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Field evaluation of dynamic adjust control and PV-based AHU load management using five-minute monitoring data in Thailand

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Abstract: This study evaluates dynamic_adjust control for photovoltaic (PV)-assisted Air Handling Unit (AHU) load management using five-minute field monitoring data from an industrial energy system in Thailand. The evaluated system consisted of a utility grid connection, smart meter, PV array, hybrid inverter, AHU load, control box, and mobile monitoring interface. Full-month dynamic_adjust datasets from March and April 2026 were analyzed to examine longer-term operation, while May 1–7 dynamic_adjust data were compared with May 8–14 manual_off data. After data cleaning, the March and April datasets contained 19 and 25 valid operating days, respectively. April showed more stable grid behavior than March, with peak grid demand decreasing from 4.96 to 2.18 kW and P95 grid demand decreasing from 2.30 to 0.83 kW. In the weekly comparison, dynamic_adjust reduced peak grid demand from 2.42 to 1.03 kW, representing a 57.4% reduction. Daily grid energy decreased by 16.9%, and time above the 0.70 kW threshold decreased by 92.2%. The results provide field evidence that dynamic_adjust control can improve grid power stability and support electricity cost reduction in PV-based AHU load management.

Keywords: *AHU load, Dynamic_adjust, Five-minute data, Grid power control, Industrial energy management, Photovoltaic system, Smart meter.*

1. Introduction and Problem Statement

Electricity demand management has become an important issue for industrial and commercial facilities because electricity costs are affected not only by total energy use but also by the timing and magnitude of power demand. Many facilities operate electrical loads that fluctuate throughout the day, creating short periods of high grid import. These short-duration peaks can increase demand-related costs and place additional stress on electrical equipment. Therefore, practical energy management strategies that reduce peak grid power while maintaining operational reliability are increasingly important [1-4].

Air Handling Unit (AHU) systems are common electrical loads in industrial and production facilities. They are used for ventilation, thermal comfort, humidity control, and process-related air quality management. In facilities such as pharmaceutical, food, herbal-product, and controlled-environment manufacturing plants, AHU operation is closely related to production quality and indoor environmental control. Consequently, AHU load management should reduce excessive grid demand without interrupting the air-handling function.

Photovoltaic (PV) generation can reduce grid electricity consumption during daytime operation. However, PV generation alone does not always reduce peak demand because the timing of solar output

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may not coincide with load peaks. If a load peak occurs during low solar generation or unstable irradiance, the facility may still import high power from the grid. This limitation highlights the need for a control strategy that coordinates PV-based operation with monitored load behavior [5-7].

Dynamic grid power control is one practical approach for managing grid import. In the dynamic_adjust mode, the control system uses monitored grid power and system status to limit excessive grid import and regulate the operating behavior of the PV-based load system. In contrast, manual_off operation represents a baseline condition in which the active control strategy is not applied. Comparing these two modes can clarify whether the control strategy provides measurable benefits under field conditions [8-10].

Previous studies have investigated peak shaving, demand response, battery energy storage, PV-based load management, and building energy control. However, many studies rely on simulation, assumed load profiles, or aggregated daily and monthly energy data. In practical industrial environments, high-resolution monitoring data are required because peak demand may occur during short intervals that are not visible in low-resolution datasets [11-15].

Recent literature has further emphasized the value of combining PV-battery systems, demand response, and building load control for reducing grid energy costs and peak demand. Wamalwa and Ishimwe developed an optimal control strategy for a grid-tied solar PV-battery microgrid in a public building under demand response, while Camblong et al. implemented a rule-based energy management system using IoT data to enhance PV self-consumption through HVAC control in a real building. Zanetti et al. also demonstrated HVAC demand flexibility using model predictive control in a commercial building field study. These recent studies support the need for field-level control evaluation using monitored operational data [16-18].

The research gap addressed in this study is the limited field evidence on dynamic_adjust control for PV-based AHU load management using high-resolution monitoring data. Although the concept of peak demand control is well established, fewer studies provide practical field analysis comparing dynamic_adjust and manual_off operation in a real AHU load system [19-22].

The novelty of this study lies in its field-based evaluation of a PV-based AHU load-management system using actual five-minute monitoring data from multiple operating periods. Full-month dynamic_adjust operation in March and April 2026 was analyzed to describe longer-term behavior, while the May 2026 dataset was used to compare the dynamic_adjust and manual_off operations. This design provides both monthly operating evidence and direct mode-based performance comparison [23-26].

Therefore, this study aimed to evaluate the performance of dynamic_adjust control for PV-based AHU load management in an industrial facility. The specific objectives were: (1) to describe the system architecture of the PV-based AHU load management system; (2) to analyze monthly dynamic_adjust operation in March and April 2026; (3) to compare dynamic_adjust and manual_off operation using May 2026 monitoring data; and (4) to interpret the potential implications for peak demand reduction, grid energy reduction, and electricity cost management [27, 28].

2. Materials and Methods

2.1. Study Area and System Context

The field evaluation was conducted using monitoring data from an industrial energy system in Thailand. The system was installed to support AHU load management through PV generation, smart metering, hybrid inverter operation, a control box, and mobile monitoring. The selected AHU load represents an auxiliary industrial load that can contribute to short-duration grid demand peaks.

The system operated under real-field conditions, where PV generation, grid import, AHU load behavior, and device response varied according to the actual operating environment. This is important because field operations include fluctuations in solar irradiance, load demand, control response, and equipment interactions. The analysis therefore emphasizes measured operating behavior rather than theoretical design capacity alone. The results should be interpreted as a case study of practical control performance in an industrial AHU-load system.

2.2. PV-Based AHU Load Management System

The evaluated system consisted of a utility-grid connection, smart meter, PV array, hybrid inverter, AHU load, control box, and mobile monitoring interface. The PV array served as an on-site renewable power source. The hybrid inverter provided the interface between PV generation, grid supply, and the controlled load. The smart meter measured grid power, while the control box and mobile interface supported system monitoring and operational decision-making [29].

The AHU load was connected after the hybrid inverter and represented the main controlled load in this study. In the system architecture, the control box was placed after the AHU load to represent the local control and communication unit. The mobile monitoring interface received data from the control box and provided real-time visualization of system operation [30-33].

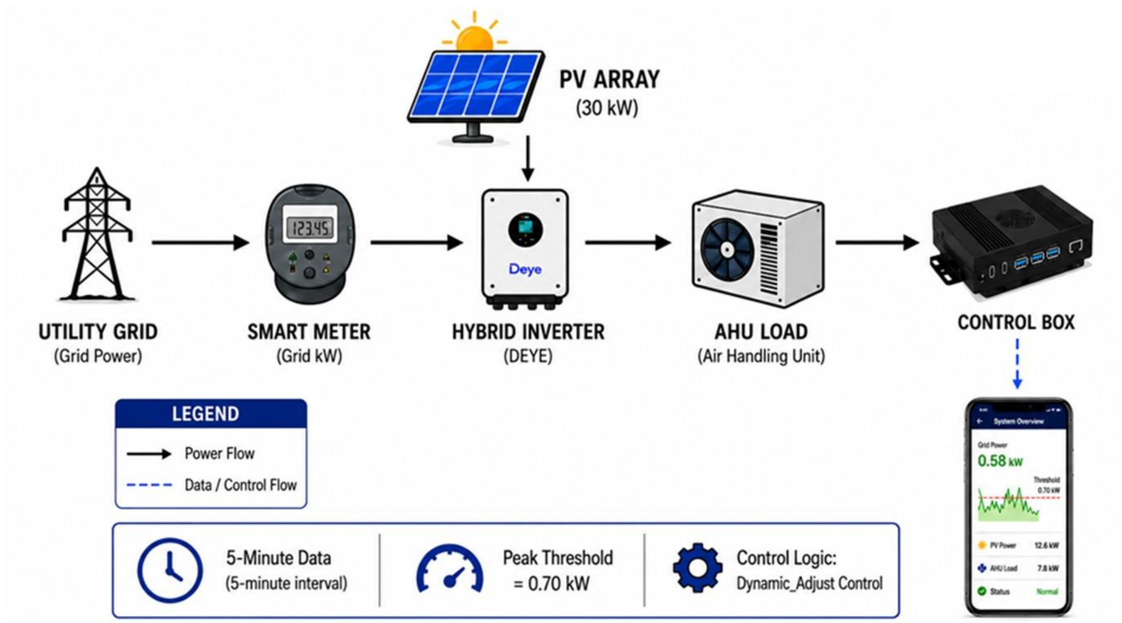

Figure 1.
System architecture of the PV-based AHU load management system with control box and mobile monitoring interface.

2.3. Control Modes Evaluated in the Study

Two operating modes were evaluated: dynamic_adjust and manual_off. The dynamic_adjust mode refers to the active control condition in which grid power is managed according to the control objective and monitored system behavior. In this study, the threshold used for evaluating grid power control was 0.70 kW. When grid power exceeded this threshold, the control strategy was expected to limit excessive grid import through system-level adjustment.

The manual_off mode refers to the baseline condition in which the active dynamic_adjust control strategy was not applied. The manual_off dataset was used as the comparison period to evaluate grid power behavior without the active control mode. This comparison distinguishes the performance of the proposed control approach from ordinary operating behavior.

2.4. Data Collection

The main dataset consisted of five-minute monitoring records collected from the system. The recorded variables included time, grid power, consumption, PV production, inverter-related power, energy-storage-related operation where available, and system-status variables such as state of charge. The five-minute interval was suitable for evaluating short-duration peak-demand events because it captured rapid changes in grid import that could be hidden in hourly or daily summaries.

Three groups of data were used. First, full-month dynamic_adjust datasets from March and April 2026 were analyzed to evaluate longer-term operation. Second, dynamic_adjust data from May 1–7, 2026, were compared with manual_off data from May 8–14, 2026, to quantify the performance difference between the two modes. Third, the May 2026 monthly energy summary was used to evaluate the overall contribution of PV generation and grid-purchase reduction.

2.5. Data Cleaning and Validity Screening

Because the data were obtained from field monitoring files, data cleaning was required before analysis. Records with duplicated actual dates, incomplete daily records, and inconsistent timestamps were screened. The analysis used valid operating days and available five-minute records after removing duplicate or incomplete records. This step was necessary to avoid overcounting or misrepresenting daily energy and peak indicators.

The March dataset contained 19 valid operating days and 5,409 five-minute records after cleaning. The April dataset contained 25 valid operating days and 7,178 five-minute records. The completeness of the valid datasets was 98.85% for March and 99.69% for April. For the May weekly comparison, the dynamic_adjust period and manual_off period were processed using normalized indicators such as kWh/day and minutes/day to allow a fair comparison even when the number of valid records differed between periods.

2.6. Performance Indicators

The primary performance indicator was peak grid demand, defined as the maximum value of the five-minute grid power data during the analyzed period. This indicator is important because high short-duration grid demand can contribute to demand-related electricity costs and equipment loading. The second indicator was the 95th-percentile grid demand (P95), which represents the upper range of high-load operation while reducing the influence of isolated extreme points.

Average grid power and daily grid energy were used to evaluate overall grid dependence. Daily grid energy was calculated by integrating grid power over the five-minute intervals and normalizing the result to kWh/day. Time above the 0.70 kW threshold was calculated as the total duration during which grid power exceeded the target threshold. Excess energy above the threshold was calculated as the integrated energy associated with grid power above 0.70 kW.

2.7. Calculation Methods

Grid energy was calculated from the five-minute power data using an interval duration of 5/60 h. Therefore, the grid energy for each record was calculated as grid power multiplied by 5/60. The total grid energy for each period was obtained by summing all interval-energy values. Grid energy per day was then calculated by dividing the total grid energy by the number of valid operating days.

The improvement of dynamic_adjust relative to manual_off was calculated using the manual_off value as the reference. For indicators where a lower value is better, the percentage reduction was calculated as the difference between the manual_off value and the dynamic_adjust value divided by the manual_off value. This approach was applied to peak grid demand, average grid power, daily grid energy, time above threshold, and excess energy above threshold.

2.8. Monthly Energy Contribution Analysis

In addition to the five-minute peak control analysis, the March–May 2026 monthly energy summary was used to evaluate the contribution of PV generation and grid purchase to total electricity demand. The monthly energy contribution analysis included total consumption, PV energy, and grid purchase/grid energy across March, April, and May 2026, as recorded in the monitoring summary.

The PV-to-consumption ratio was calculated as PV production divided by total consumption. The grid purchase ratio was calculated as grid purchase divided by total consumption. The battery discharge contribution was calculated as battery discharge divided by total consumption. These ratios were used to describe energy contribution, not peak-shaving performance.

2.9. Data Treatment and Interpretation

The study was designed as a field evaluation of operational data. The results were interpreted descriptively because the datasets represented different field-operating periods rather than randomized experimental replicates. The March and April datasets were used to describe dynamic_adjust behavior over longer periods, while the May comparison was used to estimate the difference between dynamic_adjust and manual_off operation.

The analysis emphasizes practical energy management indicators rather than detailed electrical modeling. Battery degradation, inverter internal control parameters, tariff-specific billing, and full economic payback were not modeled in detail. Instead, the study uses grid power and energy indicators to evaluate the practical potential of the control strategy under field conditions [34, 35].

3. Results and Discussion

3.1. System Architecture and Operating Concept

Figure 1 presents the system architecture used in this study. The utility grid supplies power through the smart meter to the hybrid inverter. The PV array provides on-site renewable energy to the inverter, and the AHU load is connected as the main controlled load. The control box is installed after the AHU load and provides the local control and communication pathway. The mobile interface is connected to the control box for monitoring system status and operating data.

The architecture represents a practical field system rather than a purely simulated configuration. The smart meter and mobile interface allow grid power and load behavior to be monitored. The control box supports the implementation of a control pathway between measured data and operational response. This configuration is suitable for evaluating AHU load management under real operating conditions.

3.2. Monthly Dynamic Adjust Operation in March and April 2026

The monthly dynamic_adjust operation results are summarized in Table 1 and illustrated in Figure 2. The March dataset contained 19 valid operating days and 5,409 five-minute records, while the April dataset contained 25 valid operating days and 7,178 records. Data completeness was high in both months, reaching 98.85% for March and 99.69% for April.

During the March dynamic_adjust operation, peak grid demand was 4.96 kW, and P95 grid demand was 2.30 kW. Average grid power was 0.660 kW, and total grid energy was 297.4 kWh, corresponding to 15.65 kWh/day. In contrast, the April dynamic_adjust operation showed lower grid-power indicators, with peak grid demand of 2.18 kW, P95 grid demand of 0.83 kW, average grid power of 0.413 kW, and daily grid energy of 9.88 kWh/day.

As shown in Figure 2(a), April 2026 had lower peak grid, P95 grid, and average grid values than March 2026, indicating fewer and less severe high-power grid import events. Figure 2(b) further shows that excess energy above the 0.70 kW threshold decreased from 4.550 kWh/day in March to 0.841 kWh/day in April. This reduction suggests that the dynamic_adjust mode was more effective in limiting grid import above the target threshold during April.

The difference between March and April indicates that dynamic_adjust performance can vary depending on operating conditions, including AHU operating schedule, PV generation, weather conditions, and facility activity. Nevertheless, the March–April monthly datasets provide extended field evidence that the dynamic_adjust mode can be used to monitor and control grid power behavior over longer operating periods.

Table 1.
Monthly dynamic_adjust operation in March and April 2026.

Indicator	March 2026	April 2026
Mode	Dynamic_adjust	Dynamic_adjust
Valid operating days	19	25
Five-minute records	5,409	7,178
Completeness (%)	98.85	99.69
Peak grid (kW)	4.96	2.18
P95 grid (kW)	2.30	0.83
Average grid (kW)	0.660	0.413
Grid energy (kWh)	297.4	247.0
Grid energy/day (kWh/day)	15.65	9.88
Consumption (kWh)	593.9	440.2
PV energy (kWh)	347.4	247.6
Battery activity (kWh)	85.0	77.9
Time > 0.70 kW (min/day)	825.5	741.6
Excess energy > 0.70 kW (kWh/day)	4.550	0.841

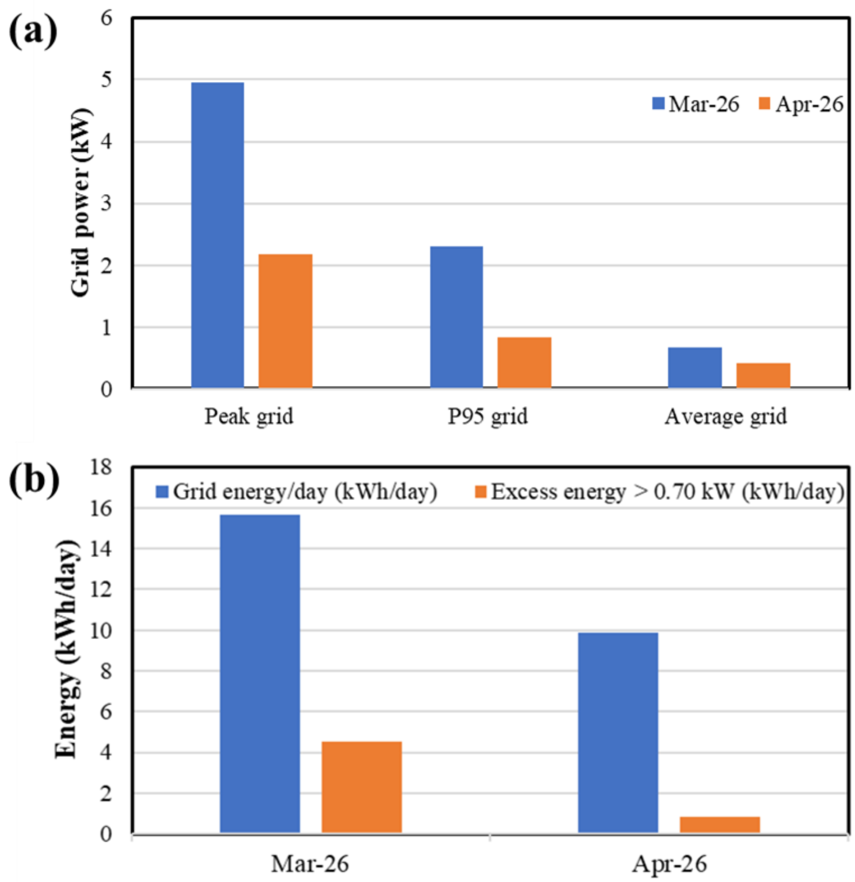

Figure 2.
Monthly dynamic_adjust performance based on March and April 2026 five-minute monitoring data: (a) grid power indicators, including peak grid demand, P95 grid demand, and average grid power; and (b) daily grid energy and excess energy above the 0.70 kW threshold.

The results show that April had substantially lower grid power indicators than March. Peak grid demand decreased from 4.96 kW in March to 2.18 kW in April. P95 grid demand decreased from 2.30 to 0.83 kW, and average grid power decreased from 0.660 to 0.413 kW. These results suggest that the April operating period had fewer high-grid-import events and better threshold control.

Excess energy above the 0.70 kW threshold decreased from 4.550 kWh/day in March to 0.841 kWh/day in April. This is an important finding because excess energy above the threshold represents the portion of energy associated with higher-than-target grid import. A reduction in excess energy indicates improved control of grid import above the target level.

The observed monthly differences may be related to changes in AHU operating schedules, PV output, weather conditions, production activity, or equipment operation. Because this study used field data rather than controlled laboratory conditions, such variation is expected. The key contribution of the monthly analysis is that it demonstrates extended dynamic_adjust operation and provides context for the weekly mode comparison.

3.3. Weekly Comparison Between Dynamic Adjust and Manual-Off Modes

The weekly comparison between the dynamic_adjust and manual_off operations is summarized in Table 2. Dynamic_adjust data from May 1–7, 2026, were compared with manual_off data from May 8–14, 2026. The purpose of this comparison was to quantify the performance difference between active control and baseline operation under the same PV-based AHU load-management system.

Peak grid demand under manual_off operation was 2.42 kW, while the dynamic_adjust period showed a peak grid demand of 1.03 kW. This corresponds to a 57.4% peak reduction. P95 grid demand decreased from 1.20 kW under manual_off operation to 0.70 kW under dynamic_adjust operation, representing a 41.8% reduction.

The threshold-related indicators showed the greatest improvement. The proportion of time above the 0.70 kW threshold decreased from 50.40% under manual_off operation to 3.92% under dynamic_adjust operation. In terms of daily duration, time above threshold decreased from 725.7 min/day to 56.4 min/day, corresponding to a 92.2% reduction. Excess energy above the threshold decreased from 1.568 to 0.037 kWh/day, representing a 97.7% reduction. Figure 3 illustrates the percentage improvements achieved by the dynamic_adjust operation compared with the manual_off operation. The largest improvements were observed for excess energy above the 0.70 kW threshold, time above the threshold, and peak grid demand.

Table 2.
Comparison between dynamic_adjust and manual_off operations in May 2026.

Indicator	Dynamic_adjust 1-7 May	Manual_off 8-14 May	Improvement
Peak grid (kW)	1.03	2.42	57.4% reduction
P95 grid (kW)	0.70	1.20	41.8% reduction
Average grid (kW)	0.418	0.503	16.9% reduction
Grid energy/day (kWh/day)	10.04	12.07	16.9% reduction
Time > 0.70 kW (%)	3.92	50.40	92.2% reduction
Time > 0.70 kW (min/day)	56.4	725.7	92.2% reduction
Excess energy > 0.70 kW (kWh/day)	0.037	1.568	97.7% reduction

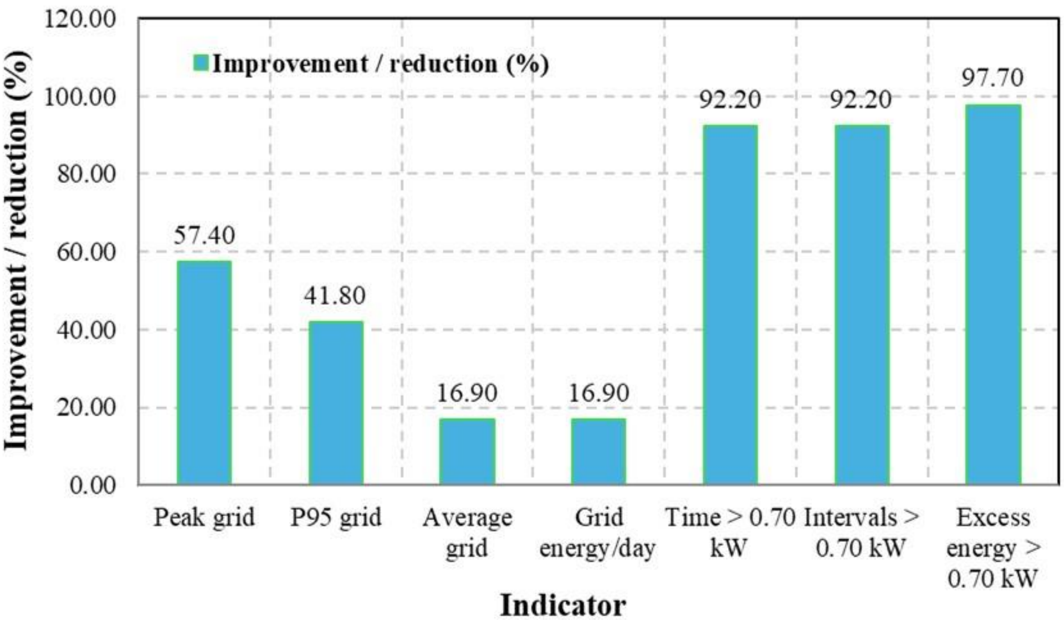

Figure 3.
Performance improvement of the dynamic_adjust operation compared with the manual_off operation.

3.4. Practical Meaning of Peak Grid Reduction

Peak grid demand was calculated as the maximum value of the five-minute grid power data. This definition is practical for energy management because it directly reflects the highest grid import observed during the monitoring period. The reduction from 2.42 to 1.03 kW means that dynamic_adjust reduced the highest observed grid import by 1.39 kW relative to manual_off operation.

The reduction in P95 grid demand is also important. Peak values can be influenced by a single short event, but P95 represents the upper range of typical high-load operation. The decrease from 1.20 to 0.70 kW indicates that dynamic_adjust reduced not only a single peak but also the broader high-load operating range.

The reduction in time above the threshold shows that dynamic_adjust improved operating stability. Under manual_off operation, grid power exceeded 0.70 kW for more than half of the operating time. Under the dynamic_adjust operation, exceedance occurred during only 3.92% of the time. This suggests that the control strategy reduced frequent threshold violations and maintained grid import closer to the target level.

3.5. Grid Energy Reduction and Electricity Cost Implications

The dynamic_adjust mode reduced daily grid energy from 12.07 to 10.04 kWh/day. This corresponds to a reduction of approximately 2.03 kWh/day, or 16.9%. This reduction can contribute to lower electricity charges when the facility pays for imported grid electricity on a kWh basis. If an average energy charge is applied, the reduction in imported energy can be converted into a direct energy-cost saving.

However, the financial implication of peak demand reduction depends on the tariff structure. If the facility is subject to demand charges based on maximum kW demand, the reduction in peak grid demand may create additional cost savings. In this study, peak grid demand decreased by 1.39 kW in the weekly comparison. Whether this reduction affects the actual monthly bill depends on whether the controlled AHU load coincides with the facility-level billing peak.

The energy and peak demand results suggest that dynamic_adjust has the potential to reduce both energy-related and demand-related electricity costs. Nevertheless, larger-scale implementation should evaluate total plant load, actual billing records, tariff category, power factor, demand charge rules, and month-level peak coincidence before confirming actual financial savings.

3.6. Monthly Energy Contribution from March to May 2026

The monthly energy contribution from March to May 2026 is presented in Table 3 and Figure 4. Consumption, PV energy, and grid purchase/grid energy were compared across the three months to describe the overall energy contribution of the PV-based AHU load management system. Total consumption during the month was 775.0 kWh, while PV production was 446.4 kWh. Grid purchase was 334.8 kWh. These values indicate that PV generation supplied a substantial portion of on-site demand. The PV-to-consumption ratio was 57.6%, while the grid purchase ratio was 43.2%.

The monthly results should be interpreted as energy contribution indicators rather than peak-shaving indicators. Monthly energy totals do not capture short-duration peaks or threshold-exceedance behavior. Therefore, five-minute grid power data were required to evaluate dynamic_adjust control and peak-demand reduction.

Table 3.
Monthly energy contribution of the PV-based system from March to May 2026.

Month	Consumption (kWh)	PV energy (kWh)	Grid purchase / Grid energy (kWh)
March 2026	593.9	347.4	297.4
April 2026	440.2	247.6	247.0
May 2026	775.0	446.4	334.8

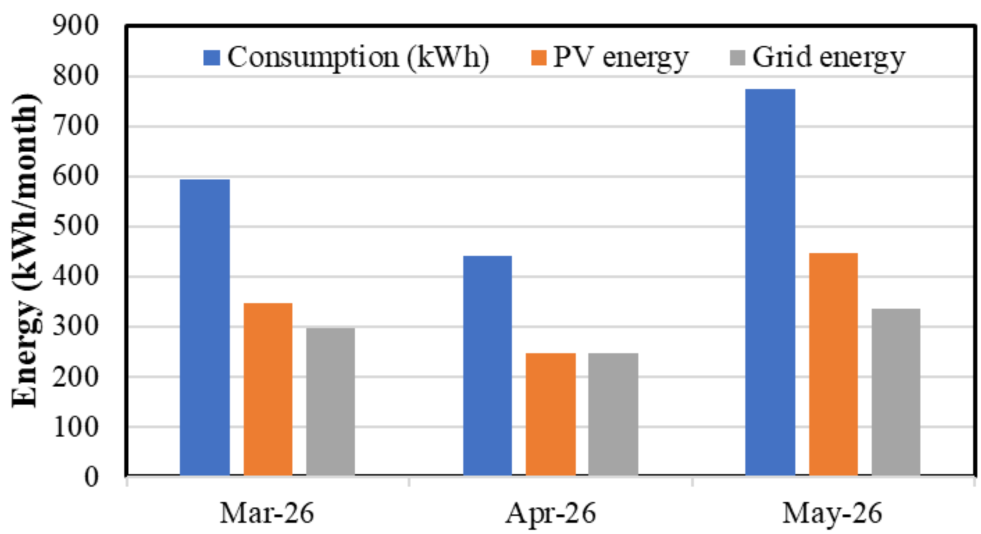

Figure 4.
Monthly energy performance of the PV-based AHU load management system during March, April, and May 2026.

3.7. Integrated Evaluation of Dynamic Adjust Performance

The integrated results show that dynamic_adjust provided clear benefits in grid power control. The monthly March and April datasets demonstrated that the control mode could operate over extended periods, while the May weekly comparison quantified its benefit against manual_off operation. This combination of monthly and weekly analyses strengthens the evaluation because it shows both longer-term operating behavior and direct mode-based performance improvement.

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The strongest evidence of dynamic_adjust performance is the reduction in threshold exceedance. In the weekly comparison, time above the 0.70 kW threshold decreased by 92.2%, and excess energy above the threshold decreased by 97.7%. These indicators show that the control strategy was highly effective in limiting grid import above the target level. The 57.4% reduction in peak grid demand further confirms that the control mode reduced short-duration high-grid-demand events.

The 16.9% reduction in daily grid energy indicates that dynamic_adjust also reduced overall grid dependence during the comparison period. This result may be associated with improved coordination among PV generation, load operation, and control response. However, because the compared periods were not randomized and may have differed in weather or operating schedule, the energy reduction should be interpreted as field evidence rather than a universal guarantee.

3.8. Comparison with Previous Energy Management Concepts

The results are consistent with the general principle of demand-side energy management, where control actions are used to reduce high grid demand and improve load stability. PV-based systems can reduce grid energy consumption, but their effectiveness for peak-demand control depends on timing and control response. This study demonstrates that a field-level dynamic_adjust strategy can substantially reduce peak-grid demand and threshold exceedance in an AHU load system.

Compared with studies that use only simulation, the present study contributes measured field data and a practical system architecture. The use of five-minute monitoring data allows short-duration grid power behavior to be observed. This is important because hourly or daily data can mask brief but important peak events. The field-based approach also captures real equipment and monitoring behavior, which is useful for practical implementation.

At the same time, the system scale in this study was relatively small. The observed peak values were in the kW range rather than the hundreds of kW typically found in large industrial plants. Therefore, the study should be interpreted as a pilot-scale or subsystem-level evaluation. The approach can be scaled to larger loads, but larger-scale validation is required before generalizing the financial benefit to full industrial facilities.

3.9. Methodological Considerations and Limitations

Several limitations should be considered. First, the dynamic_adjust and manual_off datasets were collected during different calendar periods. Therefore, differences in weather, PV generation, AHU operating schedules, and facility activity may have influenced the comparison. Second, the analysis used available monitoring data after removing duplicate and incomplete records. Although the cleaned datasets had high completeness, field monitoring data can still contain measurement errors or system-communication issues.

Third, the study did not verify cost savings using actual electricity bills. The electricity cost discussion is based on implications derived from grid energy reduction and peak-demand reduction. Actual cost savings depend on tariff category, billing-demand calculation, facility-level peak coincidence, power factor, and monthly billing rules. Fourth, battery degradation, inverter efficiency under all operating conditions, and control delay were not modelled in detail. These factors should be included in future long-term technoeconomic evaluations.

Fifth, the study focused on AHU load management. Although AHU systems are important industrial auxiliary loads, the results may not directly represent other loads such as compressors, pumps, chillers, or production machinery. Future studies should include multiple load types and investigate whether the same dynamic_adjust strategy can control larger and more variable industrial loads.

3.10. Practical Recommendations

Based on the field results, dynamic_adjust control should be considered for facilities that experience repeated grid power exceedance at the subsystem level. The control strategy is especially useful when high-resolution monitoring data are available and when grid power thresholds can be defined according to operational or economic objectives. The control box and mobile monitoring interface are practical components because they support real-time visualization and local operational awareness.

For future implementation, the control threshold should be optimized rather than fixed. A threshold of 0.70 kW was used in this evaluation, but the best threshold may depend on AHU load requirements, PV output, available storage capacity, inverter constraints, and electricity tariff. Adaptive threshold control could improve performance by adjusting the grid limit according to time of day, solar availability, state of charge, and expected load behavior.

Facility managers should also evaluate whether subsystem-level peak control contributes to whole-building or plant-level billing peak reduction. If the controlled AHU load occurs at the same time as the facility peak, dynamic_adjust may reduce demand charges. If the facility peak is dominated by other loads, additional load coordination will be required. Therefore, future deployment should integrate AHU control with whole-facility energy monitoring.

4. Conclusion

This study evaluated dynamic_adjust control and PV-based AHU load management using five-minute monitoring data from an industrial energy system in Thailand. The system consisted of a utility grid, smart meter, PV array, hybrid inverter, AHU load, control box, and mobile monitoring interface. Full-month dynamic_adjust datasets from March and April 2026 were analyzed to assess longer-term operating behavior, while May 2026 data were used to compare dynamic_adjust with manual_off operation.

The monthly dynamic_adjust results showed that the April operation was more stable than the March. Peak grid demand decreased from 4.96 kW in March to 2.18 kW in April, while P95 grid demand decreased from 2.30 to 0.83 kW. Average grid power decreased from 0.660 to 0.413 kW, and grid energy per day decreased from 15.65 to 9.88 kWh/day. Excess energy above the 0.70 kW threshold decreased from 4.550 to 0.841 kWh/day, indicating improved grid power control.

The weekly comparison demonstrated the practical benefit of dynamic_adjust relative to manual_off operation. Dynamic_adjust reduced peak grid demand from 2.42 to 1.03 kW, corresponding to a 57.4% reduction. Average grid power and daily grid energy decreased by 16.9%. Time above the 0.70 kW threshold decreased by 92.2%, while excess energy above the threshold decreased by 97.7%. These results indicate that dynamic_adjust substantially improved threshold compliance and reduced excessive grid import.

The monthly energy contribution analysis showed that the PV-based system supplied a substantial portion of on-site electricity demand during March, April, and May 2026. In May 2026, PV production was 446.4 kWh/month compared with total consumption of 775.0 kWh/month, corresponding to a PV-to-consumption ratio of 57.6% and a grid purchase ratio of 43.2%. These results confirm that the PV-based system contributed substantially to on-site electricity supply. Overall, the study provides field evidence that dynamic_adjust control can improve grid power stability, reduce peak demand, and support electricity cost-reduction potential in PV-based AHU load management. Future work should include longer monitoring periods, actual electricity bill validation, battery degradation analysis, adaptive control thresholds, and full-facility load integration.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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