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# An intelligent weather-aware energy management framework for resilient smart-grid operation using adaptive battery control

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**ABSTRACT**

Extreme weather conditions such as heatwaves and high-temperature events can adversely affect the stability, reliability, and operational performance of modern smart grids. This paper presents an intelligent energy management framework for weather-aware smart-grid operation using real-world meteorological data and renewable-energy integration. Hourly temperature, solar irradiance, and wind-speed data were obtained from the NASA POWER Data Access Viewer for Chennai, India, from 2020 to 2024. The framework integrates temperature-dependent load demand, solar-energy generation with PV efficiency degradation, adaptive grid-stress thresholds, and battery energy management for charging, discharging, and idle operation. The proposed system was evaluated using grid-stress analysis, normalized voltage assessment, and renewable-energy contribution before and after intelligent energy management. Simulation results showed a reduction in average grid stress from 90.47 to 90.43 and a 9.09% reduction in peak grid stress from 109.97 to 99.97. The normalized voltage indicator increased from 0.81906 to 0.81914, while renewable-energy support reduced modelled grid dependency during solar availability. Overall, the proposed framework provides a computationally efficient supervisory approach for weather-aware, renewable-integrated, battery-assisted smart-grid energy management.

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## 1. INTRODUCTION

The increasing integration of renewable energy, rising electricity demand, and modernization of electrical infrastructure are transforming conventional power networks into intelligent smart grids. Smart-grid technologies combine renewable energy resources, distributed generation, communication systems, and automated control to improve power-system efficiency, reliability, and sustainability [1], [2]. However, climate-induced extreme weather events, particularly heatwaves and high-temperature conditions, pose growing challenges to reliable grid operation [3], [4].

Heatwaves can substantially increase electricity demand because of cooling and air-conditioning requirements, particularly in densely populated regions [5]. At the same time, extreme temperatures can

affect renewable-energy generation, equipment performance, voltage conditions, and overall network operation [6], potentially increasing grid stress and the risk of operational disturbances [7]. Solar photovoltaic (PV) generation is particularly sensitive to environmental conditions. Although solar energy supports renewable-energy integration and reduces dependence on conventional generation [8], [9], PV output is influenced by solar irradiance and ambient temperature, with elevated temperatures generally reducing PV conversion efficiency [10], [11].

Battery energy storage systems (BESS) provide an important means of improving renewable-energy utilization, load balancing, peak-demand management, and grid support [12]. Their coordinated operation with renewable generation and load demand can improve the flexibility of smart-grid systems under changing operating conditions [13]. In practical applications, battery systems are typically connected through bidirectional power-electronic converters, making supervisory energy management essential for coordinating charging, discharging, renewable-energy availability, and grid conditions.

Recent research has investigated intelligent energy management, renewable-energy forecasting, adaptive battery control, and climate-resilient smart-grid operation [14]–[19]. Renewable-integrated energy management and battery-assisted resilience have also been investigated for microgrids and smart grids under varying operating and extreme-weather conditions [20]–[23]. Recent studies have further considered adaptive control and operational scheduling for renewable-integrated power systems [24], [25]. However, many existing approaches involve computationally intensive optimization, machine-learning, or deep-learning techniques [26]. Other studies primarily address economic scheduling, load forecasting, or renewable-energy prediction, with comparatively limited emphasis on simplified smart-grid operation specifically under extreme heatwave conditions using real-world weather data [27], [28]. Furthermore, practical factors such as temperature-dependent PV efficiency and adaptive grid-stress thresholds are not consistently incorporated, while fixed control thresholds may not adequately reflect changing weather and load conditions [29].

Based on these limitations, five research gaps are identified: i) Limited weather-aware resilience analysis under extreme heatwave conditions using real-world meteorological data; ii) Dependence on computationally intensive intelligent optimization approaches; iii) Insufficient consideration of temperature-dependent PV degradation and practical operating constraints; iv) Limited adaptability of fixed grid-stress thresholds; and v) Limited comparative evaluation of grid stress, normalized voltage response, and renewable-energy contribution before and after energy management.

To address these gaps, this study proposes a computationally efficient, weather-aware intelligent energy management framework using hourly meteorological data for Chennai, India, from 2020–2024 obtained from the NASA POWER Data Access Viewer [30]. The framework integrates temperature-based heatwave analysis, temperature-dependent load modeling, PV generation estimation, adaptive grid-stress threshold calculation, and battery charging, discharging, and idle control. The proposed method uses statistical characteristics of grid stress to dynamically determine battery-control thresholds rather than relying on fixed limits.

The main contributions of this study are: i) Development of a weather-aware smart-grid framework using real-world hourly meteorological data; ii) Integration of heatwave-based load modeling with temperature-dependent PV generation; iii) Implementation of adaptive battery energy management based on grid-stress conditions; iv) Dynamic estimation of upper and lower grid-stress thresholds using statistical characteristics; and v) Comparative evaluation of grid-stress reduction, normalized voltage response, and renewable-energy contribution before and after energy management.

The proposed framework provides a simple, computationally efficient, renewable-integrated, and battery-assisted supervisory approach for weather-aware smart-grid energy management under extreme weather conditions. The present study focuses on supervisory-level energy management and therefore uses simplified battery, grid-stress, and normalized-voltage models rather than detailed electrochemical battery, converter, or network simulations. These aspects, together with benchmarking against alternative energy-management strategies, are considered important directions for future work.

## 2. METHODOLOGY

The proposed methodology develops a weather-aware intelligent energy management framework for smart-grid operation under extreme weather conditions. The framework comprises weather-data acquisition, preprocessing, heatwave identification, temperature-dependent load and PV modeling, grid-stress estimation, adaptive battery control, normalized voltage assessment, renewable-energy analysis, and performance evaluation. The simulation was implemented in Python using the Kaggle computational environment. The overall workflow of the proposed weather-aware intelligent energy management framework is illustrated in Figure 1.

### 2.1. Weather data collection

Hourly meteorological data for Chennai, India, covering 2020–2024, were obtained from the NASA POWER Data Access Viewer. The selected parameters were ambient temperature at 2 m (T2M), direct normal irradiance (DNI; ALLSKY_SFC_SW_DNI), and wind speed at 10 m (WS10M). T2M and DNI were used in the proposed load and solar-generation models, while WS10M was retained for weather characterization; wind-energy generation was not modeled because the framework focuses on solar-assisted battery energy management. Table 1 summarizes the meteorological parameters used in the proposed framework. T2M was used for heatwave identification and temperature-dependent load modeling, while DNI was used for solar-generation estimation. WS10M was retained to characterize the prevailing weather conditions, although wind-energy generation was not modeled in the present study. The hourly timestamp was used for temporal analysis of the weather and energy profiles.

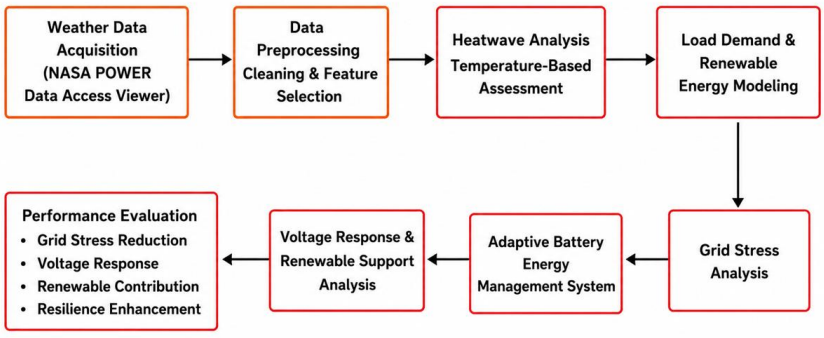


Figure 1. Overall workflow of the proposed weather-aware intelligent energy management framework

Table 1. Weather dataset parameters

| Parameter | Description | Unit | Role |
|---|---|---|---|
| T2M | Ambient temperature at 2 m | °C | Heatwave and load modeling |
| DNI | Direct normal irradiance | W/m² | Solar-generation estimation |
| WS10M | Wind speed at 10 m | m/s | Weather characterization |
| Time | Hourly timestamp | — | Temporal analysis |

### 2.2. Data preprocessing

The downloaded CSV data were processed using Python. Unnecessary metadata were removed, required weather variables were extracted, and missing or invalid entries were excluded. The resulting dataset contained temporal information together with temperature, solar irradiance, and wind-speed data for subsequent analysis.

### 2.3. Heatwave modeling

Extreme weather conditions were modeled using temperature-based heatwave analysis. In this study, a heatwave operating condition was identified whenever the ambient temperature exceeded 38°C. The heatwave indicator is expressed as (1):

$$H(t) = \begin{cases} 1, \text{if } T2M > 38\,^{\circ}C \\ 0, \text{otherwise} \end{cases} \quad (1)$$

where H(t) represents the heatwave indicator at time *t*, and T2M(t) denotes the ambient temperature at 2 m height (°C).

### 2.4. Load demand modeling

Temperature-dependent load demand was modeled to represent increased electricity consumption associated with cooling requirements:

$$L(t) = 50 + 1.5 \times T2M(t) \quad (2)$$

where L(t) is the estimated load demand, 50 is the assumed baseline demand, and 1.5 represents the assumed temperature sensitivity coefficient.

### 2.5. Temperature-dependent solar-energy generation

Solar generation was estimated from DNI with a temperature-dependent PV efficiency correction:

$$S(t) = 0.001 \times DNI \times (1 - 0.004(T2M - 25)) \quad (3)$$

where S(t) is estimated solar generation, 0.004/°C is the assumed PV temperature coefficient, and 25 °C is the reference temperature. The formulation accounts for both solar-resource availability and temperature-related PV performance reduction.

### 2.6. Grid-stress analysis

Grid stress was represented by the residual demand after solar contribution:

$$GS(t) = L(t) - S(t) \quad (4)$$

where GS(t) denotes modeled grid stress. Higher values indicate greater residual demand and dependence on grid-supplied energy.

### 2.7. Adaptive grid-stress threshold estimation

Adaptive battery-control thresholds were calculated from the statistical characteristics of the grid-stress profile:

$$TH_{high}=\mu_{GS}+\sigma_{GS} \quad (5)$$

$$TH_{low}=\mu_{GS}-\sigma_{GS} \quad (6)$$

where μGS and σGS are the mean and standard deviation of grid stress, respectively. These thresholds provide operating limits for battery charging, discharging, and idle modes.

### 2.8. Adaptive battery energy management

The battery operates in three modes according to the adaptive thresholds:

$$\text{Battery Mode(t)}=\begin{cases} Discharge\ GS(t) > TH_{high} \\ Charge\ GS(t) < TH_{low} \\ Idle\ , Otherwise \end{cases} \quad (7)$$

The battery action is represented by the following control signal:

$$\text{Battery action _Action (t)} =\begin{cases} -10, if\ GS(t) > TH_{high} \\ +10, if\ GS(T) < TH_{low} \\ 0, Oherwise \end{cases} \quad (8)$$

A negative action represents battery discharge and a positive action represents charging. The corrected grid stress is calculated as:

$$GS_{corr}(t) = GS(t) + \text{Battery_Action (t)} \quad (9)$$

Thus, discharge reduces modeled grid stress, while charging increases it under low-stress conditions.

### 2.9. Normalized voltage assessment

A simplified normalized voltage indicator was used to compare the modeled voltage response before and after battery intervention

$$V(t)=1-0.002\times GS(t) \quad (10)$$

After battery intervention:

$$V_{corr}(t)=1-0.002\times GS_{corr}(t) \quad (10)$$

where 0.002 is the assumed voltage-sensitivity coefficient. This formulation provides a normalized indicator for comparing the modeled voltage response under the two operating conditions.

### 2.10. Renewable-energy contribution

The renewable-energy contribution was evaluated using the solar-to-load ratio:

$$RS(t) = \frac{S(t)}{L(t)} \times 100 \quad (9)$$

where RS(t) represents the renewable-support percentage. Higher values indicate greater solar contribution and lower modeled dependence on conventional grid resources.

Table 2 summarizes the key parameters and control settings used in the proposed energy management model. The heatwave threshold defines the temperature condition used for heatwave identification, while the base-load and temperature-load coefficient determine the temperature-dependent demand. The PV temperature coefficient and reference temperature are used to account for temperature-related PV performance variation. The upper and lower grid-stress thresholds determine battery discharge and charging actions, respectively, while the idle action represents periods without battery intervention. The voltage sensitivity coefficient is used for the normalized voltage assessment.

Table 2. Parameters used in the proposed energy management model

| Parameter | Value | Purpose |
|---|---|---|
| Heatwave threshold | 38 °C | Heatwave identification |
| Base load | 50 | Load model |
| Temperature-load coefficient | 1.5 | Temperature-dependent demand |
| PV temperature coefficient | 0.004/°C | Temperature correction |
| Reference PV temperature | 25 °C | PV efficiency reference |
| High-stress threshold | μGS+σGS | Battery discharge |
| Low-stress threshold | μGS−σGS | Battery charging |
| Battery discharge action | −10 | Grid-stress reduction |
| Battery charge action | +10 | Battery charging |
| Idle action | 0 | No intervention |
| Voltage sensitivity coefficient | 0.002 | Normalized voltage assessment |

### 2.11. Performance evaluation

The proposed framework was evaluated using grid-stress reduction, normalized voltage response, renewable-energy contribution, battery-support effectiveness, and performance under heatwave conditions. Comparative analysis was performed before and after battery-based energy management to assess the modeled effectiveness of the proposed framework.

## 3. RESULTS AND DISCUSSION

### 3.1. Weather and heatwave characteristics

The hourly meteorological dataset for Chennai was analyzed to identify periods of elevated temperature and corresponding changes in solar irradiance. An operational heatwave condition was defined when the ambient temperature exceeded 38 °C. The temperature and solar-irradiance characteristics of the analyzed dataset are shown in Figure 2. These periods were associated with increased modeled electricity demand and provided the basis for evaluating weather-induced grid stress.

### 3.2. Grid-stress reduction

The modeled grid stress was evaluated before and after implementation of the adaptive battery-control strategy. The comparison of grid stress before and after battery intervention is presented in Figure 3. The average grid-stress value decreased from 90.47 to 90.43, while the peak grid stress decreased from 109.97 to 99.97, corresponding to a 9.09% reduction. This reduction demonstrates that the adaptive battery strategy primarily contributes during high-stress operating periods. When grid stress exceeds the upper adaptive threshold, the battery is commanded to discharge, thereby reducing the effective residual demand.

### 3.3. Load demand and solar generation analysis

The estimated load demand and solar generation during the simulation period are compared in Figure 4. The load demand remained substantially higher than solar generation, with the estimated demand varying approximately between 82 and 93 units. Solar generation provided partial daytime support but was insufficient to meet the total demand. The temperature-dependent PV model also accounts for efficiency reduction at elevated temperatures, thereby reflecting the combined effects of solar availability and thermal losses. The persistent difference between load demand and solar generation indicates the need for supplementary energy management through battery storage.

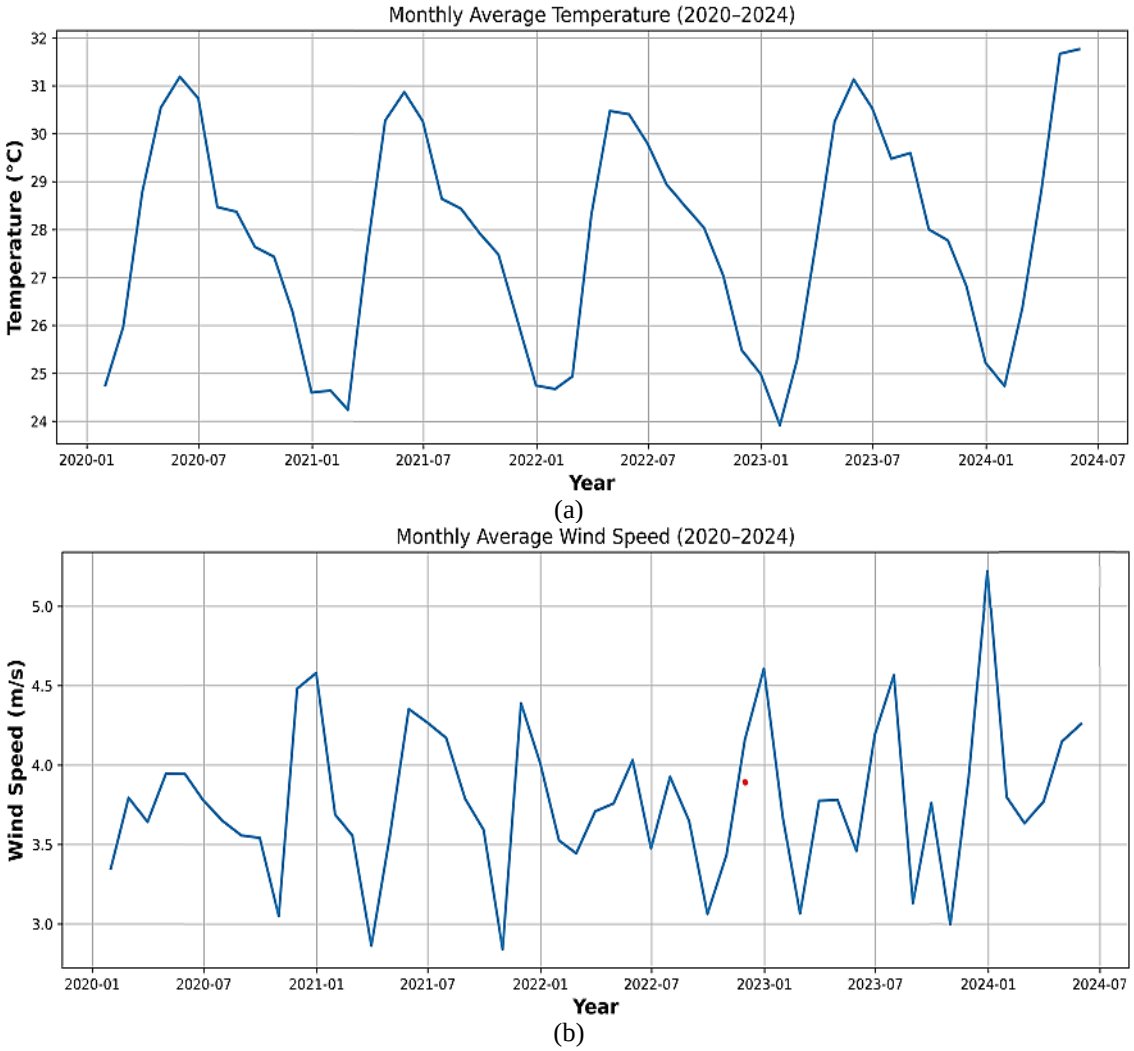


Figure 2. Monthly average: (a) temperature and (b) solar irradiance (2020–2024)

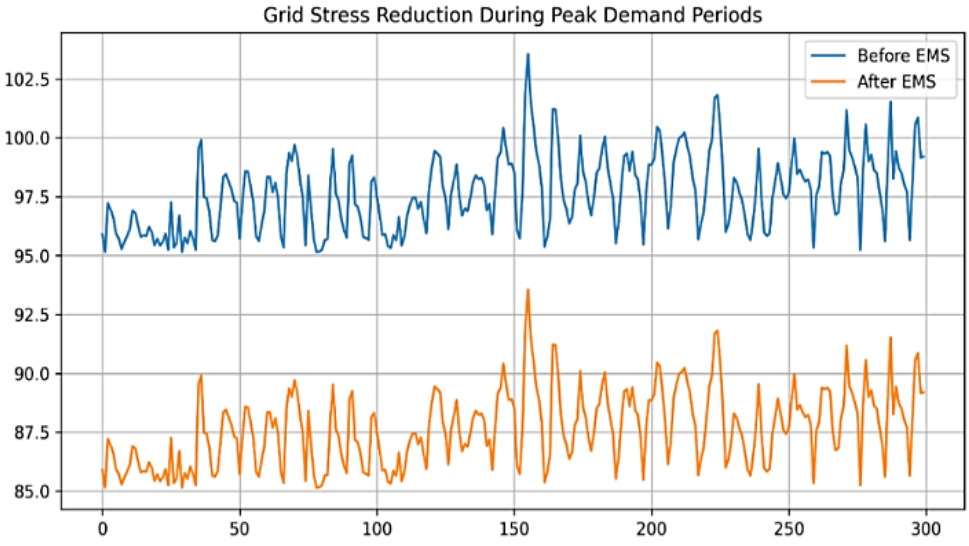


Figure 3. Grid-stress comparison before and after adaptive energy management during peak-demand periods

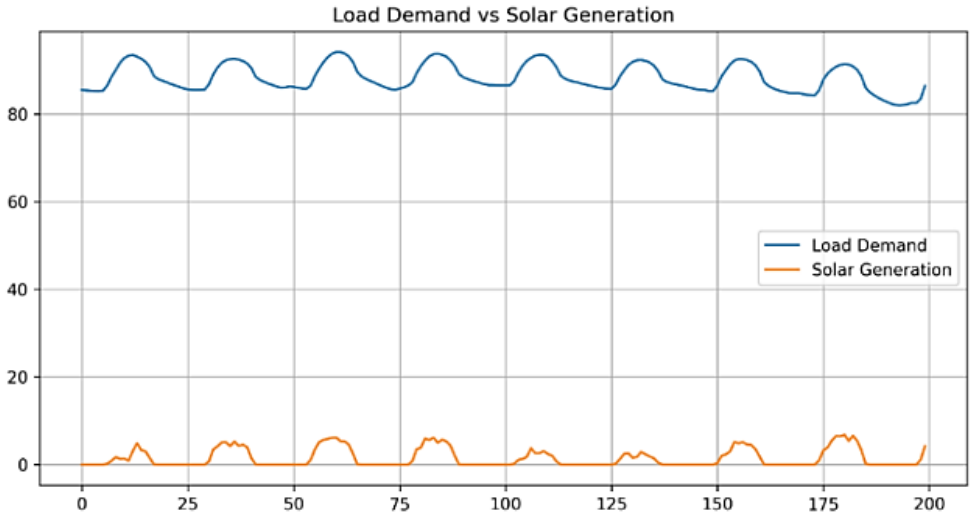


Figure 4. Load demand vs solar generation

### 3.4. Normalized voltage response

The normalized voltage indicator was calculated using the modeled relationship between grid stress and voltage response. The modeled voltage response before and after battery intervention is shown in Figure 5**.** Before battery intervention, the average normalized voltage was 0.81906 p.u., while after battery intervention it increased to 0.81914 p.u. Although the improvement is numerically small, the increase is consistent with the reduction in modelled grid stress.

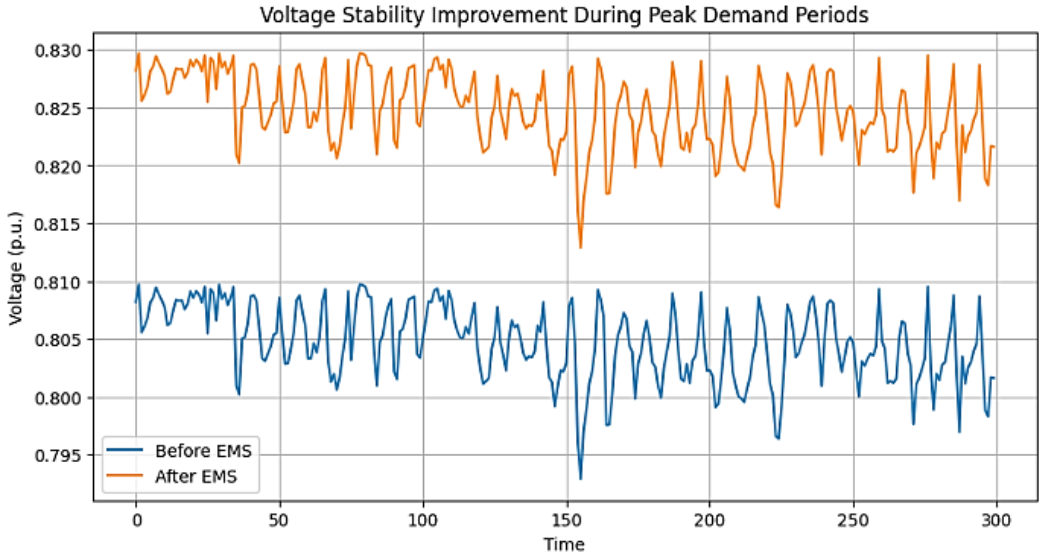


Figure 5. Comparison of modeled normalized voltage response before and after battery intervention

### 3.5. Renewable-energy contribution

The solar-energy generation profile obtained using the temperature-dependent PV model is shown in Figure 6**.** Solar generation contributed to reducing the modeled residual grid demand during periods of solar availability. The temperature-dependent PV formulation accounts for the reduction in PV performance at elevated temperatures.

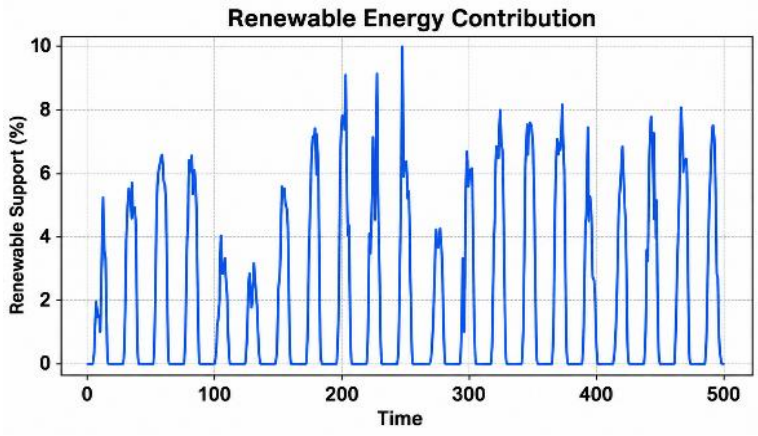


Figure 6. Temperature-dependent solar-energy generation under varying irradiance conditions

### 3.6. Overall discussion

The results demonstrate that the proposed weather-aware energy management framework can reduce grid stress and improve the modelled voltage response under the considered operating conditions. The 9.09% reduction in peak grid stress indicates that adaptive battery support is particularly useful during high-stress periods. Solar generation provides additional daytime support, although its contribution remains lower than the modelled load demand.

The proposed framework uses simplified mathematical models and supervisory battery control; therefore, the results represent a simulation-based assessment rather than a detailed network-level power-flow analysis. Battery state of charge, converter losses, battery degradation, and detailed grid constraints were not explicitly modeled. Nevertheless, the framework provides a computationally efficient approach for preliminary assessment of renewable-integrated battery energy management under extreme weather conditions. Table 3 summarizes the comparative performance of the proposed energy management system before and after EMS implementation. The results show a small reduction in average grid stress from 90.47 to 90.43, while the peak grid stress decreases from 109.97 to 99.97, corresponding to a 9.09% reduction. The average normalized voltage increases slightly from 0.81906 to 0.81914 p.u. The renewable-energy support remains 1.36% in both cases because the solar-generation profile is unchanged by the battery-control operation. These results indicate that the proposed EMS primarily contributes to peak grid-stress mitigation rather than significantly changing the overall average operating level.

Table 3. Comparative performance evaluation

| Performance metric | Before EMS | After EMS | Improvement (%) |
|---|---|---|---|
| Average grid stress | 90.47 | 90.43 | 0.05 |
| Peak grid stress | 109.97 | 99.97 | 9.09 |
| Average voltage (p.u.) | 0.81906 | 0.81914 | 0.01 |
| Renewable support (%) | 1.36 | 1.36 | – |

## 4. CONCLUSION

This study presented a weather-aware intelligent energy management framework for resilient smart-grid operation under extreme heatwave conditions. The framework used real-world hourly meteorological data for Chennai from 2020–2024 and integrated temperature-dependent load modelling, temperature-dependent PV generation, adaptive grid-stress thresholds, and battery energy management. The simulation results showed that adaptive battery intervention reduced the average grid stress from 90.47 to 90.43 and the peak grid stress from 109.97 to 99.97, representing a 9.09% reduction. The modelled normalized voltage response also improved from 0.81906 to 0.81914 p.u. Solar generation provided additional daytime support, although it remained lower than the modelled load demand.

Overall, the results indicate that the proposed supervisory strategy can effectively mitigate peak grid stress and provide a computationally efficient approach for weather-aware renewable-integrated battery management. The framework can serve as a practical basis for further studies incorporating detailed power-flow models, battery state-of-charge constraints, converter losses, and real-time grid operating conditions.

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**AUTHOR CONTRIBUTIONS STATEMENT**

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
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| K. Arulvendhan | | ✓ | | | | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| R. Naveena Bhargavi | ✓ | | ✓ | ✓ | ✓ | | ✓ | | | ✓ | ✓ | | ✓ | ✓ |
| T. Sathish Kumar | | ✓ | ✓ | | | ✓ | | ✓ | ✓ | ✓ | | ✓ | | |
| R. J. Vijaya Saraswathi | ✓ | ✓ | ✓ | ✓ | ✓ | | | ✓ | | ✓ | ✓ | | ✓ | ✓ |
| G. K. Jabash Samuel | ✓ | | | | ✓ | ✓ | | ✓ | | ✓ | | ✓ | | ✓ |

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

**CONFLICT OF INTEREST STATEMENT**

The authors declare that they have no conflicts of interest.

**DATA AVAILABILITY**

The data that support the findings of this study are available from the corresponding author, [SS], upon reasonable request.

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