Weather-Driven Energy Consumption Modeling of the Laman Hikmah Library Utilizing Machine Learning

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Received: 30 September 2025 | Revised: 6 November 2025 | Accepted: 17 November 2025

ABSTRACT

The objective of this study is to analyze the relationship between weather variables and daily energy usage at the Laman Hikmah Library (LHL) at Universiti Teknikal Malaysia Melaka (UTeM) using Least Squares Support Vector Machine (LSSVM) and Support Vector Machine (SVM). The findings indicate that LSSVM achieved $R^2 = 0.65$ and RMSE = 747 kWh, outperforming the SVM with the temperature, humidity, and pressure emerging as dominant predictors. This study provides empirical evidence for climate-responsive energy modelling in tropical regions and demonstrates the value of advanced machine learning in supporting Malaysia's energy transition agenda. By aligning with the United Nations Sustainable Development Goals, this study contributes to both national policy frameworks and global sustainability targets.

Keywords-energy consumption; weather data; energy modeling; machine learning

I. INTRODUCTION

The building sector is one of the largest contributors to global energy consumption, accounting for nearly 40% of total final demand and approximately one third of greenhouse gas (GHG) emissions. As the impacts of climate variability intensify, the role of weather conditions in shaping building energy demand is becoming increasingly critical for achieving energy efficiency and sustainability. International frameworks such as the Paris Agreement and the United Nations Sustainable Development Goals (SDGs) emphasize the urgent need to decarbonize buildings, with SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action) being particularly relevant. In tropical regions, the challenges are amplified by persistently high temperatures, elevated humidity, and intense rainfall, which drive cooling loads and intensify reliance on Heating, Ventilation, and Air Conditioning (HVAC) systems. Unlike temperate regions, where heating dominates energy use, tropical climates require continuous cooling throughout the year, making them highly sensitive to weather fluctuations. This context is especially relevant for Malaysia, where academic buildings such as libraries and laboratories operate for extended hours and accommodate dense occupancy. These operational characteristics result in significant cooling demand, which is further influenced by microclimatic variability.

Nationally, Malaysia has introduced the National Energy Transition Roadmap (NETR) to promote low-carbon development, energy efficiency, and sustainable energy practices. However, despite policy momentum, the empirical research on weather–energy interactions in Malaysian academic facilities remains limited. Most existing studies emphasize temperate and subtropical contexts, leaving tropical academic buildings underrepresented. Addressing this gap is essential to provide evidence-based insights for campus energy management, reduce operational costs, and support Malaysia's national sustainability agenda. Against this background, the present study focuses on the Laman Hikmah Library (LHL) at Universiti Teknikal Malaysia Melaka (UTeM) to evaluate weather-driven energy consumption patterns using Machine Learning (ML) approaches.

Academic libraries are characterized by extended operational hours, dense occupant loads, extensive plug-in equipment, and stringent indoor thermal comfort requirements. These factors contribute to disproportionately high cooling energy intensity, making such facilities significantly more energy-intensive than lecture halls or administrative buildings. LHL, in particular, is a fully air-conditioned four-level building, equipped with a dedicated elevator. It operates for up to 16 hours daily and remains open every day during revision and examination periods, while closing only on weekends and public holidays during regular semesters. Notably, one Level of the LHL operates 24 hours a day after the main counter closes. These operational and spatial characteristics position LHL as a representative example of an energy-intensive academic facility and justify its selection as the case study for this study.

A. Literature Review

Reliable weather datasets are the foundation of accurate energy modeling. In [1], the use of weather data in thermal simulations was reviewed and it was emphasized that conventional Typical Meteorological Year (TMY) files often fail to represent climate variability, leading to uncertainty in predictions. To overcome this limitation, authors in [2] introduced a data-driven approach for generating Test Reference Year (TRY) files using XGBoost weighting, which better reflects extreme weather events. Similarly, authors in [3] provided a real-world building energy management dataset covering six years of operation, enabling model validation, anomaly detection, and optimization. Complementing these studies, in [4] the impact of using updated versus older weather files was examined, showing that outdated climate inputs can bias energy simulation outcomes. Together, these contributions underscore the necessity of high-quality, representative weather datasets for reliable energy modeling.

Building on data improvements, ML has emerged as a dominant approach for predicting weather–energy interactions. Authors in [5] proposed a hybrid statistical–ML model (SSRXLR) that integrates Seasonal Autoregressive Integrated Moving Average (SARIMA), XGBoost, and LSTM, achieving superior accuracy compared to standalone techniques. Authors in [6] further demonstrated the importance of preprocessing, where correlation analysis and normalization methods enhanced LSTM prediction accuracy for U.S. commercial buildings. Expanding scalability, authors in [7] applied AutoML to estimate energy savings across public buildings, reducing the need for manual model selection. In benchmarking contexts, authors in [8] introduced the Machine Learning Baseline Energy Model (MLBEM), where LSTM delivered the highest R^2 compared to other methods. Likewise, authors in [9] showed that combining ML with weather forecasting models improved photovoltaic production predictions by at least 3.7%. More recently, authors in [10] explored weather clustering as a preprocessing step, reporting significant gains in accuracy by grouping hourly data into representative clusters. Collectively, these studies demonstrate that advanced ML techniques; whether hybrid, automated, or clustering-based are substantially improve the accuracy and adaptability of energy prediction models. The interpretability of ML models has also become a growing research priority. Authors in [11] investigated the role of temperature and humidity in residential building energy efficiency using explainable AI techniques. By applying SHapley Additive exPlanations (SHAP) analysis, they highlighted the relative contribution of each variable, thereby enhancing trust and transparency in predictive modeling. This shift towards explainability ensures that ML tools can inform practical decision-making, rather than functioning as "black box" systems.

Case studies provide valuable evidence of how weather affects energy demand in specific building contexts. Authors in [12] applied ML models in climate-based building energy consumption studies, confirming temperature as the most influential parameter. Regarding subtropical regions, authors in [13] examined sustainable cooling strategies, showing that ultra-efficient chillers could reduce annual electricity consumption by up to 13%. Authors in [14] integrated microclimate data with ML models, achieving $R^2 = 0.98$ for cooling load prediction and authors in [15] applied a Group

Method of Data Handling–Polynomial Neural Network (GMDH-PNN) for an educational building, which outperformed conventional regression techniques in accuracy. In [16], a superior R^2 of 0.86 using a Deep Neural Network (DNN) model was reported for an educational building in a warm tropical climate, while authors in [17] achieved $R^2 = 0.73$ through Support Vector Regression (SVR) applied to tropical buildings. These case studies confirm that contextualized data inputs, whether microclimate, advanced cooling systems, or tailored algorithms, enhance the reliability of weather-driven modeling.

In Malaysia, growing attention has been paid to institutional buildings. Authors in [18] investigated the retrofitting strategies for conventional offices, achieving nearly 60% energy reductions and more than 132,000 kg of CO_2 savings annually. Authors in [19] audited campus buildings at Samarinda Polytechnic and observed that although Energy Consumption Index (ECI) benchmarks were met, thermal comfort fell below acceptable levels. These findings reveal the importance of adapting energy policies to balance efficiency with occupant well-being. Benchmarking and energy management frameworks further demonstrate the role of weather in energy planning. A scalable benchmarking approach for 1,768 multi-residential buildings was developed in [20], incorporating LightGBM with weather diversity. For net-zero contexts, authors in [21] proposed a two-layer hierarchical framework for NZEBs, combining long-term resource allocation with daily scheduling. These approaches demonstrate how systematic energy management, when weather-sensitive, strengthens building resilience.

On the urban and climate-change scale, weather-driven energy demand becomes even more complex. Authors in [22] examined the impact of Urban Heat Islands (UHI) and found that localized warming significantly increased cooling loads, yet these effects are often omitted in standard simulations. Similarly, in [23], the retrofit effectiveness under future climate scenarios (2050–2080) was analyzed, and it was concluded that the long-term benefits of energy conservation measures diminish as extreme climates become more frequent. These works highlight the importance of adaptive modeling frameworks that account for climate change and urbanization.

Beyond building-focused studies, related research expands the weather–energy nexus to other domains. Authors in [24] investigated the impact of ambient temperature on electric vehicle energy consumption, demonstrating strong sensitivity of range predictions to weather conditions. Authors in [25] modeled data-centre cooling systems using TiDE, showing that ML achieved the lowest prediction error when compared to conventional methods.

Finally, residential energy performance remains a critical dimension. Authors in [26] analyzed the thermal performance in Saudi residential buildings, confirming the significant influence of weather variations on compliance with energy codes. Authors in [27] further emphasized the vulnerability of residential houses to intraday weather fluctuations, while authors in [28] developed an ANN-based monitoring and forecasting system that achieved very low MAPE values. Authors in [29] reviewed building energy modeling techniques, concluding that while top-down approaches capture macro-level patterns, bottom-up models better represent occupant-driven variability. These findings underscore the need for methodological integration that balances accuracy, interpretability, and contextual relevance. The key findings and accuracy results of the reviewed studies are summarized in Table I.

TABLE I. KEY FINDINGS AND ACCURACY OF CONSIDERED STUDIES

Ref	Method	Accuracy Performance
[5]	Employed SARIMAX with LSTM and Random Forest (RF)	RMSLE = 0.043
[6]	Applied a computational approach using LSTM models with six data normalization techniques	Min-Max, VSS, and Relative IQR normalization models showcased superior accuracy (from 2.32% to 18.44 %) and decreased error rates.
[8]	Applied LSTM, SVR, and ARIMAX	SVR achieved $R \approx 1$ and $R^2 \approx 0.99$, LSTM model had MAE =f 2.790, and highest $R^2 = 0.700$
[15]	GMDH-PNN	MSE = 1.01, ANN = 1.35, SVM = 1.42
[16]	DNNs	$R^2 = 0.86$
[17]	SVR	$R^2 = 0.73$ for SVR
[23]	RF, XGBoost, TiDE, and TSMixer	N-RMSE of TiDE = 0.1270, of XGBoost = 0.1275
[26]	ANNs	MAE = 0.0537

B. Synthesis and Research Gaps

Taken together, these studies demonstrate significant progress in weather-driven building energy modelling, spanning datasets, ML innovations, and practical applications. However, three critical gaps remain. First, most empirical research is concentrated in temperate and subtropical regions, leaving tropical contexts, where persistently high humidity and rainfall strongly influence cooling demand. Second, while hybrid and automated ML methods have shown promise in enhancing predictive accuracy, questions of interpretability and transferability across building types remain insufficiently addressed. Third, despite Malaysia's policy commitments under the NETR, academic libraries, facilities with extended occupancy, intensive HVAC usage, and high operational relevance have received little empirical investigation. This study addresses these gaps by focusing on the LHL at UTeM, evaluating weather–energy correlations and developing predictive models using LSSVM and SVM. In doing so, it contributes empirical evidence from a tropical academic context and provides practical insights to support sustainable campus energy management strategies.

II. CASE STUDY DESCRIPTION

The LHL (Figure 1), is a four-storey academic facility characterized by high occupancy and intensive reliance on air-conditioning. The building is equipped with a centralized HVAC system and includes large window openings that contribute to its sensitivity to external climatic conditions. With a gross floor area of 10,063.68 m², the library provides seating capacity for approximately 500 users. To accommodate academic activities, the facility operates on an extended schedule, including 24-hour service on the first floor. These features make the LHL, an example of tropical academic buildings, where high cooling demands, extended operating hours, and window-dominated designs increase the sensitivity of energy consumption to weather variability. As such, the LHL provides a practical context for investigating weather-driven energy modelling in Malaysia.

A. Data Collection

The initial phase for this study involves collecting and preparing two primary datasets:

- Energy consumption data: Daily electricity usage data in kWh for the year 2024 were obtained from the Centre for Smart Environment (CENSEi) UTeM. These energy data exclusively represented the total daily electricity consumption of the LHL, extracted from the building-level smart metering system. Campus-level loads are excluded to ensure building-specific accuracy.
- Weather parameters: Daily meteorological variables of temperature (◦C), Cooling Degree Days (CDD) (◦C), dewpoint (◦C), pressure (hPa), humidity (%), and wind speed (m/s) for the considered time duration were collected from OpenWeather.org. The dataset spans a complete annual cycle for the year of 2024 to ensure the inclusion of seasonal variability, consistent with benchmarking and climate-responsive energy analyses.

Fig. 1. Location and photo of the LHL.

B. Methodology

The conceptual framework for assessing the impact of weather conditions on energy consumption modeling for the LHL by applying machine learning is shown in Figure 2.

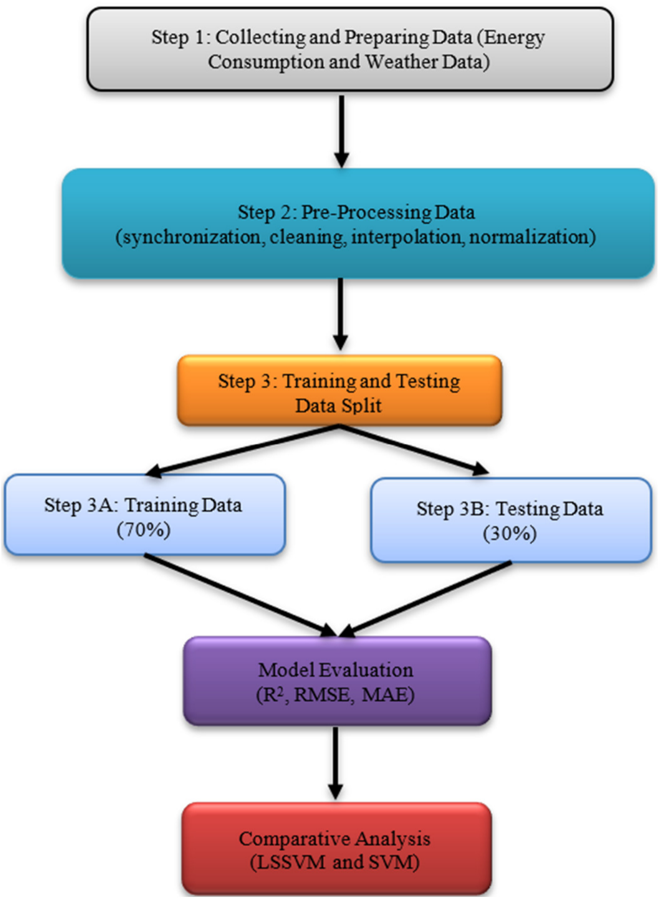

Fig. 2. Conceptual framework applied to assess the weather conditions impact on energy consumption modeling for the LHL.

1) Data Preprocessing

This step involves cleaning and preparing the data collected to be suitable for ML model training. The raw data were first synchronized to ensure temporal consistency between energy and weather datasets. Missing data, representing less than 0.5% of all records, were interpolated using cubic-spline interpolation. Outliers exceeding ±3 standard deviations from the mean were replaced using local mean smoothing to avoid biasing the model. Each predictor variable was normalized using Min–Max scaling to the [0, 1] range prior to model training to stabilize the convergence of the learning algorithms.This preprocessing pipeline is fully automated within MATLAB R2025a to ensure consistent data preparation across all iterations of model training.

2) Predictive Modeling

The predictive modelling framework comprised two approaches:

- LSSVM was adopted as the primary predictive method due to its ability to model nonlinear relationships with reduced computational overhead
- SVM was implemented as a comparative baseline to assess the effectiveness of LSSVM.

Both models were developed to forecast the daily energy usage (kWh) of the LHL using data from January 1 to December 31, 2024.

a) LSSVM Modeling in MATLAB

The LSSVM regression was executed in MATLAB R2025a using the LSSVMlab toolbox. Each weather feature; temperature, visibility, CDD, dew point, pressure, humidity, and wind speed was individually tested to identify the most significant single-variable predictor. The model employed a Radial Basis Function (RBF) kernel to capture nonlinear dependencies. Hyperparameters γ (regularization parameter) and σ^2(kernel width) were optimized using the simplex search algorithm combined with leave-one-out cross-validation via the *tunelssvm* function, minimizing the MAE criterion. The search domain for optimization was defined as $\gamma \in [10^{-2}, 10^{2}]$ and $\sigma^2 \in [0.1, 10]$ as to balance model smoothness and sensitivity to local variations in the input space. Both ranges for γ and σ^2 are commonly adopted in LSSVM energy forecasting studies, allowing the model to balance generalization and accuracy by exploring both low- and high-regularization regimes. The MATLAB coding for this process is summarized in Figure 3.

```
% Hyperparameter tuning for LSSVM regression
type = 'function estimation';
kernel = 'RBF_kernel';
[best_gam, best_sig2] = tunelssvm({X, Y, type, [], [], kernel}, ...
    'simplex', 'leaveoneoutlssvm', {'mae'});
fprintf('Best gamma = %.4f | Best sigma^2 = %.4f\n', best_gam, best_sig2);
```

Fig. 3. Summary of Matlab coding for the *tunelssvm* function.

To ensure statistical reliability, each model configuration was repeated 50 times with randomized 70:30 train–test partitions generated using MATLAB's *cvpartition* function. Input data were normalized using *mapminmax*. The output from each iteration was evaluated using the coefficient of determination (R^2), with the mean and standard deviation recorded to assess consistency. The results were then compiled into a ranked summary to identify the most influential weather variable. The top-ranked predictor was then selected for detailed visualization. Predictions were generated for both the test subset and the entire dataset, producing three main curves which are All Data History, Actual Test Data and LSSVM Predictions. These plots illustrated that the LSSVM model accurately followed real consumption trends and generalized effectively across the full temporal range.

b) SVM Modeling Using Python

A comparable SVM regression model was implemented in Python (v3.12) using the *scikit-learn* library to validate the robustness of the MATLAB results. The input dataset incorporated both meteorological and temporal features to account for autocorrelation and calendar effects. After removing missing entries, the data were standardized using *StandardScaler* and were split into 70% training and 30% testing subsets using *train_test_split* with random_state=42. The SVM model employed an RBF kernel with parameters $C = 100, \gamma =$ auto, and $\epsilon = 0.1$, determined through iterative tuning to minimize MAE. Model performance was evaluated using R^2, RMSE, and MAE. The result $R^2 \approx 0.53$, indicates a good agreement between predicted and actual consumption. Predictions were visualized using scatter plots distinguishing the Training Data, the Actual Test Data, and SVM Predictions, plotted against the full data history.

Some methodological limitations are recognized in this study. While daily data effectively capture long-term weather–energy patterns and reduce random noise, they cannot fully represent intraday dynamics such as peak cooling loads or short-term occupancy-driven fluctuations. In addition, the absence of real-time occupancy data may restrict the model's ability to account for behavioral influences on energy use.

C. Evaluation Metrics

The performance of both LSSVM and SVM models was assessed using the established statistical indicators of Coefficient of Determination (R^2), RMSE, and MAE which are consistent with validation practices in state-of-the-art building energy modeling in the literature. While both models demonstrated strong predictive accuracy, the optimized LSSVM model outperformed the conventional SVM with higher R^2 and lower error variability, confirming its superior suitability for nonlinear energy demand forecasting in weather-sensitive environments.

R^2 measures the variability between the predicted and the actual values of the model and thus evaluating the goodness-of-fit:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (1)$$

RMSE quantifies the model's accuracy by measuring the differences between the predicted values and the actual observations:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)} \quad (2)$$

MMAE quantifies the average magnitude of errors, providing a straightforward measure of accuracy and predicted model reliability:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\lceil y_i - \hat{y}_i \rceil \quad (3)$$

III. RESULTS AND DISCUSSION

Figure 4 presents the daily electricity consumption profile of the LHL for the overall cycle of 2024. The results confirm that cooling loads represent the dominant share of total demand, which is consistent with observations in other tropical academic and commercial facilities as investigated in the literature. Analysis of seasonal patterns further revealed that higher monthly consumption was recorded during hotter and drier months, particularly in April–May and October–November, when cooling demand is elevated. In contrast, lower consumption values were observed in March and December, reflecting reduced occupancy due to UTeM academic semester break.

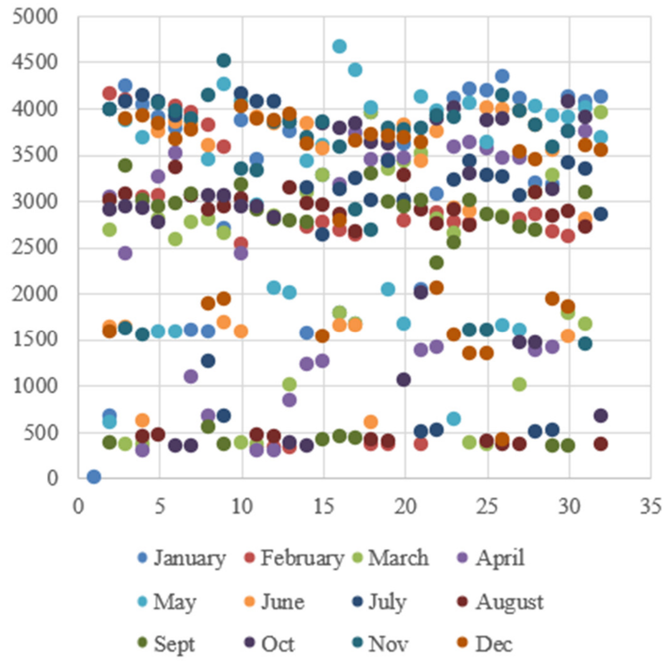

Fig. 4. LHL daily energy consumption for 2024.

A. Model Performance Evaluation

The LSSVM correlation analysis in Table II demonstrates that pressure (R^2 = 0.647), temperature (R^2 = 0.608), and humidity (R^2 = 0.574) emerge as the most influential weather parameters in energy consumption prediction at the LHL. These variables explain more than half of the variance in energy demand, confirming the strong role of both thermal and atmospheric conditions in driving cooling loads. Wind speed (R^2 = 0.545) shows a moderate relationship, while CDD (R^2 = 0.500) and dew point (R^2 = 0.446) exhibit comparatively weaker predictive power.

The dominance of temperature and humidity is consistent with the climate-responsive nature of HVAC systems in tropical regions, where small changes in thermal comfort parameters and building envelope characteristics, such as window exposure, significantly influence energy demand. The relatively high contribution of atmospheric pressure indicates that stability and variations in weather fronts also affect building load patterns. Conversely, dew point and CDD, while relevant, explain less the variability, suggesting that aggregated thermal indices may not fully capture the short-term dynamics of cooling energy consumption. These findings fulfil the objective of this study by quantifying the relative importance of weather parameters hence establishing a clear predictor hierarchy.

TABLE II. LSSVM CORRELATION PERFORMANCE

Weather Parameter	R^2
Pressure	0.6469
Temperature	0.6082
Humidity	0.5744
Wind Speed	0.5448
CDD	0.4996
Dew Point	0.4464

B. Comparative Analysis

The predictive accuracy values of LSSVM and SVM models are summarized in Table III and Figure 5. It can be seen (Table II) that the best weather parameter with the highest R^2 is pressure. The LSSVM model consistently outperformed SVM, achieving higher R^2 values and lower RMSE and MAE. Specifically, LSSVM achieved R^2 = 0.6469, RMSE = 747.37 and MAE =17.77%. SVM, on the other hand, achieved R^2 = 0.5288 with comparatively higher errors. These findings validate prior research where LSSVM demonstrated superior accuracy and efficiency over conventional SVM in energy modeling.

TABLE III. BEST PARAMETER PERFORMANCE COMPARISON

Model	R^2	RMSE (kWh)	MAE (kWh)
LSSVM	0.6469	747.37	492.5 (17.8% of average load)
SVM	0.5288	758.94	532.03 (18.26% of average load)

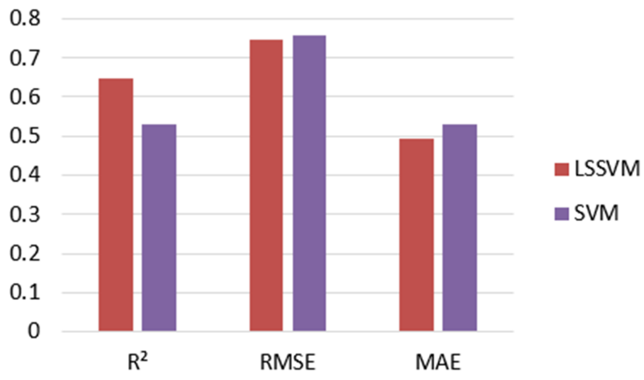

Fig. 5. Best parameter performance comparison between LSSVM and SVM.

The comparison of predicted daily energy consumption using LSSVM and SVM is illustrated in Figures 6 and 7. The red line-curves closely follow the actual consumption pattern (blue dots), capturing both peaks and troughs with high fidelity. This reflects its ability to generalize across varying conditions. In contrast, SVM reveals the predictions (red crosses) deviate substantially from the actual test data, particularly during extreme demand points, resulting in greater dispersion and higher error levels. Quantitatively, the LSSVM achieves an R^2 of 0.647, with RMSE and MAE values of 747.37 kWh and 492.54 kWh, respectively, corresponding to only 17.8% of the average daily load, while the SVM shows weaker correlation and larger residual errors.

The $R^2 = 0.65$ and RMSE = 747 kWh obtained in this study are within the acceptable range for weather-driven energy prediction in tropical contexts. The performance is consistent with prior research while reflecting the influence of dataset resolution and data diversity. Although the present model's accuracy is slightly lower than that of some reviewed studies, the results remain reasonable given the use of daily rather than hourly data and the absence of real-time occupancy inputs. Nevertheless, the outcomes demonstrate robust generalization for daily-scale forecasting and can be further improved by addressing the limitations discussed in the following section.

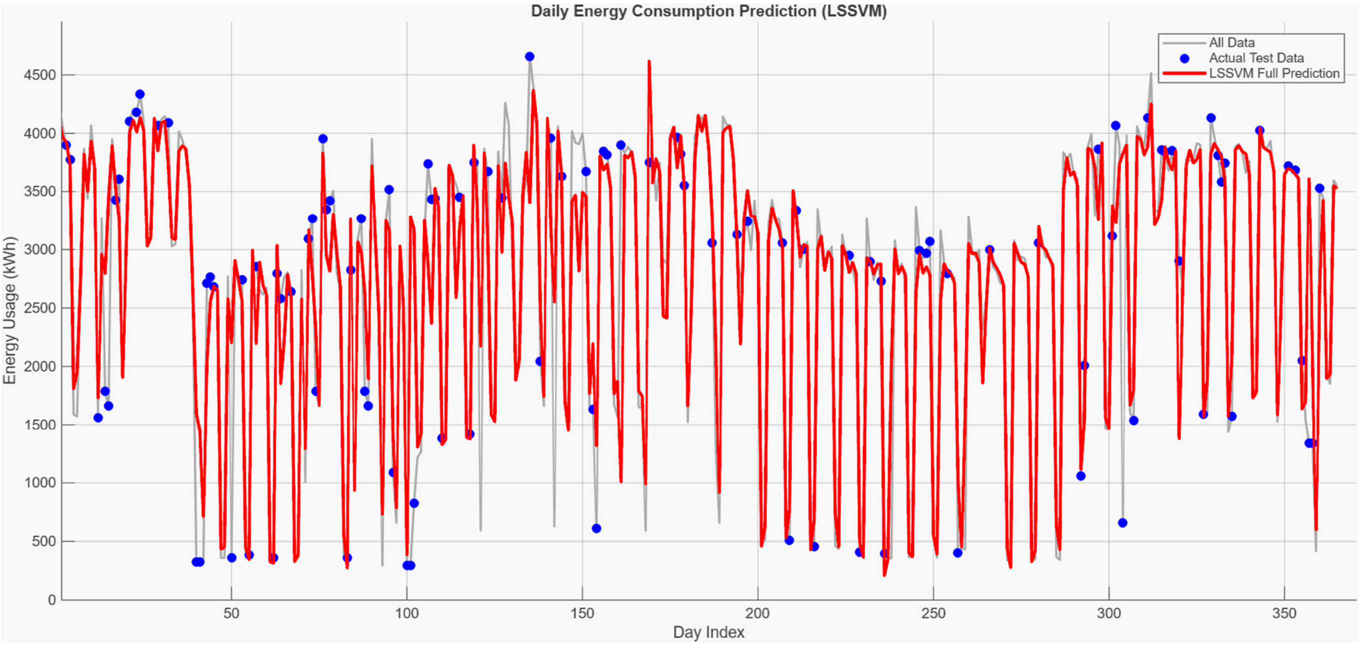

Fig. 6. Daily energy consumption prediction using LSSVM.

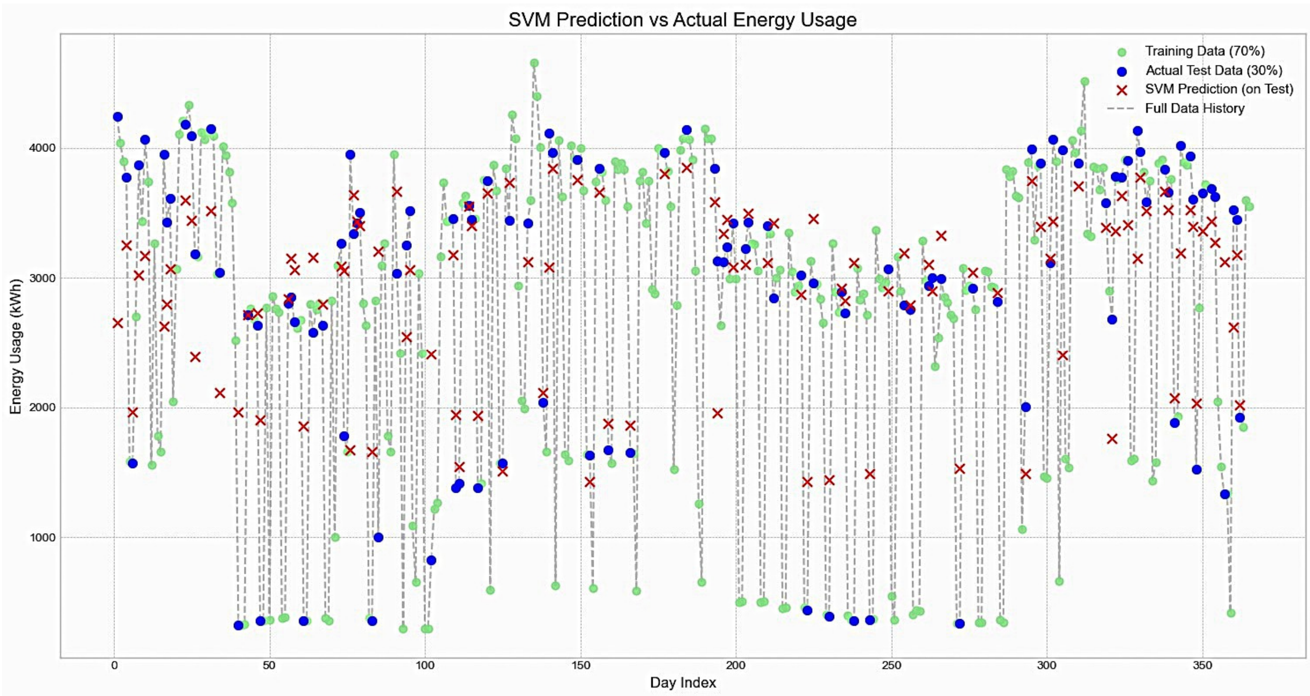

Fig. 7. Daily energy consumption prediction using SVM.

C. Discussion

The results highlight that weather variability strongly influences building energy demand in tropical facilities. The superior performance of LSSVM confirms its suitability for capturing nonlinear weather–energy interactions, extending the evidence base from earlier ML applications in diverse climates. The findings also underscore the practical significance of weather-sensitive modeling for energy management strategies. In line with benchmarking frameworks and energy audits, the results reinforce the necessity of integrating tropical-specific climatic conditions into predictive models. By enhancing forecasting accuracy, LSSVM-based modeling can provide actionable insights to support Malaysia's National Energy Transition Roadmap (NETR) through targeted conservation strategies in higher education institutions. From non-technical aspects, the outcomes of this study demonstrate clear contributions to the United Nations Sustainable Development Goals (SDGs):

- SDG 7 (Affordable and Clean Energy): The application of LSSVM enables more efficient energy management, reducing consumption and operational costs while maintaining indoor comfort.
- SDG 13 (Climate Action): By mitigating electricity demand and associated emissions, the study supports climate adaptation and decarbonization strategies, particularly under future weather variability.

Collectively, the study advances technical, institutional, and policy-level actions toward energy-efficient and climate-adaptive buildings, thereby reinforcing both national priorities and global sustainability agendas.

IV. CONCLUSION

This study investigated the impact of weather conditions on the energy consumption of tropical academic buildings, with regard to the case study of the Laman Hikmah Library (LHL) of the Universiti Teknikal Malaysia Melaka (UTeM). Daily energy consumption and weather conditions for 2024 were analyzed. The developed predictive models utilized Least Squares Support Vector Machine (LSSVM) and Support Vector Machine (SVM) and the results were compared. The results revealed that pressure, temperature, and humidity are the dominant drivers of energy consumption. Comparative evaluation demonstrated that the LSSVM outperformed SVM across all metrics, achieving higher accuracy (R^2) and lower RMSE and MAE values. These findings confirm the robustness of LSSVM in capturing nonlinear weather–energy interactions and highlight its suitability for building energy prediction in tropical climates. The study further underscores the importance of integrating multiple weather parameters into predictive models, rather than relying solely on temperature.

Predictive models play a crucial role in supporting decision-making within energy policy and management frameworks by enabling the evaluation of future scenarios, assessment of policy impacts, and mitigation of uncertainties. In the context of campus operations, predictive models can optimize energy management by forecasting consumption patterns, which supports efficient resource allocation and demand-response strategies. Machine Learning (ML) algorithms, such as the LSSVM approach applied in this study, enhance the accuracy and reliability of these predictions, contributing to the integration of renewable and low-carbon energy solutions within smart building systems. Therefore, integrating this LSSVM-based forecasting framework into campus energy dashboards would enable early detection of abnormal consumption patterns, more efficient scheduling of chiller operations, and data-driven decision-making for retrofitting or load management. These applications not only improve operational efficiency but also align institutional energy practices with national policy targets. Beyond technical contributions, the outcomes have practical implications. Accurate energy forecasting supports proactive energy management, cost reduction, and informed decision-making in campus facilities, thereby contributing to Malaysia's National Energy Transition Roadmap (NETR). At the global scale, the study advances SDG 7 (Affordable and Clean Energy) through improved efficiency, SDG 13 (Climate Action) by mitigating emissions, and SDG 11 (Sustainable Cities and Communities) by promoting sustainable practices in academic buildings.

Despite the promising results, several limitations are acknowledged. (1) The analysis was focused on a single academic building, which limits the generalization across diverse facility types. (2) The one-year dataset may not capture inter-annual climate variability. (3) The use of daily rather than hourly data constrains the model's ability to capture intraday dynamics such as peak cooling loads or short-term occupancy-driven fluctuations. Future studies that incorporate hourly metering could reveal transient HVAC responses under tropical extremes, thereby improving temporal resolution and predictive accuracy. (4) Real-time occupancy data were unavailable, constraining behavioral correlations. (5) Weather data were obtained from open-source APIs rather than on-site sensors, potentially introducing spatial bias. Addressing these aspects in future work, e.g. by considering multi-building, multi-year datasets, including high-frequency sensor and occupancy data, and exploring hybrid ML frameworks such as LSTM–SVM or ensemble deep learning, could enhance model robustness, interpretability, and transferability across tropical institutional buildings.

ACKNOWLEDGEMENT

The authors would like to thank Universiti Kuala Lumpur (UniKL) and Universiti Teknikal Malaysia Melaka (UTeM) for their support in this research.

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