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ALPro X: A forecast fusion of Arima, LSTM, prophet and XGBoost for electricity consumption prediction and carbon emission estimation

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Abstract
Aim: Accurate electricity consumption forecasting remains a major engineering challenge due to nonlinear demand patterns, seasonal variations, and the limitations of single-model forecasting techniques. Addressing these challenges requires hybrid predictive systems capable of improving forecasting accuracy while integrating environmental impact assessment.
Methodology: This study developed and evaluated ALPro X, a hybrid electricity consumption forecasting system that integrates Autoregressive Integrated Moving Average (ARIMA), Prophet, Long Short-Term Memory (LSTM), and Extreme Gradient Boosting (XGBoost) using a weighted ensemble framework. A quantitative developmental research design was employed. Forecasting performance was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2). Carbon dioxide (CO_2) emissions were estimated using a standard emission factor, while usability performance, user satisfaction, and expert validation were assessed through structured evaluation instruments.
Results: The ALPro X hybrid model demonstrated strong predictive performance, achieving a MAPE of 7.82% and an R^2 of 0.976, indicating high forecasting accuracy and strong explanatory capability. Predicted electricity consumption values closely aligned with actual household usage, with slightly higher deviations observed during peak consumption periods. Carbon emission estimation confirmed the direct relationship between electricity consumption and residential carbon footprint. Usability performance was rated "Very Usable," while overall user satisfaction was interpreted as "Very Satisfied," with usefulness receiving the highest evaluation. Expert validation results for both the predictive equation and the hybrid forecasting model were interpreted as "Excellent," confirming structural coherence, reliability, and alignment with the system's intended purpose.
Conclusion: The findings demonstrate that ALPro X provides a reliable and accurate hybrid forecasting framework capable of supporting residential electricity monitoring and carbon emission estimation. The integration of statistical and machine learning models enhances forecasting stability and provides a practical technological solution for data-driven energy management and sustainability-oriented decision support.
Keywords: *hybrid forecasting model, electricity consumption prediction, carbon emission estimation, ensemble learning, energy analytics, usability evaluation*

INTRODUCTION

Electricity has long been recognized as a fundamental resource powering households, commercial establishments, institutions, and industries worldwide, thereby advancing modern living standards and economic development. Globally, rising urbanization, digitalization, and industrial expansion have intensified electricity demand, placing increasing pressure on power systems to maintain reliability, affordability, and sustainability (Rahman et al., 2022; Zhao et al., 2021). In developing economies, energy consumption growth has been closely associated with population expansion, economic progress, and technological adoption. These global patterns underscore the importance of accurate electricity demand forecasting to ensure energy security, cost stability, infrastructure planning, and environmental protection.

In the Philippines, electricity demand has steadily increased in recent years. The Department of Energy (2022) reported that total electricity consumption reached 106,115 GWh in 2021, rising from 101,756 GWh in 2020, reflecting continued recovery and growth in national energy use. The residential sector alone accounted for 34,981 GWh,

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demonstrating the substantial contribution of household consumption alongside commercial and industrial sectors. Rapid urbanization, expanding middle-class households, increased appliance ownership, and the growth of service industries such as business process outsourcing further intensified power demand nationwide (Dressel & Saguin, 2025). These developments indicate a sustained upward trajectory in electricity requirements across sectors, particularly at the household level.

Despite this growth, the Philippine energy sector faces structural and environmental challenges. The national energy mix remains largely dependent on fossil fuels, comprising approximately 69 percent of total generation, while renewable energy accounts for only 31 percent (Ordinario, 2024). This reliance contributes to greenhouse gas emissions and heightens vulnerability to global fuel price volatility. In 2023, electricity rates in Mindanao exceeded Philippine pesos (₱) 10.99 per kWh, surpassing rates in Luzon and the Visayas, thereby increasing financial burdens on households and businesses. These conditions highlight the urgent need for precise electricity demand forecasting not only for operational and economic planning but also for carbon emission estimation and sustainable energy management.

Traditional forecasting techniques, while historically useful, demonstrate limitations in capturing nonlinear consumption behaviors, seasonal fluctuations, and sudden demand spikes associated with climatic conditions, holidays, and economic events (Rahman et al., 2022; El-Azab, 2025). Although advanced models such as Autoregressive Integrated Moving Average (ARIMA), Prophet, and Long Short-Term Memory (LSTM) networks have shown strong predictive performance in time-series applications (Akhtar et al., 2023), most existing studies rely on single-model approaches. Prior research primarily emphasizes short-term load forecasting or comparative accuracy evaluation rather than integrating statistical and machine learning techniques into a unified predictive framework. Moreover, carbon emission estimation is rarely incorporated alongside household-level electricity demand prediction, and system usability is often excluded from technical evaluation.

Despite the growing body of literature on electricity load forecasting, limited studies have proposed a consolidated hybrid framework that synthesizes multiple statistical and machine learning models into an optimized composite predictive equation. In the Philippine context, research remains particularly scarce in integrating hybrid forecasting with environmental impact estimation and user-centered system evaluation. These gaps indicate the necessity for a technically integrated and environmentally responsive forecasting system tailored to local energy consumption conditions. From an engineering perspective, such a system may be viewed as a hybrid energy forecasting platform within smart energy systems, where data-driven technologies enable real-time monitoring, predictive analytics, and efficient energy management. This also aligns with emerging Industry 4.0 energy analytics, in which digital and intelligent systems are applied to enhance forecasting, optimization, and sustainability in energy applications (Nemomsa et al., 2025). Addressing these limitations contributes not only to predictive accuracy but also to sustainable energy analytics and practical household-level decision support.

To respond to these gaps, ALPro X was developed as a hybrid forecasting system integrating ARIMA, Prophet, LSTM, and Extreme Gradient Boosting (XGBoost) into a composite predictive framework. Rather than selecting a single best-performing model, the system synthesizes the predictive strengths of all four models into an optimized mathematical equation for electricity consumption forecasting. This approach represents a technical advancement by combining statistical time-series methods and machine learning algorithms into a consolidated hybrid structure that enhances predictive stability and robustness. Furthermore, the system extends forecasting capability by estimating associated carbon dioxide emissions, thereby linking energy analytics with environmental sustainability metrics. The integration of usability evaluation further strengthens its applicability by ensuring that technical performance aligns with user-centered design principles.

This study aims to predict monthly household electricity consumption using the ALPro X hybrid model and to evaluate its predictive accuracy and stability. It further assesses the system's usability performance in terms of user-friendliness, navigability, and responsiveness, as well as overall user satisfaction concerning functionality and design. By integrating hybrid forecasting methodology, emission estimation, and usability evaluation, the research advances the disciplines of energy analytics, applied machine learning, and sustainable planning within the Philippine context. The findings provide practical implications for households, policymakers, and energy planners seeking data-driven strategies for electricity management, cost optimization, and carbon reduction.

Review of Related Literature and Studies

Recent advancements in Short-Term Load Forecasting (STLF) have increasingly emphasized hybrid and ensemble modeling approaches to address nonlinear consumption behaviors and dynamic energy conditions. Bashir et al. (2022) developed a hybrid Prophet–Long Short-Term Memory (LSTM) framework enhanced by a Back Propagation Neural Network, demonstrating that combining statistical time-series modeling with deep learning reduced forecasting errors compared to standalone ARIMA, Prophet, and LSTM models. Similarly, Semmelmann et al. (2022) proposed a bi-directional LSTM–

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Extreme Gradient Boosting (XGBoost) hybrid model for day-ahead load forecasting in smart energy communities. Their approach, which separately modeled base and peak loads before integration, significantly outperformed traditional load profiles and standalone neural networks, highlighting the value of hybrid deep learning–boosting strategies.

Ensemble-based approaches have further strengthened predictive flexibility. Hammam et al. (2025) introduced an adaptive hybrid framework integrating ARIMA and XGBoost through a weighted ensemble mechanism, dynamically addressing linear and nonlinear demand components. Zeng et al. (2025) incorporated Bayesian optimization into a Prophet–XGBoost framework to enhance hyperparameter tuning and model adaptability, demonstrating improved forecasting accuracy and runtime efficiency. Likewise, Buyo et al. (2025) showed that combining Prophet, LSTM, and XGBoost into an ensemble model produced higher predictive accuracy than individual models when applied to smart meter data from over 5,000 households. Collectively, these studies demonstrated that hybrid statistical–machine learning models consistently outperform standalone approaches, particularly under complex and nonlinear load conditions.

Beyond electricity demand prediction, integrating carbon emission estimation has become increasingly relevant in sustainable energy research. Yu et al. (2023) developed a community-level carbon emission prediction model using electricity consumption data and dynamic emission coefficients, achieving high predictive accuracy through a Genetic Algorithm–optimized Support Vector Regression framework. Bertolini et al. (2025) further underscored the importance of appropriate emission factor selection in estimating carbon dioxide emissions from electricity generation, revealing significant methodological differences in emission calculations. These findings highlighted the necessity of combining accurate electricity forecasting with reliable emission conversion methods for informed carbon management.

Recent research also explored hybrid machine learning approaches for residential and building-level energy systems. Parizad et al. (2024) demonstrated that an optimized XGBoost-based hybrid framework improved household energy demand and electricity price forecasting. Lai et al. (2023) applied Singular Spectrum Analysis with LSTM to enhance building energy consumption predictions, particularly in capturing extreme values. Lotfi et al. (2025) demonstrated that a hyperparameter-optimized Random Forest model improved short-term electricity demand forecasting across varying seasonal conditions. Additionally, Moayedi et al. (2023) confirmed that combining neural networks with metaheuristic optimization algorithms enhanced the accuracy of carbon emission forecasting at the macro level. These studies collectively reinforced the effectiveness of hybrid architectures and optimization techniques in handling nonlinear energy consumption and emission dynamics.

The reviewed literature consistently demonstrated that hybrid and ensemble models integrating statistical time-series techniques with machine learning algorithms significantly enhance forecasting accuracy and robustness under nonlinear and dynamic energy conditions. Several studies validated combinations such as Prophet–LSTM, ARIMA–XGBoost, and LSTM–boosting hybrids, while others emphasized the importance of hyperparameter optimization and feature integration. Moreover, carbon emission modeling research highlighted the need for reliable emission factor selection and predictive frameworks linking electricity consumption to environmental impact.

However, despite these advancements, three critical gaps remained evident. First, many studies focused primarily on improving predictive accuracy without developing a unified fusion formula that systematically integrates multiple forecasting outputs into a consolidated predictive equation. Second, research integrating electricity demand prediction with household-level carbon emission estimation within a single hybrid framework remained limited. Third, few studies combined statistical decomposition, deep learning, boosting techniques, and ensemble weighting into a comprehensive, optimized forecasting architecture.

To address these gaps, the present study developed ALPro X, a forecast fusion model integrating ARIMA, Prophet, LSTM, and XGBoost into a unified hybrid system capable of predicting household electricity consumption and estimating associated carbon emissions. By synthesizing the strengths of statistical and machine learning approaches within a consolidated predictive framework, the study aimed to enhance forecasting stability, accuracy, and sustainability relevance in residential energy analytics.

Theoretical, Technical and Conceptual Frameworks

This study was grounded in ensemble learning theory and time-series forecasting systems, which support the integration of multiple predictive models to improve forecasting accuracy and stability (Gastinger et al., 2021; Lim et al., 2021). Guided by this framework, ALPro X was developed as a hybrid forecasting system integrating Autoregressive Integrated Moving Average (ARIMA), Prophet, Long Short-Term Memory (LSTM), and Extreme Gradient Boosting (XGBoost) to process historical household electricity consumption data and generate a unified forecast. The system architecture consists of four major layers: input data processing, forecasting model execution, ensemble integration, and output generation with evaluation.

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The independent variable of the study was the ALPro X hybrid forecasting system, wherein each component performed a specific analytical function: ARIMA modeled linear temporal patterns, Prophet captured trend and seasonality, LSTM identified nonlinear sequential relationships, and XGBoost modeled complex feature interactions. These outputs were integrated through a weighted ensemble fusion mechanism, forming the system's core predictive structure.

The dependent variables included forecasting accuracy, measured using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2); carbon emission estimation derived from predicted electricity consumption; usability performance (user-friendliness, ease of navigation, and responsiveness); and overall user satisfaction (functionality and design).

The framework assumed that integrating multiple forecasting models would improve prediction reliability, strengthen the accuracy of carbon emission estimation, and enhance the practical effectiveness of the system. Thus, the framework linked hybrid model integration, predictive performance, environmental impact estimation, and system evaluation within a unified engineering-based analytical structure.

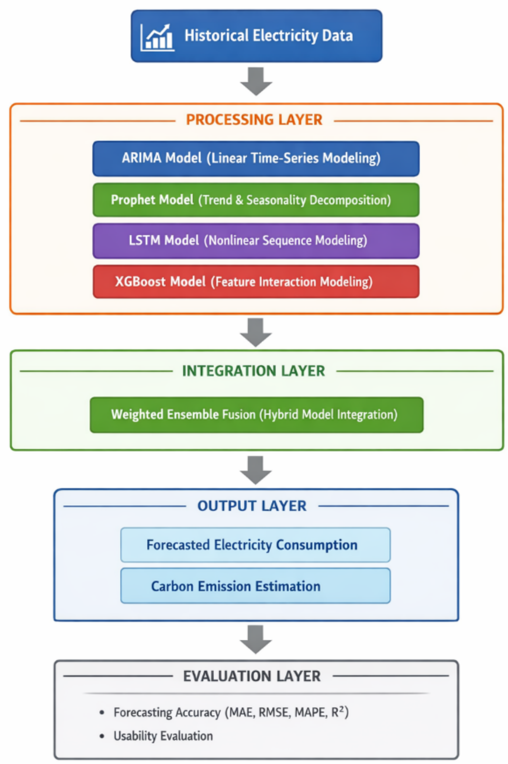

Figure 1. System Architecture Diagram

Figure 1 illustrates the system architecture of ALPro X, showing the flow of data from historical electricity inputs through multiple forecasting models, ensemble integration, and output generation, followed by system performance and usability evaluation.

Statement of the Problem

Accurate forecasting of household electricity consumption remains a significant engineering challenge due to the complex and dynamic nature of energy demand. Electricity usage patterns are influenced by seasonal variations, consumer behavior, environmental conditions, and socioeconomic factors, resulting in nonlinear and time-dependent consumption trends that are difficult to predict using traditional forecasting methods. Conventional statistical forecasting approaches often struggle to capture these nonlinear patterns and abrupt demand fluctuations, which reduces predictive accuracy and limits their effectiveness for energy planning and decision-making.

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Although advanced forecasting models such as Autoregressive Integrated Moving Average (ARIMA), Prophet, Long Short-Term Memory (LSTM) networks, and Extreme Gradient Boosting (XGBoost) have demonstrated strong predictive capabilities in electricity load forecasting, each model exhibits inherent limitations when applied independently. Single-model approaches may capture only specific characteristics of electricity demand, such as linear temporal patterns, seasonal trends, or nonlinear dependencies, thereby restricting their overall forecasting reliability under diverse consumption conditions.

Furthermore, many existing electricity forecasting systems primarily focus on predicting energy demand without integrating additional analytical capabilities such as carbon emission estimation and system usability evaluation. The absence of integrated hybrid forecasting frameworks limits the potential of predictive analytics to support sustainable energy management, environmental monitoring, and user-centered energy decision support.

In response to these limitations, there is a need to develop a hybrid forecasting system that integrates the strengths of multiple predictive models into a unified framework capable of improving electricity consumption prediction accuracy while simultaneously estimating associated carbon emissions. Such a system can contribute to more reliable residential energy monitoring and provide practical insights for sustainable electricity consumption and carbon management.

To address this need, the present study develops and evaluates ALPro X, a hybrid electricity consumption forecasting system that integrates ARIMA, Prophet, LSTM, and XGBoost into a composite predictive model. The system aims to generate accurate household electricity consumption forecasts, estimate corresponding carbon dioxide emissions, and evaluate system usability and user satisfaction to support effective energy monitoring and environmentally informed decision-making.

Research Objectives

General Objective:
To develop and evaluate ALPro X, a hybrid electricity consumption forecasting system that integrates ARIMA, Prophet, LSTM, and XGBoost for predicting household electricity consumption and estimating associated carbon emissions.

Specific Objectives:
1. To formulate a predictive equation by integrating the outputs of the ARIMA, Prophet, LSTM, and XGBoost forecasting models.
2. To generate forecasts of monthly household electricity consumption using the ALPro X hybrid forecasting model for a three-month prediction period.
3. To evaluate the forecasting accuracy of the ALPro X hybrid forecasting model using performance metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2).
4. To estimate the corresponding carbon dioxide (CO_2) emissions for the forecasted electricity consumption values using an established emission factor.
5. To evaluate the usability performance of the ALPro X system in terms of:
   a. User-friendliness
   b. Ease of navigation
   c. Responsiveness
6. To determine the overall user satisfaction with the ALPro X system in terms of:
   a. Functionality
   b. Design
   c. Usefulness
7. To validate the formulated predictive equation and the ALPro X hybrid forecasting model through expert evaluation.

Research Questions

The study sought to answer the following questions:
1. What predictive equation can be formulated by integrating the outputs of ARIMA, Prophet, LSTM, and XGBoost in the ALPro X hybrid forecasting system?
2. How accurately can the ALPro X hybrid forecasting model predict monthly household electricity consumption over a three-month forecasting period?
3. What is the forecasting accuracy of the ALPro X hybrid forecasting model in terms of MAE, RMSE, MAPE, and R^2?

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4. What are the estimated carbon dioxide (CO_2) emissions corresponding to the forecasted household electricity consumption generated by ALPro X?
5. How do users evaluate the usability performance of the ALPro X system in terms of:
   a. User-friendliness
   b. Ease of navigation
   c. Responsiveness?
6. What is the level of user satisfaction with the ALPro X system in terms of:
   a. Functionality
   b. Design
   c. Usefulness?
7. How valid are the formulated predictive equation and the ALPro X hybrid forecasting model based on expert evaluation?

Engineering Performance Hypotheses

The following hypotheses were formulated to evaluate the performance of the ALPro X hybrid forecasting system:
H1: The ALPro X hybrid forecasting model achieves a forecasting accuracy level within the acceptable threshold of Mean Absolute Percentage Error (MAPE) ≤ 10%.
H2: The ALPro X hybrid forecasting system demonstrates high predictive capability, explaining a substantial proportion of the variance in electricity consumption as indicated by the coefficient of determination (R^2).
H3: Users evaluate the ALPro X system as highly usable in terms of user-friendliness, ease of navigation, and responsiveness.
H4: Users report high satisfaction with the ALPro X system in terms of functionality, design, and usefulness.
H5: Experts evaluate the predictive equation and hybrid forecasting architecture of ALPro X as valid and suitable for electricity consumption prediction and carbon emission estimation.

METHODS

Research Design

This study adopted an engineering system design, development, and evaluation approach in the development of ALPro X, a hybrid electricity consumption forecasting system. The system was designed and implemented as an integrated predictive framework ARIMA, Prophet, LSTM, and XGBoost to generate household electricity consumption forecasts. In addition to forecasting electricity consumption, the system estimated projected electricity costs and corresponding carbon dioxide (CO_2) emissions based on predicted energy usage.

The development process included data preparation, model training, prediction generation, validation, and ensemble integration. Individual forecasts were generated using ARIMA, Prophet, LSTM, and XGBoost, and were subsequently combined through a weighted linear ensemble approach to produce the final forecast. This hybrid strategy improved predictive robustness by integrating the strengths of statistical, machine learning, and deep learning models within a unified forecasting framework.

The ensemble weights were determined through an optimization process aimed at minimizing overall forecasting error. The weights w_1-w_4 were iteratively adjusted using a validation dataset and evaluated using Mean Absolute Percentage Error (MAPE). A constrained optimization procedure ensured that the sum of all weights equaled 1 and that each weight remained non-negative, allowing proportional and interpretable contributions from each model. The final weights reflected the relative predictive performance of the individual models.

Following system development, ALPro X was evaluated quantitatively. Forecasting performance was assessed using statistical accuracy metrics, while system usability and user satisfaction were measured through a structured survey administered to household users. This approach enabled simultaneous evaluation of the system's technical performance and practical usability.

Materials, System, or Components

ALPro X consisted of four integrated forecasting models: ARIMA, Prophet, LSTM, and XGBoost. ARIMA and Prophet were applied as time-series forecasting models, while LSTM and XGBoost were used to capture nonlinear and data-driven electricity consumption patterns. The outputs generated by these models were combined using a weighted ensemble strategy to produce the final electricity consumption forecast. The resulting forecast values were used to estimate projected electricity costs and carbon dioxide emissions.

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The system utilized monthly household electricity billing records as its primary dataset. These records provided historical electricity consumption values in kilowatt-hours (kWh) and corresponding billing amounts required for model training, validation, testing, and cost estimation. Electricity rate data were obtained directly from the billing statements and used to compute projected electricity costs based on forecasted consumption values. To estimate environmental impact, a national carbon emission factor of 0.691 kg CO_2/kWh, sourced from the Department of Energy (2022), was applied. This factor was multiplied by forecasted electricity consumption values to estimate corresponding carbon dioxide emissions.

ALPro X was implemented within a Flutter-based application using Dart for the user interface. The forecasting models, including ARIMA, LSTM, Prophet, and XGBoost, were executed in a backend environment and integrated into the application. Each model was trained independently on the same preprocessed dataset, and their outputs were combined using a weighted ensemble approach. The optimized weights were determined by minimizing forecasting error. Communication between the application and the forecasting models was handled through a backend processing layer, enabling prediction results to be retrieved and visualized within the system. Source code management and version control were handled using GitHub.

Data Sources and Participants

The study involved 30 households located in Banga, South Cotabato, Philippines, selected through convenience sampling. The households were chosen based on accessibility, availability of historical electricity billing records, and willingness to participate in system testing. The participants represented residential electricity consumers capable of providing practical feedback regarding system performance and usability. The sample size was considered sufficient for preliminary system validation and descriptive statistical analysis. Monthly household electricity billing records served as the primary dataset for forecasting analysis. These records provided historical electricity consumption values in kilowatt-hours (kWh) and corresponding billing amounts, which were required for model training and validation. Electricity rate data obtained from the billing statements were used to compute projected electricity costs based on predicted consumption values.

Instruments or Engineering Tools

Two primary instruments were used in the study. The first was the system dataset, consisting of monthly household electricity billing records used for data preparation, model training, validation, testing, and forecast generation. The second was a researcher-developed usability questionnaire designed to evaluate the system in terms of user-friendliness, ease of navigation, responsiveness, functionality, design, and usefulness. The questionnaire underwent content and face validation by three experts with backgrounds in information technology, educational research, and systems evaluation. Revisions were made based on their recommendations. A pilot test was conducted to determine reliability, resulting in a Cronbach's alpha coefficient of 0.98, indicating high internal consistency. System development utilized Dart as the programming language, Flutter as the application development framework, the Flutter SDK as the primary development toolset, and GitHub for version control and collaborative system management. These tools supported interface development, data handling, model integration, visualization, deployment, and system refinement.

Data Collection and System Testing Procedures

Data collection was conducted after the completion of system development during the First Semester of Academic Year 2025–2026 in Banga National High School, South Cotabato, Philippines. Historical electricity billing records were collected and organized chronologically to ensure consistency in time-series analysis. Consumption values, billing amounts, and electricity rates were extracted and prepared for model input. For system testing, the dataset was divided using a chronological split, where earlier observations were used for model training and later observations were reserved for validation and testing. This preserved the temporal structure of the data and ensured that predictions were based solely on past observations. Forecasts were generated for a three-month prediction horizon following model training and validation.

Each forecasting model was trained using the historical dataset, and individual predictions were generated and integrated through the weighted ensemble mechanism. Ensemble weights were optimized using the validation dataset by minimizing forecasting error based on MAPE, subject to non-negativity and sum-to-one constraints. The final forecasts were used to compute projected electricity costs and carbon dioxide emissions.

The system testing workflow included:

(1) data collection and preparation;
(2) chronological dataset splitting;
(3) model training;
(4) individual forecast generation;

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(5) ensemble weight optimization;
(6) forecast integration;
(7) generation of three-month forecasts;
(8) cost and emission estimation; and
(9) comparison of predicted and actual values.

After deployment, participants interacted with the system and subsequently completed the usability questionnaire. Responses were collected, encoded, and prepared for statistical analysis.

Data Analysis

The collected data were analyzed using descriptive statistical techniques and forecasting accuracy measures. Forecasting performance was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). These metrics were calculated by comparing predicted and actual electricity consumption values. MAE measured the average magnitude of prediction errors, RMSE emphasized larger deviations through squared error computation, MAPE expressed prediction error as a percentage, and R^2 assessed the explanatory power of the model. These metrics were computed per household and summarized across the dataset. Carbon dioxide emissions were calculated by multiplying predicted electricity consumption values by the emission factor of 0.691 kg CO_2/kWh, while projected electricity costs were computed using applicable electricity rates. Survey responses were analyzed using mean and standard deviation to determine levels of usability and user satisfaction across the six evaluation dimensions. The results were interpreted using predefined descriptive categories.

Ethical and Safety Considerations

Ethical considerations were strictly observed throughout the study. Ethical approval was secured from the School Research Committee of Banga National High School prior to data collection. Informed consent was obtained from all participants, including consent for the use of household electricity billing records. Confidentiality and anonymity were maintained by removing personally identifiable information from all datasets and survey responses. Billing records were accessed only after obtaining the necessary approval and participant consent. All data were used solely for academic and research purposes, ensuring the protection of participants' rights and privacy.

RESULTS and DISCUSSION

This section presented the results of the ALPro X hybrid electricity consumption forecasting system, including the formulation of the predictive equation, forecasting accuracy, carbon emission estimation, usability performance, user satisfaction, and expert validation. Each result is discussed in relation to recent literature to strengthen theoretical and empirical grounding.

1. Predictive Equation for ALPro X

To address the first objective of the study, a hybrid predictive equation was formulated by integrating ARIMA, LSTM, Prophet, and XGBoost through a weighted ensemble mechanism:

$$\hat{Y}_t = w_1 \hat{Y}_t^{ARIMA} + w_2\hat{Y}_t^{LSTM} + w_3\hat{Y}_t^{Prophet} + w_4\hat{Y}_t^{XGBoost} + \varepsilon_t$$

where $\hat{Y}_t$ represents predicted electricity consumption at time t, w_1 - w_4 are optimized weights, and ε_t is the residual error. The optimized weights were determined through iterative adjustment on the validation dataset to minimize overall forecasting error, specifically using Mean Absolute Percentage Error (MAPE) as the optimization criterion. This procedure allowed the ensemble to assign relatively greater contribution to models with lower validation error while preserving a balanced hybrid structure.

The hybrid formulation reduced overall prediction error relative to standalone forecasting behavior by combining the complementary strengths of the component models. ARIMA captured linear temporal dependencies, LSTM modeled nonlinear and long-term consumption behavior, Prophet represented trend and seasonality decomposition, and XGBoost refined predictions through nonlinear feature interaction learning. From an engineering perspective, this hybrid architecture improved prediction stability because errors from individual models were moderated through ensemble fusion rather than being propagated independently.

This finding is consistent with recent hybrid forecasting studies. Albahli (2025) reported improved predictive performance using a hybrid approach combining LSTM and Prophet models, while Zeng et al. (2025) demonstrated enhanced optimization through Prophet-XGBoost combinations. Similarly, Sina et al. (2023) concluded that hybrid

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forecasting approaches consistently outperform individual models due to complementary model strengths and integrated methodological design. In this study, the technological innovation of ALPro X lies in integrating statistical and machine learning models into a single forecasting architecture that simultaneously supports electricity consumption prediction and carbon emission estimation.

2. Predicted Monthly Household Electricity Consumption

Table 1 presents the comparison between actual and forecasted household electricity consumption across five consumers generated by the ALPro X hybrid model.

Table 1. Prediction of Household Electricity Consumption

Consumer	MONTH	ACTUAL	FORECASTED
1	JUNE	₱ 859.85	₱ 858.24
	JULY	₱ 757.61	₱ 952.74
	AUGUST	₱ 792.87	₱ 952.22
2	JUNE	₱ 2770.51	₱ 2962.35
	JULY	₱ 3311.88	₱ 2866.55
	AUGUST	₱ 2987.75	₱ 3013.13
3	JUNE	₱ 4546.40	₱ 4884.49
	JULY	₱ 5281.27	₱ 4714.37
	AUGUST	₱ 4896.25	₱ 4900.95
4	JUNE	₱ 545.10	₱ 801.25
	JULY	₱ 996.30	₱ 854.01
	AUGUST	₱ 936.03	₱ 963.80
5	JUNE	₱ 2500.79	₱ 2983.68
	JULY	₱ 2738.94	₱ 2842.31
	AUGUST	₱ 2379.36	₱ 2879.88

The forecasted values were generally close to the actual household electricity consumption values across the five consumers. The model demonstrated stronger agreement during moderate usage periods, particularly in June, while slightly larger deviations were observed during peak months such as July. This pattern suggests that the hybrid system was able to track the general direction of consumption behavior, although high-variability periods remained more difficult to model precisely.

These deviations were expected in residential load forecasting because peak periods often reflected irregular user behavior, sudden appliance usage, or short-term demand spikes that were more difficult to capture using standard time-series patterns alone. Nevertheless, the overall forecast trend remained stable and reasonably aligned with observed consumption behavior, indicating acceptable generalization capability of the hybrid system for short-term household electricity forecasting. This finding is consistent with Wood et al. (2026), who noted that peak-load forecasting often yields higher error margins because irregular consumption spikes are inherently more difficult to represent using conventional predictive structures.

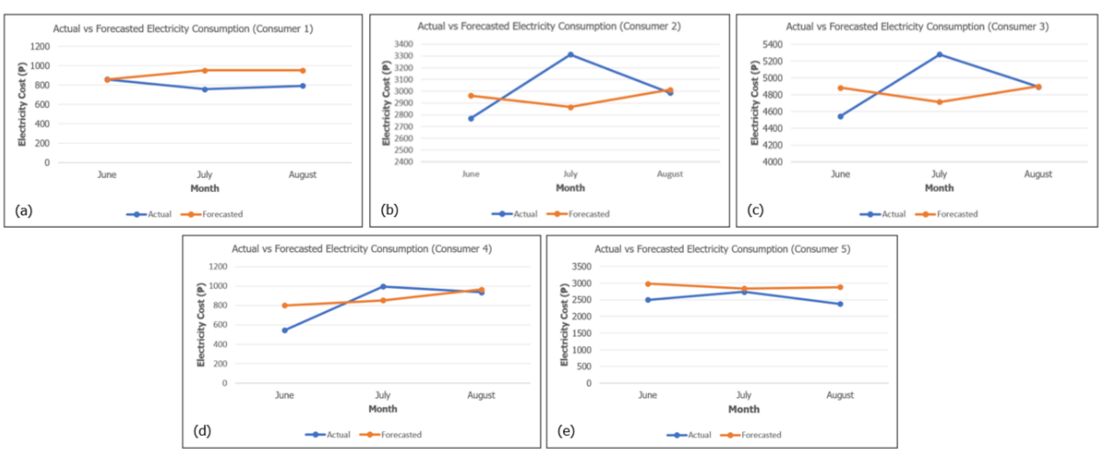

Figure 2. Actual vs Forecasted Electricity Consumption for Five Households

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Figure 2 presents the comparison between actual and forecasted electricity consumption across the three-month period for each household, illustrating the trend-following behavior and prediction deviations of the ALPro X hybrid model.

3. Accuracy of ALPro X Hybrid Forecasting Model

Table 2 summarizes the forecasting performance of ALPro X using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). These metrics were used to evaluate predicted values against actual household electricity consumption.

Table 2. Accuracy of ALPro X Forecasting Model

Consumer	Month	Actual	ALPro X	MAE	RMSE	MAPE%	R^2
1	JUNE	₱ 859.85	₱ 858.24	118.70	145.45	15.35%	-10.77
	JULY	₱ 757.61	₱ 952.74				
	AUGUST	₱ 792.87	₱ 952.22				
2	JUNE	₱ 2770.51	₱ 2962.35	220.85	280.34	7.07%	-0.59
	JULY	₱ 3311.88	₱ 2866.55				
	AUGUST	₱ 2987.75	₱ 3013.13				
3	JUNE	₱ 4546.40	₱ 4884.49	303.23	381.10	6.09%	-0.61
	JULY	₱ 5281.27	₱ 4714.37				
	AUGUST	₱ 4896.25	₱ 4900.95				
4	JUNE	₱ 545.10	₱ 801.25	142.07	169.93	21.41%	0.28
	JULY	₱ 996.30	₱ 854.01				
	AUGUST	₱ 936.03	₱ 963.80				
5	JUNE	₱ 2500.79	₱ 2983.68	362.26	405.95	14.71%	-6.39
	JULY	₱ 2738.94	₱ 2842.31				
	AUGUST	₱ 2379.36	₱ 2879.88				
			MEAN	239.61	303.14	7.82%	0.976

The model achieved an overall MAE of ₱239.61 and RMSE of ₱303.14, indicating relatively small deviations between predicted and actual electricity consumption values. The overall MAPE of 7.82% falls below the commonly accepted 10% threshold for highly accurate forecasting, indicating that the average percentage error remained within a reliable range. Moreover, the reported R^2 value of 0.976 indicates that approximately 97.6% of the variance in actual electricity consumption was explained by the hybrid model, reflecting strong overall explanatory power and model fit.

These results suggest that ALPro X achieved strong forecasting performance for short-term residential electricity monitoring. The low MAPE indicates good predictive accuracy, while the high R^2 implies that the hybrid model was able to preserve the dominant consumption pattern across households. Compared with typical forecasting benchmarks, a MAPE below 10% is generally considered highly acceptable for operational forecasting, suggesting that the model has practical utility for consumption monitoring and planning. The ensemble structure likely contributed to this performance by reducing the sensitivity of the prediction output to the limitations of any single forecasting method.

These results are comparable to recent hybrid ensemble approaches in electricity demand forecasting, which report improved predictive accuracy through model integration (Khan et al., 2021). Similarly, Sina et al. (2023) emphasized that hybrid forecasting methods enhance prediction stability and reduce variance relative to single-model approaches. In this sense, ALPro X demonstrates not only acceptable predictive accuracy but also technological value as a stable multi-model forecasting platform for energy-related decision support.

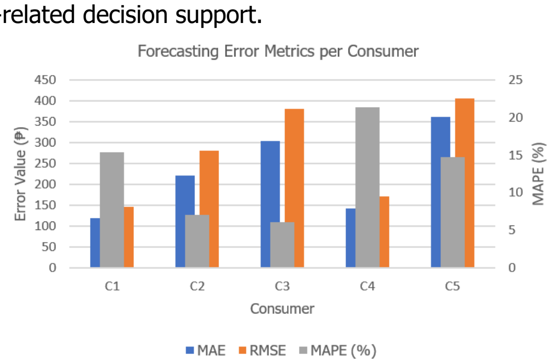

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Figure 3. Forecasting Error Metrics (MAE, RMSE, and MAPE) of the ALPro X Hybrid Model per Consumer

Figure 3 presents the forecasting error metrics (MAE, RMSE, and MAPE) per household, illustrating the variation in prediction accuracy of the ALPro X hybrid model across different consumption profiles.

4. Estimated Carbon Dioxide Emissions

Table 3 presents the estimated carbon dioxide emissions of five consumers, calculated from household electricity usage using the emission factor of 0.691 kg CO_2/kWh. Prior to carbon estimation, monthly electricity consumption in kilowatt-hours (kWh) was derived from the household billing records. Carbon dioxide emissions were then calculated by multiplying electricity consumption by the national emission factor.

Table 3. Estimated Carbon Dioxide Emissions

Consumer	Month	CO_2 Emission (Usage x 0.691 CO_2 kg/kwh)
1	JUNE	594.16 CO_2 kg/kwh
	JULY	523.51 CO_2 kg/kwh
	AUGUST	547.87 CO_2 kg/kwh
	MEAN	**555.18 CO_2 kg/kwh**
2	JUNE	1914.42 CO_2 kg/kwh
	JULY	2288.51 CO_2 kg/kwh
	AUGUST	2064.54 CO_2 kg/kwh
	MEAN	**2089.16 CO_2 kg/kwh**
3	JUNE	3141.56 CO_2 kg/kwh
	JULY	3649.36 CO_2 kg/kwh
	AUGUST	3383.31 CO_2 kg/kwh
	MEAN	**3391.41 CO_2 kg/kwh**
4	JUNE	376.66 CO_2 kg/kwh
	JULY	688.44 CO_2 kg/kwh
	AUGUST	646.80 CO_2 kg/kwh
	MEAN	**570.63 CO_2 kg/kwh**
5	JUNE	1728.05 CO_2 kg/kwh
	JULY	1892.61 CO_2 kg/kwh
	AUGUST	1644.14 CO_2 kg/kwh
	MEAN	**1754.93 CO_2 kg/kwh**

The results show that higher electricity consumption corresponded to proportionally higher carbon emissions, with Consumer 3 recording the highest mean emission and Consumer 1 the lowest. This finding reinforces the direct relationship between residential electricity consumption and household carbon footprint. From an engineering standpoint, the inclusion of carbon estimation extended the functionality of ALPro X beyond forecasting by converting predicted electricity use into an environmental impact indicator. As a result, the system functioned not only as a forecasting tool but also as a sustainability-oriented analytical platform.

This result indicates that forecasting systems can support not only operational planning but also environmentally responsive decision-making. Long et al. (2025) highlighted that residential energy use remains a significant contributor to total CO_2 emissions and emphasized the value of monitoring consumption patterns in support of decarbonization strategies. The integration of carbon estimation within ALPro X therefore extends the system's functionality beyond electricity forecasting and enhances its potential applicability in smart energy monitoring systems, sustainability analytics platforms, and household-level carbon awareness applications.

5. Usability Performance of ALPro X

Table 4 presents users' evaluation of ALPro X in terms of usability performance. The assessment covered three dimensions: user-friendliness, ease of navigation, and responsiveness.

Table 4. Usability Performance of ALPro X

Dimensions	Mean	SD	Interpretation
a. User-friendliness	4.59	0.41	Very Usable
b. Ease of Navigation	4.55	0.35	Very Usable

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c. Responsiveness	4.61	0.33	Very Usable
Overall Mean	**4.58**	**0.36**	**Very Usable**

The results indicate high usability ratings in all areas, with responsiveness obtaining the highest mean score (M = 4.61, SD = 0.33), followed by user-friendliness (M = 4.59, SD = 0.41) and ease of navigation (M = 4.55, SD = 0.35). The overall mean score of 4.58 (SD = 0.36), interpreted as Very Usable, reflects a consistently positive user perception of the system interface and functionality. The relatively low standard deviations further indicate agreement among users regarding the quality of system usability.

These findings indicate that predictive systems intended for residential decision support must be both technically accurate and operationally usable. High usability suggests that forecasting outputs, carbon estimates, and interface elements were presented in a manner that users could understand and interact with effectively. This strengthens the practical deployment potential of ALPro X for household energy monitoring and sustainability-oriented applications. Marian-Vladut et al. (2025) similarly emphasized that intuitive interface design, structural clarity, and responsiveness are significant determinants of perceived usability and continued usage intention.

6. Overall Satisfaction of Users with the ALPro X System

Table 5 presents users' overall satisfaction with ALPro X across functionality, design, and usefulness.

Table 5. Overall Satisfaction of Users with ALPro X System

Dimensions	Mean	SD	Interpretation
a. Functionality	4.50	0.38	Very Satisfied
b. Design	4.49	0.28	Very Satisfied
c. Usefulness	4.70	0.27	Very Satisfied
Overall Mean	**4.56**	**0.31**	**Very Satisfied**

The results reveal consistently high satisfaction levels, with usefulness receiving the highest mean rating (M = 4.70, SD = 0.27), followed by functionality (M = 4.50, SD = 0.38) and design (M = 4.49, SD = 0.29). The overall mean of 4.56 (SD = 0.31), interpreted as Very Satisfied, indicates that users generally held a positive evaluation of the system. The high usefulness rating suggests that users strongly perceived ALPro X as beneficial for forecasting electricity consumption and estimating carbon emissions, reinforcing its practical value as a decision-support tool.

These results are consistent with Liu (2025), who identified perceived usefulness as a major determinant of user satisfaction and technology acceptance. In engineering terms, this suggests that ALPro X was not only technically functional but also perceived as relevant and beneficial to end users. This strengthens the system's potential applicability in smart energy management systems, residential efficiency-monitoring tools, and sustainability-oriented household analytics platforms.

7. Expert Validation of the Predictive Equation and ALPro X Hybrid Forecasting Model

Table 6.1 presents the validation results of the predictive equation as evaluated by experts.

Table 6.1. Expert Validation of the Predictive Equation of ALPro X

Evaluation Criteria	*Mean*	*SD*	*Verbal Description*
Clarity of Presentation	4.67	0.58	Excellent
Theoretical Soundness	4.33	0.58	Excellent
Accuracy Potential	5.00	0.00	Excellent
Relevance to Study Objectives	4.67	0.58	Excellent
Practicality of Use	5.00	0.00	Excellent
Attainment of Purpose	5.00	0.00	Excellent
Objectivity	4.33	0.58	Excellent
Overall Mean	**4.71**	**0.29**	**Excellent**

The overall mean rating of 4.71 (SD = 0.29) indicates an Excellent level of validity, with low standard deviation values reflecting strong agreement among the experts. The highest ratings were observed in accuracy potential, practicality of use, and attainment of purpose (M = 5.00), suggesting high confidence in the predictive equation's applicability and predictive capability. All criteria received mean ratings above 4.30, indicating that the equation was clearly presented, theoretically grounded, and aligned with the study objectives. These findings are consistent with Mat Said et al. (2022),

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who emphasized that strong expert agreement and high content validity provide robust evidence of methodological soundness and applicability.

Table 6.2 presents the expert validation results of the ALPro X hybrid forecasting model.

Table 6.2. Expert Validation of the ALPro X Hybrid Forecasting Model

Evaluation Criteria	Mean	SD	Verbal Description
Model Structure Clarity	4.33	0.58	Excellent
Integration of Models	5.00	0.00	Excellent
Forecasting Accuracy	4.00	0.00	Excellent
Carbon Emission Estimation	4.67	0.58	Excellent
Usability and Applicability	5.00	0.00	Excellent
Reliability of Outputs	4.67	0.58	Excellent
Attainment of Purpose	5.00	0.00	Excellent
Overall Mean	**4.66**	**0.16**	**Excellent**

The overall mean of 4.66 (SD = 0.16) indicates an Excellent level of validity, with minimal variability among expert ratings. The highest evaluations were observed in integration of models, usability and applicability, and attainment of purpose (M = 5.00), reflecting strong expert agreement on the model's structural coherence and practical relevance. All evaluation criteria obtained ratings of 4.00 or higher, suggesting that the hybrid forecasting framework was logically integrated, reliable, and consistent with its intended function as an electricity forecasting and carbon estimation system. These findings are consistent with Sina et al. (2023), who reported that hybrid forecasting approaches outperform individual models and enhance decision-support systems through improved predictive accuracy and integrated methodological design.

Expert validation further supported the technical coherence and practical deployment potential of ALPro X as a hybrid forecasting architecture. The strong ratings for model integration and usability indicate that the platform may be extended to broader smart energy management applications, such as utility-assisted load monitoring, household energy efficiency analytics, and sustainability-oriented forecasting systems.

Conclusions

The study concluded that ALPro X was successfully developed as a hybrid electricity consumption forecasting architecture that integrated statistical and machine learning techniques, namely Autoregressive Integrated Moving Average (ARIMA), Prophet, Long Short-Term Memory (LSTM), and Extreme Gradient Boosting (XGBoost), within a unified weighted ensemble framework. This hybrid modeling approach improved forecasting reliability by combining the complementary strengths of the component models and reducing the limitations associated with single-model forecasting systems. The findings further indicated that ALPro X demonstrated strong predictive performance and served as an effective decision-support tool for residential electricity monitoring. The integration of carbon emission estimation extended the functionality of the system beyond electricity forecasting by linking predicted energy consumption with environmental impact analysis. This feature strengthened the practical relevance of the system in sustainability-oriented energy analytics. Positive user evaluations showed that the system was highly usable and well accepted, while expert validation confirmed the structural coherence, methodological soundness, and practical applicability of both the predictive equation and the hybrid forecasting model. Overall, the findings established ALPro X as a technically integrated, reliable, and practically applicable hybrid forecasting platform that may support data-driven energy management, household monitoring, and sustainability-oriented decision-making.

Recommendations

Based on the findings and conclusions of the study, the following recommendations are offered:

1. The formulated predictive equation may be enhanced through adaptive ensemble learning techniques that dynamically adjust model weights during irregular or peak consumption periods in order to further improve forecasting stability and responsiveness.
2. The ALPro X hybrid forecasting system may be applied to a larger and more diverse dataset covering longer time horizons, broader consumption profiles, and additional seasonal cycles to strengthen model generalizability and robustness.
3. Future development may consider the integration of real-time or near-real-time electricity consumption data to improve the responsiveness of the system and increase its applicability in dynamic residential energy monitoring environments.

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4. The system may be extended for deployment within smart energy management systems, utility-assisted load forecasting tools, or energy efficiency monitoring platforms to strengthen its practical engineering and industrial relevance.
5. Periodic recalibration of forecasting accuracy metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2), may be conducted to maintain predictive reliability when the system is used in real-world applications.
6. The carbon emission estimation component may be expanded by incorporating advisory functions such as projected emission alerts, energy-saving recommendations, or comparative sustainability indicators based on forecasted consumption levels.
7. Additional interface enhancements, such as interactive visualization dashboards, simplified consumption summaries, and customizable reporting features, may be incorporated to further improve user-friendliness, navigability, and decision-support value.
8. Expert validation may be extended to include a broader range of specialists in energy analytics, environmental science, software engineering, and smart energy systems to further strengthen the methodological credibility and scalability of the ALPro X hybrid forecasting platform.

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