifting of loads based on real-time solar generation makes implementation ineffective, as the operation of those appliances is subject to stopping if the gap between generation and consumption is suddenly reduced due to lower power generation or increased power consumption Khalid (2018).

Furthermore, real-time scheduling often prioritizes the most essential loads to run during excess generation periods at the cost of the remaining loads, which might not have a suitable spot to run during the same day, or, if forced to run, might not be during the most optimal period Liu and Sun (2019).

A byproduct of these two challenges is also the lack of practicality and comfort when a scheduling system suddenly decides to run or stop different appliances. Such challenges make real-time scheduling unsustainable to implement Lee and Cheng (2016); Suresh et al. (2020); Mas' ud (2022); Bourhnane et al. (2020). The research presented in this paper addresses these challenges using the prediction capabilities of machine learning (ML) prediction capabilities to predict the generation of solar power on the next day, allowing scheduling of the next day to take place. This enables the implementation of an effective scheduling scheme in the target facilities, establishing a benchmark for possible savings.

2. Background

2.1. Literature Review

The efficiency of Building Energy Management Systems (BEMS) has been a focal point in recent research. Lee and Cheng's comprehensive review of 276 papers led to identifying three primary functions that significantly increase BEMS efficiencies: scheduling control, tariff and load control, and AI-enabled smart environments. These functions have contributed to increasing the energy savings in BEMS from 11.39% to 16.22% (Lee and Cheng, 2016). In parallel, Bourhnane et al. explored various methods for energy consumption prediction and scheduling, underscoring their importance in implementing energy-efficient management systems (Bourhnane et al., 2020).

The control of building appliances, as discussed by Khalid, can be automated using microcontroller-based direct digital controller (DDC) technology, which includes the scheduling of typical home appliances (Khalid, 2018). Setlhaolo et al. examined residential demand response strategies, demonstrating that shifting consumption can lead to significant savings in electricity costs, potentially more than 25% (Setlhaolo et al., 2014). This finding is supported by Goldman's study on the coordination of energy efficiency and demand response, highlighting the economic benefits of such strategies (Goldman et al., 2010).

Furthermore, a better match needs to be made between the typical load profile and the regular power generation of the Solar Power Systems. This alignment is crucial for optimizing energy use and is a key focus of current research (Khasawneh and Illindala, 2013). Several technologies are being used to overcome these challenges, especially the non-dispatchable generation, such as energy storage for later usage and electricity-based operations time scheduling through Energy Management Systems (EMS) as presented in (Illindala et al., 2015; Khasawneh and Illindala, 2014).

The integration of scheduling and artificial intelligence is crucial in addressing energy and cost-saving challenges. Mas'ud compared machine learning models for estimating hourly solar panel power output, finding the KNN pipeline to be the most accurate (Mas' ud, 2022). Pan et al. improved photovoltaic (PV) power forecasting using a Support Vector Machine (SVM) algorithm, further improved by Ant Colony Optimization (ACO), achieving better performance (Pan et al., 2020). Huang et al. proposed a model for the prediction of photovoltaic generation using a long-short memory neural network (LSTM) with an Attention mechanism, which showed higher accuracy compared to other models (Huang et al., 2019). Tan and Ding developed a pipeline based on Adaptive Boosting (AdaBoost), KNN clustering, and Markov Chain, aiding in the operation and control strategies of energy storage systems (Tan and Deng, 2017).

Suresh et al. designed various models for predicting solar power generation on different time scales. They employed a convolutional neural network (CNN) architecture, which included a convolutional layer for feature extraction from 2-D input data, a max pool layer to reduce overfitting, a flattening layer, and a fully connected layer for prediction. Furthermore, they explored a hybrid CNN-LSTM architecture for enhanced performance (Suresh et al., 2020). The use of machine learning for forecasting is further emphasized by Liu and Sun, who developed a random forest-based solar power forecast model, demonstrating the effectiveness of classification optimization in this context (Liu and Sun, 2019).

2.2. New Contribution

The development of scheduling algorithms is driven by the need to align the generation and consumption profiles of PV systems. Figure 1 illustrates this challenge, showing the hourly consumption (red) against the hourly generation from a solar system (blue). The goal of the scheduling algorithm is to align these profiles by shifting consumption to periods of excess generation, thus minimizing gaps.

[Figure 1 about here.]

These gaps present several challenges:

1. Excess consumption over generation leads to importing from the electrical grid, incurring economic expenses.
2. Excess generation over-consumption results in electrical export to the grid, which can destabilize the grid and is economically disadvantageous when the export is lower than import prices.
3. Reliance on grid electricity, often generated from fossil fuels (Ritchie and Rosado, 2020), has environmental implications.

Therefore, effective scheduling requires an accurate prediction of future power generation to plan consumption accordingly, with the aim of minimizing these gaps.

3. Methodology

3.1. Facility details

A facility located at a rural farm in the city of Al-Salt in the west of Jordan was chosen to deploy the scheduling algorithm. The facility was used to test the accuracy of the machine learning model prediction of future solar power generation, and to record the consumption exceeding the solar generation before and after scheduling, thus allowing for comparative analysis and measurement for the reduction in grid dependency. The facility was equipped with a 5kW PV system (Figure 2) and a 5KVA inverter.

[Figure 2 about here.]

To record the consumption, a power analyzer was used. The power analyzer of choice was Fluke 435-II Power Quality and Energy Analyzer. This device provided real-time information on the electrical energy consumption of the facility and was used to collect real-time consumption data for 10 days. Figure 3 displays the average power consumption per hour obtained by the FLUKE power analyzer.

[Figure 3 about here.]

To record power generation, a mechatronic system was built (shown in Figure 4).

[Figure 4 about here.]

The system contained the following components:

1. Current transformer
2. Microprocessor to log the data
3. Microcontroller to control facility appliances
4. Bluetooth modules to transmit control signals
5. Solid state relay

Selected appliances were turned on to raise the facility's power consumption above the maximum generation capability. The logging microprocessor logs the power supplied from the photovoltaic system to the facility (that is, logs the power generation). This process was repeated every 20 minutes from sunrise to sunset.

3.2. Percentage of schedulable loads survey

At the facility, not all appliances were deemed schedulable due to functionality, convenience, or comfort constraints. Therefore, a survey to understand what percentage of the facility's total power consumption can be scheduled at specified periods was made. During the survey process, it was found that some appliances may be schedulable at certain times during the day but not schedulable during others. The results of the survey are displayed in Table 1.

[Table 1 about here.]

It can be seen that for our facility, the percentage of schedulable power consumption varied during the day from the best case of 33% of consumption being schedulable to the worst case being at only 10% of consumption being schedulable.

3.3. Machine learning

The goal of the machine learning pipeline is to predict the next day's hourly solar power generation. The pipeline consists of two steps: prepossessing and regressor. Training data was collected from the solar system of the studied facility, and weather data was obtained from meteoblue.com (MeteoBlue) covering 19 metrics (such as temperature, irradiance, and cloud coverage). The training process involved two optimization methods to achieve the best performance of the pipeline. These two optimization methods are the grid search method and genetic algorithms using the Tree-based Pipeline Optimization Tool (TPOT). With the training data obtained, the ML pipeline managed to predict the next day's hourly solar generation with a root square mean error of 271.56 Watts.

3.4. Shifting algorithm

An algorithm was made using Python programming language, allowing a user to enter appliances watt ratings and the duration of operation, for the appliances intended to run the next day. The algorithm uses the ML pipeline prediction to set the next day's expected solar generation as a base. It continues to loop and shift the placement of when the appliances will run during the day to find the optimum operation time that minimizes the gaps between the expected generation and the planned consumption while adhering to the limits imposed by the percentages of schedulable appliances for each time frame as per the conducted survey.

Figure 5 and Figure 6 show the before and after application of the scheduling algorithm at the testing facility. It can be seen that shifting occurred more in the second half of the day (as the percentage of schedulable consumption is higher at that time in our facility).

[Figure 5 about here.]

[Figure 6 about here.]

4. Results

Implementing the scheduling algorithm demonstrated a significant impact on reducing grid dependency. As illustrated in Figure 6, the application of the scheduling algorithm in the selected case led to a reduction of over 26%

in grid electricity imports. This initial result was promising, indicating the potential effectiveness of the scheduling approach in optimizing energy usage.

To further assess the reliability and consistency of these savings, the algorithm was subjected to a series of tests under varying conditions. Specifically, the algorithm was tested across nine different scenarios, each characterized by distinct consumption and generation profiles. This testing involved selecting three days with highly variable consumption profiles and three days with diverse predicted generation profiles. The scheduling algorithm was then applied to all nine possible combinations of these profiles.

The outcomes of these tests are summarized in Table 2, which compares the electricity imports before and after the application of the scheduling algorithm. The table also highlights the percentage decrease in electricity imports for each of the nine tested scenarios.

[Table 2 about here.]

Analysis of the data from Table 2 reveals a consistent pattern of reduction in electricity imports across all scenarios. Notably, the decrease in electrical imports exceeded 26% in each of the nine cases. This consistency underscores the robustness of the scheduling algorithm, demonstrating its effectiveness across a range of consumption and generation conditions.

These results validate the potential of the scheduling algorithm as a tool for enhancing energy efficiency in facilities equipped with PV systems. By aligning energy consumption more closely with solar power generation, the algorithm effectively reduces reliance on grid-supplied electricity, thereby contributing to both economic savings and environmental sustainability.

5. Discussion

The results of our study, demonstrating a significant decrease in grid imports by over 26%, offer promising insights into the potential of load scheduling in conjunction with solar power generation. However, it is crucial to contextualize these findings within the specific conditions under which the experiment was conducted.

One notable limitation of the study is the seasonal aspect. The experiment was carried out during the summer months in Jordan, a period typically characterized by higher solar irradiance and more predictable weather patterns. These conditions are generally favorable for solar power generation, which likely contributed to the effectiveness of the scheduling algorithm. However, conducting similar tests during the winter months could present additional challenges. Winter conditions often bring lower solar irradiance and increased cloud cover, potentially leading to greater discrepancies between predicted and actual solar generation. Such variations could impact the algorithm's effectiveness, potentially reducing the grid import savings below the observed 26%. This seasonal variability underscores the need for a more comprehensive analysis that includes testing across different seasons to understand the algorithm's year-round efficacy fully.

Another critical aspect of our study is the schedulability constraints. The scheduling was constrained by the fact that only 10% to 33% of the total power consumption was considered scheduleable. This limitation reflects the practical realities of energy usage in a typical facility, where certain loads cannot be easily rescheduled without affecting operations or comfort. Despite these constraints, the algorithm still achieved significant savings, highlighting its potential effectiveness even in scenarios with limited flexibility in load scheduling.

The use of the Tree-based Pipeline Optimization Tool (TPOT) for prediction, with a root square mean error of 271.56 Watts, was a key component of our methodology. The relatively low error rate of the TPOT model in predicting solar generation underscores the importance of accurate forecasting in optimizing load scheduling. Future improvements in predictive modeling could further enhance the algorithm's performance, potentially leading to even greater reductions in grid dependency.

While our study presents a compelling case for the use of load scheduling in conjunction with solar power generation, it also highlights the importance of considering various factors such as seasonal variations, schedulability constraints, and the accuracy of predictive models. Future research should aim to address these factors, possibly exploring adaptive algorithms that can adjust to seasonal changes and varying levels of schedulability. Additionally, advancements in predictive modeling could further refine the scheduling process, maximizing the potential for energy savings and grid independence.

6. Conclusion and Future Work

6.1. Conclusion

The study demonstrates the feasibility and effectiveness of implementing a machine learning-based scheduling system to optimize solar power use.

Despite the limitation that only 33% or less of the total power consumption was schedulable at any given time in the studied facility, the integration of predictive machine learning algorithms successfully reduced the imports of electricity by more than 26%. The machine learning pipeline, which predicted the next day's hourly solar generation with a root mean square error (RMSE) of 271.56 Watts, was optimized using grid search methods and genetic algorithms within a Tree-based Pipeline Optimization Tool (TPOT). This approach underscores the potential of machine learning in improving the efficiency of solar power systems, even in scenarios with limited flexibility in load scheduling.

6.2. Recommendations for Future Work

The promising results of this study open several avenues for future research and application:

1. Large-Scale Adoption: Exploring the scalability of this integrated scheduling and prediction approach is a crucial next step. Future research could focus on applying these techniques to larger facilities or systems, such as public electric transport charging networks, university laboratories with high energy demands, or research centers with intensive power-consuming equipment. Understanding the dynamics and challenges of scheduling at a larger scale could contribute significantly to energy efficiency and sustainability.

2. Impact on Battery Systems: Investigating the effects of scheduling on battery usage and lifespan presents another promising research direction. Efficient scheduling could potentially reduce the required battery capacity by maximizing the direct use of solar power. Additionally, it could extend battery life by reducing the frequency and depth of discharge cycles, thus enhancing the overall sustainability of solar power systems.

3. Integration with Smart Appliances: Advancements in smart appliance technology offer opportunities to increase the schedulability of loads. Research into developing user-friendly interfaces that can seamlessly integrate with machine learning pipelines could further optimize solar power utilization. This integration could lead to more significant reductions in electrical imports and better utilization of installed PV systems, moving towards a more sustainable and self-sufficient energy model.

4. Seasonal Variability Analysis: Given the impact of seasonal changes on solar power generation, future studies should also focus on analyzing the effectiveness of the scheduling algorithm in different seasons. This would

provide a more comprehensive understanding of its year-round applicability and potential limitations.

5. Advanced Predictive Modeling: Continual improvement of predictive models, possibly through the integration of more sophisticated machine learning algorithms or the incorporation of additional environmental and consumption data, could enhance the accuracy of solar generation forecasts. This would directly translate to more effective scheduling and potentially greater energy savings.

In conclusion, the integration of machine learning with solar power scheduling holds significant promise to improve energy efficiency. The potential for large-scale application and integration with emerging technologies presents exciting opportunities for future research and development in this field.

Competing Interests

The authors declare that they have no conflict of interest.

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Data Availability Statement

Data are available on request from the authors.

CRediT Author Statement

Waseem M. Al-Khatib: Conceptualization, Methodology, Data curation, Software, Writing - Original Draft. **Zaid A. Ghazal:** Conceptualization, Methodology, Data curation, Software. **Ahmad M. Al-Hadi:** Resources, Data curation, Software. **Zaid M. Arabiyat:** Data curation, Software. **Osama Habahbeh:** Supervision, Project administration,. **Hussam J. Khasawneh:** Conceptualization, Supervision, Validation, Project administration, Writing - Review & Editing.

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Table 1: Percentage of schedulable consumption during each time interval

Time Interval	**Percentage of schedulable consumption**
12am till 5am	15%
5am till 8am	10%
8am till 5pm	33%
5am till 9pm	33%
9pm till 12am	33%

Table 2: Comparative analysis of electricity imports before and after scheduling across different scenarios

Day of Consumption <Generation>	Utility-Sourced Energy Consumption Before Scheduling (kWh)	Utility-Sourced Energy Consumption After Scheduling (kWh)	Percentage Decrease
First Day <Day1>	14.74	10.71	27.3%
First Day <Day2>	14.47	10.44	27.9%
First Day <Day3>	14.61	10.58	27.6%
Second Day <Day1>	14.04	10.17	27.6%
Second Day <Day2>	13.86	10.12	27.0%
Second Day <Day3>	13.91	10.12	27.2%
Third Day <Day1>	11.97	8.71	27.2%
Third Day <Day2>	11.71	8.48	27.6%
Third Day <Day3>	11.85	8.58	27.6%

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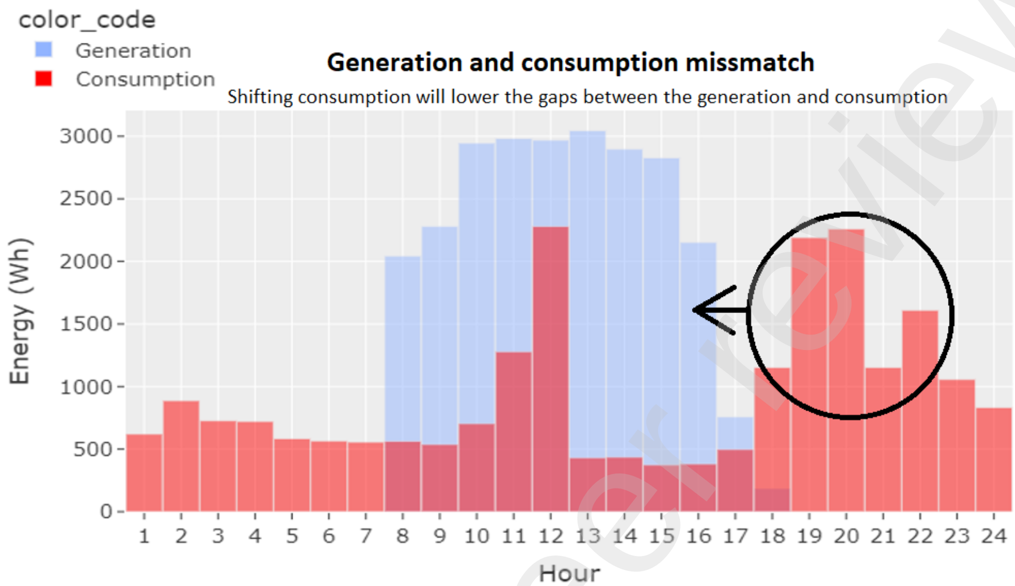

Figure 1: The algorithm aims to shift consumption into excess generation areas

Figure 2: The facility's 5kW PV system

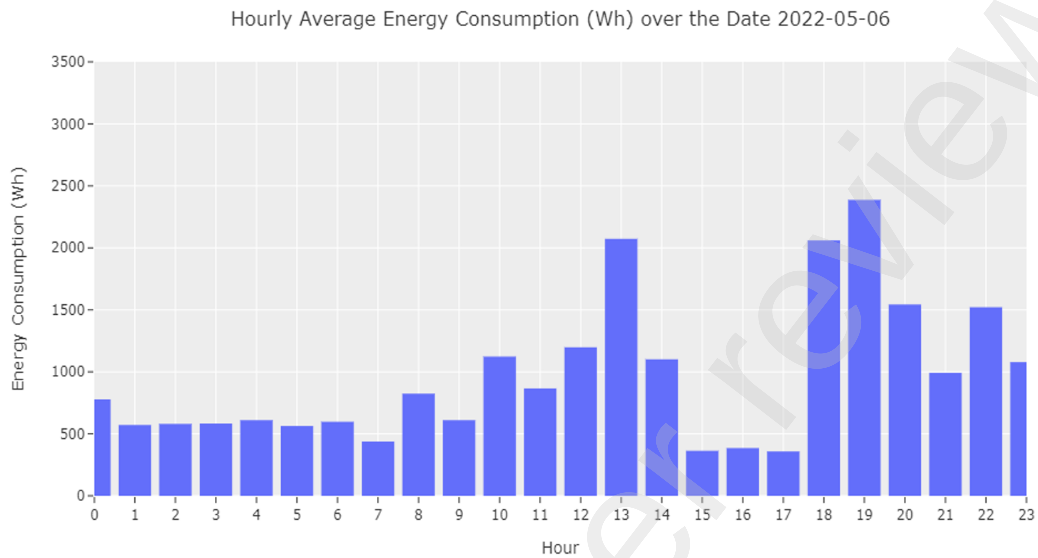

Figure 3: Hourly consumption recorded by FLUKE power analyzer

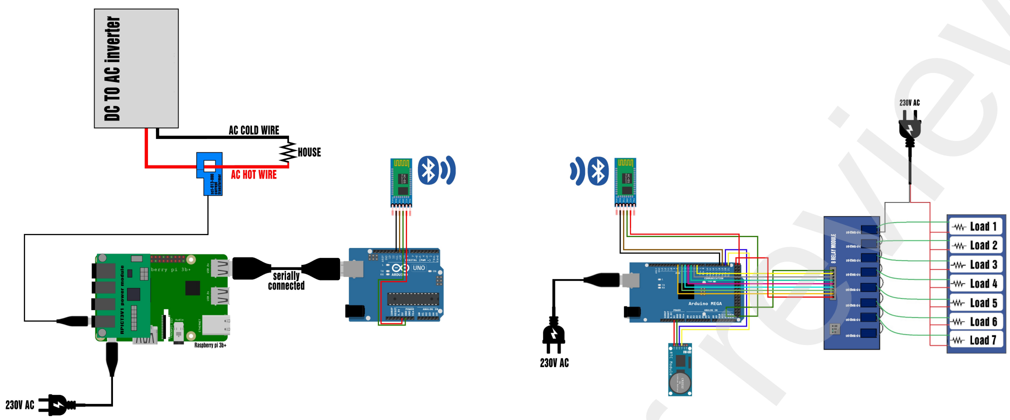

Figure 4: Solar power generation logging system

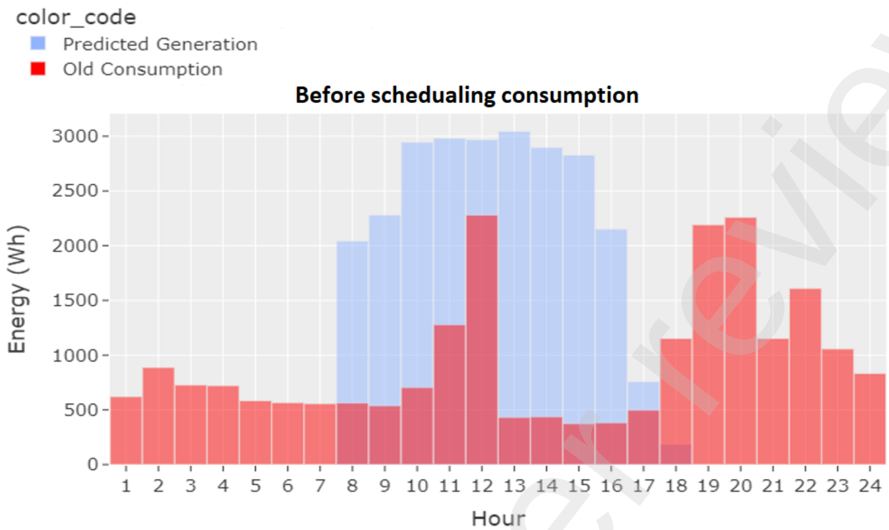

Figure 5: Consumption before scheduling

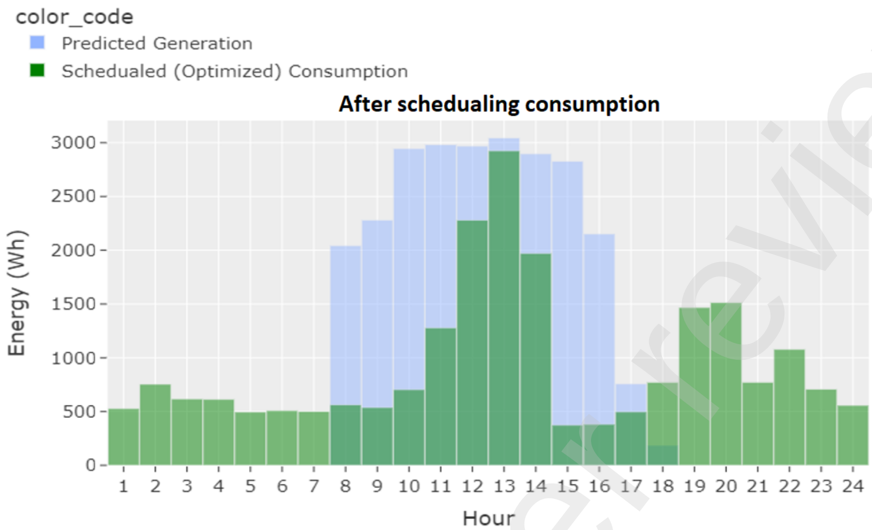

Figure 6: Consumption after scheduling