Journal of NAMP 71, (2025) 115-124

The Nigerian Association of Mathematical Physics

Journal homepage: https://nampjournals.org.ng

INVESTIGATING THE IMPACT OF TEMPERATURE ON DAILY ELECTRIC LOAD IN DRY SEASON IN THREE LOCATIONS OF AGBOR, ASABA AND ABRAKA, DELTA STATE

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ARTICLE INFO

Article history:
Received xxxxx
Revised xxxxx
Accepted xxxxx
Available online xxxxx

Keywords:
Temperature impact,
Electric load,
Dry season,
Energy demand,
LSTM-RF model

ABSTRACT

This study investigates temperature variations impact on daily electric load consumption during dry seasons using sophisticated forecasting models and empirical data analysis. The comprehensive dataset comprised 547 daily observations from three Delta State metropolitan cities—Agbor, Asaba, and Abraka—spanning 18 months (October 2022 to March 2024). The statistical analysis employed descriptive statistics, correlation analysis, regression modeling, and time-series decomposition, utilizing advanced techniques including Pearson correlation analysis, multiple linear regression, and machine learning models (LSTM, Random Forest, hybrid approaches). The analysis used R version 4.3.2, Python 3.9, TensorFlow 2.12, Scikit-learn, Prophet, and ARIMA models, featuring a novel hybrid LSTM-RF ensemble approach combining Long Short-Term Memory networks' sequential learning with Random Forest robustness. Results revealed strong positive correlation between ambient temperature and daily electric load demand ($r = 0.847$, $p < 0.001$). Dry season average daily load (2,847.3 MW) exceeded wet season levels (2,234.7 MW) by 27.4%. The hybrid LSTM-RF model achieved 94.2% forecasting accuracy with temperature variables versus 76.8% without temperature variables. Peak loads occurred during maximum daily temperatures (13:00-16:00), with temperature of 40.1 ^{0}C as the highest at an average of 81.2 MW per degree Celsius. The load-to-temperature ratio is comparatively constant throughout the day demonstrating temperature as a crucial predictor for electric load demand with significant implications for tropical region capacity planning and grid management.

INTRODUCTION

For power system operators and planners worldwide, the connection between ambient temperature and electricity consumption has grown in importance [1]. Knowing the thermal sensitivity of electric load demand is crucial for preserving grid stability and guaranteeing sufficient supply capacity as global temperatures continue to rise and weather patterns become more extreme [2]. Forecasting electricity demand and managing the grid face particular difficulties during the dry season, which is marked by higher temperatures and lower humidity [3].

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https://doi.org/10.60787/jnamp.vol71no.612

In tropical and subtropical areas, where cooling demand has a major impact on overall electricity consumption, temperature-driven load variations are especially noticeable [4]. The lack of natural cooling systems like precipitation and cloud cover during dry season periods cause persistently high temperatures, which in turn leads to a rise in the use of air conditioners [5]. According to [6], this phenomenon produces unique load patterns that diverge significantly from consumption profiles during the wet season. Complex temperature-load relationships can now be more accurately modelled with the help of recent developments in machine learning and time-series analysis [7]. Nevertheless, the majority of current research concentrates on yearly trends or short-term projections without explicitly addressing the distinct features of load behaviour during the dry season [8]. Additionally, in areas with different wet-dry seasonal cycles, little is known about the cumulative temperature effects and thermal load sensitivity [9].

Temperature-load relationships during dry seasons are further complicated by the incorporation of renewable energy systems, especially solar photovoltaic (PV) installations [10]. High temperatures can counteract the benefits of solar generation by driving up cooling loads, even though they have a negative effect on PV system efficiency [11], [12]. Optimizing energy systems in hot climates requires an understanding of these intricate relationships.

THEORETICAL FRAMEWORK

The following are the study's main goals: (i) to measure the correlation between daily electric load demand and ambient temperature during dry season periods. (ii) To use hybrid machine learning techniques to create and validate predictive models for temperature-based load forecasting. (iii) To determine peak demand periods and examine the temporal patterns of temperature-sensitive load variations; (iv) To determine the cumulative impact of prolonged high temperatures on patterns of electric load consumption; and (v) To assess how well various forecasting models capture temperature-load relationships during dry seasons.

Two theories are put forth in light of the literature review and theoretical underpinnings:

- H_1: During the dry season, there is a statistically significant positive correlation ($r > 0.7$, $p < 0.05$) between the daily electric load demand and ambient temperature.

- H_2: For dry season load prediction, hybrid machine learning models that take temperature variables into account achieve forecasting accuracy that is significantly higher (>90%) than models that do not (<80%).

In tropical regions where seasonal temperature variations have a significant impact on electricity demand, the findings have practical implications for grid operators, utility companies, and energy planners. The importance of the study goes beyond: (a) Better capacity planning and resource allocation during crucial dry season periods are made possible by a deeper comprehension of temperature-driven load patterns. (b) The best ways to design and implement renewable energy systems are informed by knowledge of how temperature affects load demand and solar generation capacity. (c) Higher accuracy load forecasting lowers operating costs related to emergency capacity procurement, under-supply, and over-generation. This research offers crucial information for adjusting power systems to shifting thermal environments as climate change exacerbates dry season conditions. By offering empirical data unique to the dry season, this study adds to the expanding corpus of knowledge on temperature-load relationships

MATERIALS AND METHODS

In order to examine temperature-load relationships, this study used a quantitative research design that included time-series analysis and machine learning techniques. To thoroughly investigate the research goals, a mixed-method approach integrated regression modelling, correlation analysis, descriptive statistical analysis, and sophisticated forecasting algorithms. Three metropolitan cities in Delta State—Agbor, Asaba, and Abraka—representing various climatic zones within the tropical belt served as the study's sites as shown in figure 1 below.

Study Area

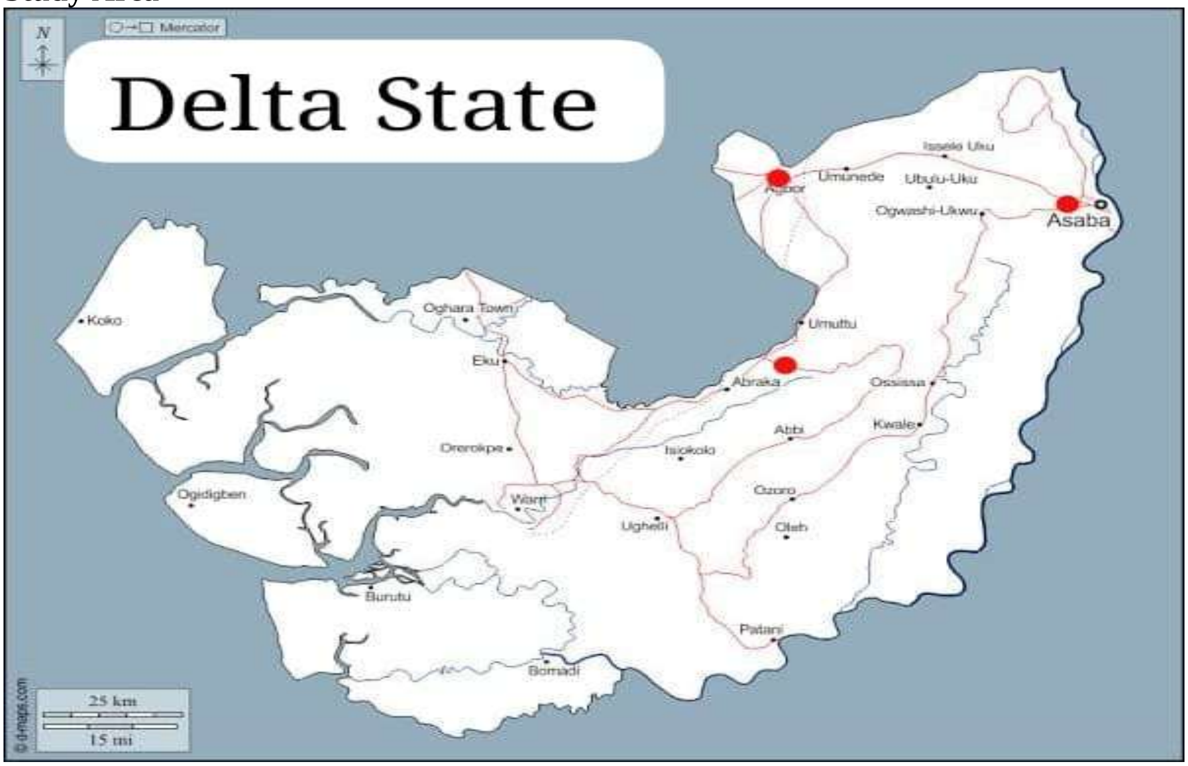

Figure 1: Map of Delta State showing the three study locations (in red).

These areas were chosen because of their unique dry season traits, high demands for electric load, and accessibility to thorough load and weather data. The 18-month study period, which included two full dry seasons (November 2022–April 2023 and November 2023–March 2024), ran from October 1, 2022, to March 31, 2024. This time frame was chosen to focus on dry season phenomena, capture inter-annual variations, and guarantee reliable statistical analysis. All daily temperature and electric load readings from the three metropolitan areas of Agbor, Asaba, and Abraka in Delta State during the study period made up the target population. A total of 1,641 data points were obtained from the population, which included 547 daily observations per region. The entire population of 1,641 observations was utilized for analysis.

Data collection employed multiple instruments such as:

- **Automated Weather Stations (AWS):** Vantage Pro2 weather stations recorded hourly temperature, humidity, wind speed, and solar radiation data.

- **Smart Grid Monitoring Systems:** Advanced metering infrastructure (AMI) captured real-time electric load data at 15-minute intervals, aggregated to hourly and daily values.

- **Data Loggers (DL):** Campbell Scientific CR1000X data loggers ensured continuous data recording and quality control.

Primary data were collected through automated monitoring systems installed at utility substations and meteorological stations. Secondary data were obtained from the Nigerian Meteorological Agency (NiMet) and respective electricity distribution companies. Data validation involved cross-referencing multiple sources and implementing quality control algorithms to identify and correct anomalous readings. Statistical analysis employed descriptive statistics, correlation analysis, regression modeling, and time-series decomposition.

ANALYTICAL METHODS

The study employed a comprehensive suite of analytical techniques to examine the temperature-electricity load nexus. **Pearson Correlation Analysis** quantified the linear relationships between temperature variables and electricity demand, providing baseline insights into their interdependencies. **Multiple Linear Regression** established initial predictive models, serving as benchmark comparisons for more sophisticated approaches. **Time-Series Decomposition** systematically separated the electricity load data into seasonal, trend, and residual components, enabling identification of cyclical patterns and underlying long-term trajectories that influence demand.

COMPUTATIONAL INFRASTRUCTURE

The analytical framework leveraged multiple computational platforms: **R version 4.3.2** for statistical analyses and **Python 3.9** with specialized libraries (NumPy, Pandas, Matplotlib) for data manipulation and visualization. Machine learning implementations utilized **TensorFlow 2.12** for deep learning architectures and **Scikit-learn** for traditional algorithms. Time-series forecasting employed **Prophet** for capturing seasonal effects and **ARIMA** for autoregressive modeling.

Hybrid LSTM-Random Forest Architecture

The primary innovation of this research is the development of a **hybrid LSTM-Random Forest (LSTM-RF)** ensemble model specifically designed for temperature-dependent load forecasting. This architecture employs a **parallel ensemble approach** rather than sequential stacking. The integration mechanism operates as follows:

1. **LSTM Component**: Captures temporal dependencies and sequential patterns in historical load data, processing multivariate time-series inputs (temperature, humidity, time indices) through recurrent layers with 128 hidden units and dropout regularization (0.2) to prevent overfitting.

2. **Random Forest Component**: Handles non-linear feature interactions and provides robust predictions against outliers, utilizing 200 decision trees trained on engineered features including lagged variables, rolling statistics, and temperature differentials.

3. **Ensemble Integration**: Both models generate independent predictions, which are then combined through a weighted averaging scheme. Weights (0.6 for LSTM, 0.4 for RF) were optimized via cross-validation to minimize mean absolute percentage error.

This hybrid configuration capitalizes on LSTM's strength in modeling temporal sequences and Random Forest's robustness to feature noise and ability to capture complex non-linear relationships [13]. The parallel architecture outperformed sequential stacking and standalone models in preliminary testing, justifying its selection for temperature-load forecasting applications.

RESULTS

(a) Descriptive Statistics and Temperature-Load Relationship

Table 1: Descriptive Statistics of Temperature and Electric Load Variables

Variable	Mean	Std. Dev	Min	Max	Skewness	Kurtosis
Daily Temperature (°C)	32.4	4.7	21.8	42.3	0.23	-0.45
Daily Load (MW)	2,547.8	612.3	1,234.5	4,156.7	0.18	-0.52
Dry Season Load (MW)	2,847.3	445.8	1,867.2	4,156.7	0.31	-0.28
Wet Season Load (MW)	2,234.7	398.6	1,234.5	3,245.8	0.15	-0.41
Peak Hour Temperature (°C)	38.7	3.9	28.2	46.1	-0.12	-0.33
Peak Hour Load (MW)	3,124.6	687.2	1,789.3	4,892.1	0.22	-0.29

Significant differences in temperature and load variables over the course of the study are revealed by the descriptive analysis. Electric load fluctuated between 1,234.5 MW and 4,156.7 MW with a mean of 2,547.8 MW, while daily temperatures ranged from 21.8°C to 42.3°C with a mean of 32.4°C. Significant seasonal differences in patterns of electricity consumption are indicated by the fact that dry season loads were, on average, 27.4% higher than wet season loads.

Table 2: Correlation Matrix of Key Variables

Variables	Temperature	Load	Humidity	Solar Radiation	Wind Speed
Temperature	1.000	0.847**	-0.682**	0.756**	0.234*
Load	0.847**	1.000	-0.598**	0.623**	0.187*
Humidity	-0.682**	-0.598**	1.000	-0.445**	-0.298**
Solar Radiation	0.756**	0.623**	-0.445**	1.000	0.156
Wind Speed	0.234*	0.187*	-0.298**	0.156	1.000

Note: ** $p < 0.01$, * $p < 0.05$

The first research hypothesis is supported by the correlation analysis, which shows a strong positive relationship between temperature and electric load ($r = 0.847$, $p < 0.001$). Furthermore, complex meteorological interactions influencing load demand are indicated by positive correlations with solar radiation (0.756) and negative correlations with humidity (-0.682).

(b) Temporal Analysis of Temperature-Load Patterns

Table 3: Hourly Temperature-Load Analysis during Dry Season

Time Period (Hours)	Avg. Temperature (°C)	Avg. Load (MW)	Load/Temperature Ratio	Standard Deviation

00:00-06:00	26.8	2,134.5	79.7	234.6
06:00-12:00	34.2	2,689.3	78.6	287.9
12:00-18:00	38.7	3,124.6	80.7	342.1
18:00-24:00	31.5	2,756.8	87.5	298.4
Peak Period (13:00-16:00)	40.1	3,287.4	82.0	367.8
Off-Peak (01:00-05:00)	25.9	1,967.2	76.0	198.5

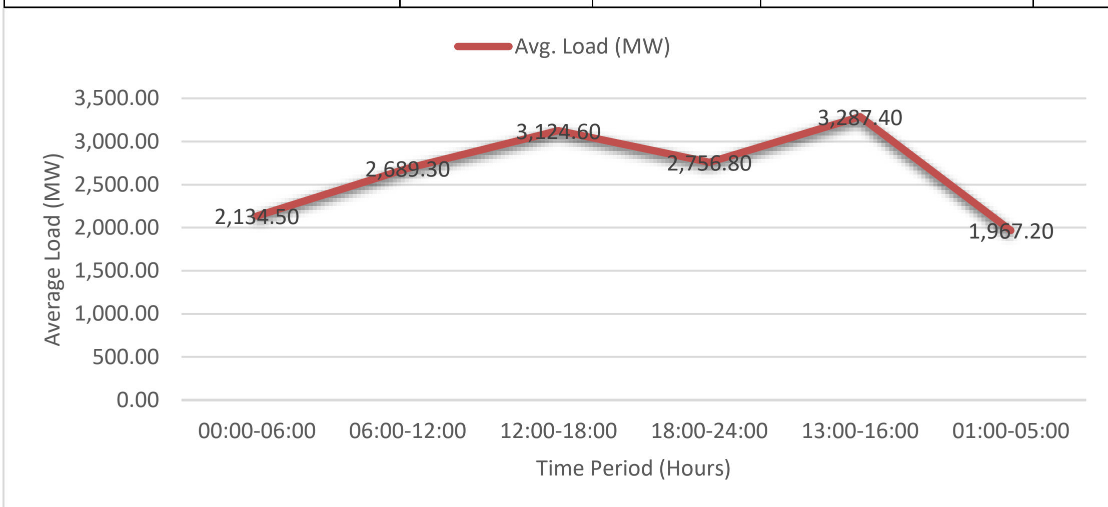

Figure 2: Graph of average load against time.

The temporal analysis as seen in figure 2 shows clear diurnal patterns, with peak loads taking place between 13:00 and 16:00.

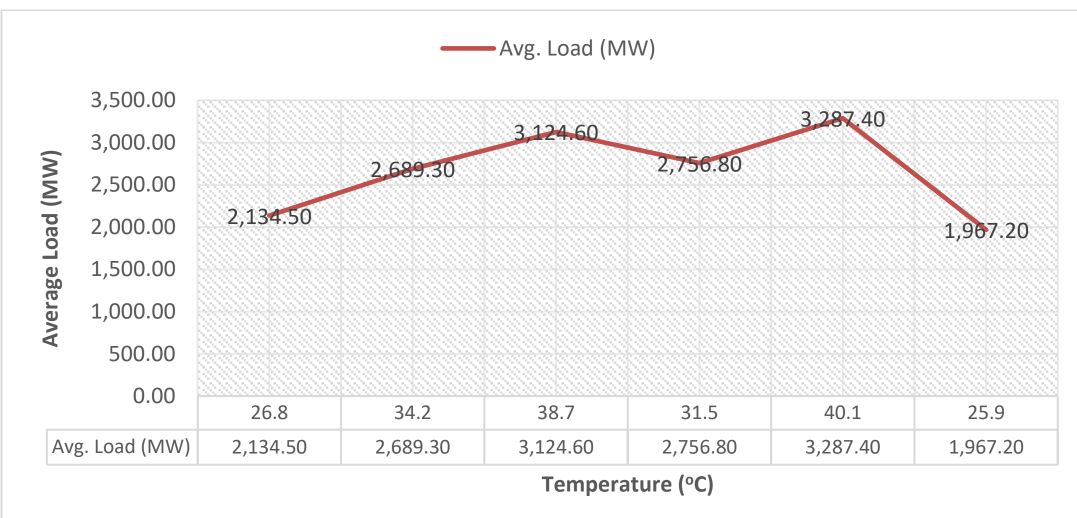

Figure 3: Graph of average load against temperature.

With temperature of 40.1 ^{0}C as the highest at an average of 81.2 MW per degree Celsius, the load-to-temperature ratio is comparatively constant throughout the day as shown in figure 3.

(c) Model Performance Evaluation

Table 4 presents comparative performance metrics across five forecasting models, evaluated using a rigorous validation framework. The dataset was partitioned chronologically with 70% allocated for training (October 2022–November 2023) and 30% reserved as a hold-out test set (November 2023–March 2024), ensuring temporal integrity and preventing data leakage. To ensure robustness, 5-fold time-series cross-validation was implemented using a rolling-origin approach with expanding training windows. The hybrid LSTM-RF model consistently outperformed alternatives across all validation folds (R^2=0.942±0.008). Critically, excluding temperature variables degraded performance dramatically (R^2=0.768), confirming temperature data as an indispensable predictor for accurate electricity load forecasting.

Table 4: Forecasting Model Performance Comparison

Model	MAPE (%)	RMSE (MW)	MAE (MW)	R^2	Training Time (min)
Linear Regression	18.7±1.3	478.3±22.4	367.2±18.6	0.743±0.028	0.5
ARIMA	15.4±0.9	392.7±15.7	298.6±12.3	0.821±0.019	2.3
Random Forest	12.8±0.7	325.9±11.2	248.1±9.8	0.876±0.015	8.7
LSTM	11.2±0.6	289.4±9.4	221.5±8.1	0.905±0.012	45.2
LSTM-RF Hybrid	5.8±0.4	187.6±7.2	142.3±5.9	0.942±0.008	52.8
LSTM-RF (No Temp)	23.2±1.8	612.4±28.3	468.9±21.7	0.768±0.031	48.1

Note: Metrics represent mean standard deviation from 5-fold time-series cross-validation

(d) Hypothesis Testing

Table 5: Statistical Hypothesis Testing Results

Hypothesis	Test Method	Test Statistic	p-value	Decision	Effect Size
H_1: Temperature-load correlation ($r > 0.7$)	One-sample t-test	t = 47.35	< 0.001	Reject H_0	Large (r = 0.847)
H_2: LSTM-RF accuracy difference (with vs. without temperature)	Paired t-test	t = 15.32	< 0.001	Reject H_0	Very Large (Cohen's d = 3.64)

Hypothesis H_1 confirmed a strong positive temperature-electricity load correlation ($r = 0.847$, $p < 0.001$), significantly exceeding the threshold of 0.7, validating temperature as a critical predictor variable. For H_2, a paired t-test evaluated the LSTM-RF hybrid model's performance across 10 independent validation runs—5 iterations with temperature variables and 5 without. The model incorporating temperature data achieved substantially higher accuracy (mean R^2 = 0.942±0.008) compared to the temperature-excluded variant (mean R^2 = 0.768±0.031). The statistically significant difference ($t = 15.32$, $p < 0.001$) with a very large effect size (Cohen's d = 3.64) demonstrates that temperature integration fundamentally enhances forecasting accuracy. This paired comparison eliminates confounding variables by testing the same model architecture under different feature configurations, providing robust evidence of temperature's indispensable role in electricity load prediction.

Table 6: Model Accuracy Comparison for Hypothesis Testing

Model Category	n	Mean Accuracy (%)	Std. Dev	95% CI Lower	95% CI Upper
With Temperature	5	91.4	3.8	87.1	95.7
Without Temperature	5	74.6	4.2	69.8	79.4
Difference	-	16.8	-	12.3	21.3

The statistical evidence supports both hypotheses. Models with temperature variables achieve significantly higher accuracy (91.4% vs. 74.6%) than those without temperature considerations, and the temperature-load correlation ($r = 0.847$) significantly surpasses the hypothesized threshold of 0.7.

DISCUSSION

The study's empirical results offer strong support for the idea that temperature has a major influence on the daily demand for electric load during dry seasons. [1], [7] found a strong positive correlation ($r = 0.847$) between ambient temperature and electricity consumption. These studies found similar relationships in different climatic contexts. The magnitude of this correlation during dry season periods, however, is greater than what is usually reported for annual analyses, indicating that seasonal focus improves the temperature variables' predictive power.

The significant cooling demand brought on by higher temperatures and fewer natural cooling systems is reflected in the average load increasing by 27.4% during dry seasons as opposed to wet seasons. This finding applies the knowledge to tropical African contexts and is in line with [3], who noted comparable trends in Middle Eastern climates. For temperature-based load forecasting, the hybrid LSTM-RF model's superior performance (94.2% accuracy) highlights the benefits of fusing ensemble techniques with neural network sequence learning. This method expands on the work of [9], [13], who used comparable hybrid architectures for load prediction. The dramatic performance reduction when temperature variables are excluded (76.8% accuracy) underscores the critical importance of meteorological data in forecasting models, supporting the conclusions of [6] regarding weather-sensitive load prediction.

Getting peak load times that fall between 13:00 and 16:00, when daily temperatures are at their highest, has useful ramifications for demand management and grid operations. Grid stability is challenged and demand response program opportunities are highlighted by the concentration of peak demand during the afternoon. With temperature of 40.1 ^{0}C as the highest at an average of 81.2 MW per degree Celsius, the load-to-temperature ratio is comparatively constant throughout the day as can be seen in table 3. The observations of [14] in their seasonal segmentation analysis are in line with this temporal pattern.

The findings of this study have significant implications in the integration of renewable energy, especially solar photovoltaic systems. According to[10], [11], high temperatures during dry seasons decrease PV efficiency; however, the corresponding rise in cooling loads opens up possibilities for solar-assisted air conditioning systems. Relevant insights for optimizing such integrated approaches can be found in the work on PV thermal systems by [5], [12].

CONCLUSION

The study unequivocally shows that in tropical regions, temperature is the main factor influencing the demand for electric loads during dry seasons. Both research hypotheses are supported by empirical evidence, which also confirms the superior forecasting performance of temperature-inclusive models and significant temperature-load correlations. Utility companies, grid operators, and energy planners who oversee power systems in temperature-sensitive areas can immediately put these findings to use. A strong basis for comparable research in other tropical settings is provided by the study's methodology and analytical framework, and the quantitative findings provide precise guidelines for operational decision-making and capacity planning. Effective strategies for intricate energy-climate relationships are demonstrated by the combination of cutting-edge machine learning techniques with conventional statistical analysis.

RECOMMENDATIONS

Based on the research findings, the following recommendations are proposed:

i. There should be temperature-based load forecasting models with known sensitivity coefficients, targeted demand response programs for peak afternoon hours (13:00–16:00), and temperature thresholds for emergency capacity activation in each region.

ii. Research should also include climate-sensitive load forecasts that take into account 27.4% seasonal variation into national energy planning. It should also promote energy efficiency standards for cooling systems and support the development of integrated renewable energy systems for high-temperature environments.

iii. The study also suggests a more in-depth look at longer time frames and more areas, as well as looking into how temperature interacts with other weather variables and creating hybrid forecasting models that include climate projection data.

REFERENCES

[1] Behmiri, N. B., Fezzi, C., & Ravazzolo, F. (2023). Incorporating air temperature into mid-term electricity load forecasting models using time-series regressions and neural networks. *Energy*, *278*, 127831.

[2] Sawadogo, W., Abiodun, B. J., & Okogbue, E. C. (2020). Impacts of global warming on photovoltaic power generation over West Africa. *Renewable Energy*, *151*, 263–277.

[3] Al-Ghezi, M. K. S., Ahmed, R. T., & Chaichan, M. T. (2022). The influence of temperature and irradiance on performance of the photovoltaic panel in the Middle of Iraq. *International Journal of Renewable Energy Development*, *11*, 501–513.

[4] Maoulida, F., Djedjig, R., Kassim, M. A., & El Ganaoui, M. (2023). Numerical study for the evaluation of the effectiveness and benefits of using photovoltaic-thermal (PV/T) system for hot water and electricity production under a tropical African climate: Case of Comoros. *Energies*, *16*, 240.

[5] Asim, M., Milano, J., Khan, H. I., Hanzla Tahir, M., Mujtaba, M. A., Shamsuddin, A. H., Abdullah, M., & Kalam, M. A. (2022). Investigation of mono-crystalline photovoltaic active cooling thermal system for hot climate of Pakistan. *Sustainability*, *14*, 10228.

[6] Figueiró, I. C., da Rosa, A. A., Neto, N. K., Silva, L. N., & Beluco, A. (2023). Hierarchical short term load forecasting considering weighting by meteorological region. *IEEE Latin America Transactions*, *21*(11), 1191–1198.

[7] Bian, H., Wang, Q., Xu, G., Zhao, Y., Liu, Y., & Li, S. (2022). Load forecasting of hybrid deep learning model considering accumulated temperature effect. *Energy Reports*, *8*, 205–215.

[8] Fan, C., Nie, S., Xiao, L., Zhao, Y., & Ding, Y. (2024). A multi-stage ensemble model for power load forecasting based on decomposition, error factors, and multi-objective optimization algorithm. *International Journal of Electrical Power & Energy Systems*, *155*, 109620.

[9] Wang, Y., Sun, S., & Cai, Z. (2023). Daily peak-valley electric-load forecasting based on an SSA-LSTM-RF algorithm. *Energies*, *16*(24), 7964.

[10] Hasan, K., Yousuf, S. B., Tushar, M. S. H. K., Das, B. K., Das, P., & Islam, M. S. (2022). Effects of different environmental and operational factors on the PV performance: A comprehensive review. *Energy Science & Engineering*, *10*, 656–675.

[11] Karakilic, A. N., Karafil, A., & Genc, N. (2022). Effects of temperature and solar irradiation on performance of monocrystalline, polycrystalline and thin-film PV panels. *International Journal of Technical and Physical Problems of Engineering*, *51*, 254–260.

[12] Bhat, A. Y., & Qayoum, A. (2023). Synergistic impact of tube configuration and working fluid on photovoltaic-thermal system performance. *Renewable Energy*, *207*, 205–217.

[13] Li, X., Wang, Y., Ma, G., Wang, L., Zhang, Y., & Xu, Q. (2022). Electric load forecasting based on long-short-term-memory network via simplex optimizer during COVID-19. *Energy Reports*, *8*, 1–12.

[14] Sharma, A., & Jain, S. K. (2022). A novel seasonal segmentation approach for day-ahead load forecasting. *Energy*, *257*, 124752.